Measuring Structural Neighborhood Effects: Using Rural Data to Help Decipher Urban Realities[1]

A large literature has emerged during the last twenty-five years that explores the presence of "neighborhood effects" on individual, family, and school outcomes—outcomes that normally involve educational attainment, cognitive skills, crime and violence, sexual behavior, or labor market success.[2] Several clear themes have emerged in analytical reviews of this literature:

1. There is some debate about which *unit of analysis* is really appropriate when speaking of a "neighborhood." Does "neighborhood" indicate a Census block group, Census tract, zip code, county, or inhabitant-defined sense of where the neighborhood begins and ends?[3] Parallel to this conversation run concerns about the method by which neighborhood attributes should be measured. The majority rely upon "structural" approaches[4] (using administratively gathered quantitative variables, like Census statistics), while some advocate "observational" approaches[5] (using the reports of trained observers), or survey approaches[6] that try to measure inhabitants' sense of the neighborhood's attributes. Some would prefer to define "neighborhood" by the linkages among the social processes that are presumed to mediate the neighborhood's attributes to

behavior outcomes,[7] but others despair of the expense and logistical difficulties of implementing this preference.[8]

2. Given a working definition of "neighborhood," there is substantial debate about the influence of family *neighborhood selection* on the measured effects of urban neighborhoods.[9] The vast majority of neighborhood-effects studies are urban studies.[10] Since families are free to choose neighborhoods within the metropolitan area, an apparent "neighborhood effect" may well be a statistical artifact of omitted-variable bias; good neighborhoods might report good outcomes only because they are filled with good parents. The neighborhood itself might be exerting little or no influence, and the measured "neighborhood attribute" may simply be the sum of the attributes of individual neighbors, not an independent exogenous force exerted upon individuals by the community.

3. Given a working definition of "neighborhood" and a means to address these selection problems, there is concern about the ways in which neighborhood, peer, family and school effects might *interact* with individuals' attributes to cause an eventual behavioral outcome. Studies that address only individual attributes, even if they include control variables for neighborhood or other contexts, risk serious mismeasurement of the attributes' influence.[11]

4. Despite these concerns, there is consensus on some important issues in each of these three methodological areas:

a. The vast majority of studies rely upon administratively-defined borders and structural measures, usually organized by Census tracts or Zip codes, and there is some sentiment that this may be the best reasonable alternative, at least in the near future.[12] The appropriate level of analysis (block-group, tract, zip code …) is probably different for different research questions.[13] Models should allow the possibility that neighborhood effects are nonlinear.[14]

b. The best hopes thus far for addressing selection issues appear to be longitudinal/time-series studies and studies that gather better data about families/individuals in order to estimate a selection model, both of which are relatively expensive options.[15]

c. Most scholars have addressed the multi-level influence issue with some version of hierarchical modeling of the mediating factors (individual, family, peer, school...) by which neighborhood/community effects might drive human outcomes.[16]

With this growing methodological consensus have come the beginnings of a consensus on the topic under study—the effects of neighborhood on behavioral outcomes. It appears that outcomes are influenced by both neighborhood relative *advantage* and relative *disadvantage*, with some evidence that advantage matters at least as much as disadvantage.[17] Neighborhood effects seem to be large enough to be significant, but are not as large as one might have expected, and probably not as important as family and peer effects.[18]

5. And now we offer some rather awkward observations: All of the resolutions reported in #4 above assume that we *know how to measure* structural neighborhood attributes. This is not the case. Collectively, studies have been criticized in literature reviews for using a hodge-podge of unevaluated approaches.[19] Some authors create scales

by adding together Likert scales.[20] Some simply include a number of individual Census measures as control variables.[21] Some add together Census variables to form a single measure.[22] Others use factor analysis to reduce Census variables to latent factors, often with a subsequent rotation in search of an intuitive interpretation of the factors.[23]

Other researchers rely on principle components analysis to create indexes of Census variables, with or without an oblique rotation to affect interpretation of the components. Many of these studies include a broad spectrum of likely variables to be placed into the principal component analysis.[24] A few authors[25] limit their principal component analysis to sub-groups of variables for which there is a theoretically coherent reason to suspect simultaneous mutual causation. Sampson et al. (1999) conduct such a principle-component analysis;[26] they also tantalizingly report that a less defensible methodology (simply summing together z-standardized Census variables, rather than forming principal components) yielded the same results.[27]

To summarize, there is no consensus about which influences should be included in neighborhood-effects modeling, nor about how to measure their influences. Some of this diversity in measures would be expected, because various analysts bring different research purposes to their work and therefore invoke different concepts and measures. But much of the lack of consensus appears to be the result of genuine inconsistency in attempting to measure the same phenomena. Jencks and Mayer (1989) were particularly pointed on this topic:

> Very few studies offer any strong theoretical or empirical rationale for focusing on one measure of a neighborhood's mean SES rather than another… What we call "mean SES" does not always measure the same thing or rank neighborhoods in the same way... Nor have investigators who experimented with several different

> measures reported the results of these experiments in enough detail for us to generalize about how the choice of one measure rather than another might affect other studies' findings… Investigators seldom report the weights they gave different neighborhood characteristics, so we cannot use their results to predict how any specific combination of neighborhood characteristics would alter children's life chances. Nor can we be sure whether the characteristics that went into the composite were weighted in such a way as to capture their full effect on the outcome of interest (125) . … Because data have been so scarce, there has never been an "invisible college" of social scientists grappling with the problems of estimating neighborhood effects, encouraging one another to use the best available analytic methods, criticizing questionable results before they reach print, or replicating important results after they are in print. Without such an invisible college, no field of inquiry makes much progress (179).

Seven years later Furstenberg and Hughes (1997) observed that there had been little progress in identifying neighborhood effects, in part because there was no consensus on which characteristics to include or how to measure those characteristics:

> Some analyses have shown correlations between certain characteristics and outcomes, while in others the associations have been weak or nonexistent. Interpreting the findings is complicated by the differences in the neighborhood characteristics employed in different studies, as well as variations in number and type of individual and family control variables… Despite the intensity of interest in neighborhood influences, the conclusion that Jencks and Mayer reached several years ago remains: Quantitative research has not demonstrated a convincing association between neighborhoods and children's development (353)… Characterizing neighborhoods requires not only greater conceptual specification; more precision in how these constructs are measured is also needed. Developing techniques to measure the properties of neighborhoods adequately is an important area for future work (360).

Writing after another seven years had passed, Pebley and Sastry (2004:33) still concluded that

> reliable methods for assessing neighborhood social and physical environments are not well developed and tested... Measurement of neighborhood characteristics is at a much more rudimentary stage of development than measurement of family processes in large-scale surveys (138).

Our Suggestion

Now consider some pairings of the five points that have been raised thus far:

a. Placing #5 next to #4 generates an obvious research question: Before trying to draw a consensus about the size of neighborhood effects, we should first work toward a consensus about how to measure structural neighborhood attributes.

b. Placing #1 next to #2 or #3 presents a major circularity obstacle: One must be able to reliably measure neighborhood effects before fixing selection and multi-level issues, but neighborhood effects can not be measured reliably without first resolving the selection issues.

c. Reading the fine print in #2 suggests a way out of this circularity: It is likely that family neighborhood selection issues will be more pronounced in urban settings than in studies of multiple dispersed small towns, each occupying a single Census tract with a single school district and a uniform property tax rate, and each located far enough from the others to minimize the potential of selection-migration between the communities under study. For this reason selection issues diminish in importance in between-community studies.[28] Small-community data, spanning an entire discrete geographic unit of analysis, can also yield measurements on units of analysis defined by the research question, less influenced by the data-collection protocols of government agencies.[29] Though the empirical estimations of a study of rural communities should not be casually interpreted as representative of urban realities, a rural-community study could establish a starting point from which to explore the proper measurement of urban neighborhood effects, and would also begin to fill a large gap in the urban-dominated literature about neighborhood effects.

How should such a small-town study proceed? The fundamental goal should be to sift the many contending proposals for the measurement of neighborhood attributes, in order to see which approaches consistently and accurately measure the underlying neighborhood realities. We are particularly intrigued by the suggestion (Sampson et al. 1999:640) that a rough-sawn measure of neighborhood attributes (summed z-standardized Census variables) was, in their case, as useful as an apparently more thoughtful measure (theoretically-grouped principal components). We propose a systematic study of the topic. With so many different specification possibilities, with uncertainty about which things the models are able to discern and where their limitations lie, and with serious policy issues at stake, the time seems ripe for such work.

The core difficulty with such a project is that one does not know in advance what the underlying neighborhood realities are, so it is difficult to recognize a precise metric when one is encountered. Researchers only observe the results of a process, and need to induce the causes and their relative magnitudes. One might hope to settle the dispute by simply seeing which model “best fits the data.” Unfortunately this is less straightforward than one might hope. As the literature review has demonstrated, many different specifications of neighborhood-effects models can be made to "work" in the sense that they generate statistical tests that tend to corroborate the specification’s validity. Given enough data and enough multicollinearity, and therefore enough Type-I error, many (substantially) insignificant factors can be made to appear (statistically) significant.

“Monte Carlo” and bootstrap simulations were meant for just such agnostic moments.[30] In such simulations the researcher creates groups of artificial but reasonable data sets; within each group the researcher *knows* which influences are significant and which irrelevant. Then various alternative specifications of a model are statistically estimated using one of these groups of data, using the same procedures that would be used if the researcher *did not know* which influences were significant. This process demonstrates which specifications of the model most frequently and faithfully report the known data-generating process.

A Word about Multicollinearity

Our primary aim is to weigh the many possible measures of neighborhood attributes, in order to identify the approaches that best measure underlying neighborhood realities. We hope to also make some modest progress on relieving the complications of selection bias by using non-urban data. A tertiary goal of a good study should be progress, however modest, on the related and thorny issue of multicollinearity's influence on the measurement of neighborhood effects. Neighborhood attributes are usually measured by more than one variable, and these variables tend to move together across observations. In such situations individual regression coefficients may be arbitrarily exaggerated by small changes in association between an independent variable and the dependent variable; thus individual coefficients are rather unreliable. In addition, regression coefficients may be individually insignificant (in the statistical sense), while being highly significant as a group; it becomes difficult to differentiate the clinically relevant variables from other less important influences, and therefore difficult to infer which interventions would actually affect the neighborhood outcomes. Sampson and Lauritsen (1994:65-66) consider multicollinearity to be the reason for the abundance of mutually-inconsistent studies attempting to document neighborhood effects.

Multicollinearity is the tuberculosis of empirical research: The symptoms can be subtle, there is no obvious diagnostic or treatment regime, and the effects of untreated multicollinearity range from annoyance to complete system failure. Jencks and Mayer (1989:177) suggest that researchers respond by including control variables for only "the most politically salient and easily understood differences between neighborhoods, such as their poverty rate and racial composition." That proposal might limit multicollinearity, but would do so at the expense of risking excluded-variables bias to the estimated coefficients. It is also the case that the variances of parameter estimates can be dramatically increased (and thus statistical significances dramatically reduced) by incorrectly deleting a variable, which raises another serious problem with this approach to multicollinearity.

Morenoff and Sampson (1997:41) exemplify another common treatment, reducing variables (13 census variables, in their case) via principal components analysis and retaining only components with eigenvalues greater than one.[31] This approach is also beset by difficulties that often are not acknowledged by researchers:

a. Unless the included variables have a defensible combined theoretical interpretation the empirical results have little meaning, and if they are not naturally measured in common units the method is difficult to justify.[32]

b. The method also quietly assumes that the coefficient on small-eigenvalue components is zero, an assumption that usually remains statistically untested and introduces unmeasured bias into the estimations. Even when tested, this assumption still results in estimators that are frequently inferior to least-squares estimators.[33]

c. Principal-component reduction of data is not guided by any underlying model (other than finding combinations of variables that maximize variance), such that the component with the least total variation (which therefore would be removed from the study) may actually have the most explanatory power in the regression.[34]

These problems are compounded when researchers transgress beyond principal-components data reduction by employing factor analysis.

Other approaches to multicollinearity (in other literatures) include formalizing the relationship among independent variables within a simultaneous-equations model, incorporating parameter estimates from external studies, and shrinking the parameter estimates towards a zero vector in hopes or reducing the mean squared error of the estimates (usually by using a ridge estimator or Stein estimator).[35]

Duncan and Raudenbush (1999:31) point out that multicollinearity should be less a problem in national or multi-site data than when studying single cities or homogeneous sites. Thus our study of dispersed small towns should have some natural immunity from multicollinearity. We also measure all independent variables in all models as unit-variance zero-mean standardized variables to mitigate the problems associated with non-uniform units of measurement and, in the process, help to control some of the potential multicollinearity in the data. For the multicollinearity that remains, one strength of the Monte Carlo technique is that it allows one to explore the relative merits of various methods of treatment. In particular, we include a “drop most variables” model and a principal-components model in our estimations.

The Monte Carlo Models

We begin with five stylized competing models[36] of the relationship between neighborhood attributes and a behavioral outcome—in our case, adolescent alcohol consumption in twenty-two rural upper-Midwestern towns. For each model, we use census data and original survey data collected from all 6th through 8th grade students in twenty-two small towns (average population 936, ranging from 319 - 2485) in four central-plains states to estimate the model parameters. We present a comparison of the apparent influence of neighborhood attributes across these estimates.

We then sequentially take each estimated model to be a virtual reality--a true data-generating process--and generate bootstrap estimates of the other models from each virtual reality's data-generating process.[37] We then draw conclusions about which models seem to be best at reporting the underlying effects we know to be in the data, without reporting false negatives and false positives.

The Data Sources

In this study, rural communities are defined as those with populations of 2,500 or fewer people, located at least 30 miles from a metropolitan area and not adjacent to interstate highways. Four states were selected from the 1999 National Household Survey on Drug Abuse (DHHS, 2000), scoring among the highest nationally in adolescent (aged 12-17) binge drinking: North Dakota (the highest nationally), South Dakota, Wyoming, and Wisconsin.[38] In addition to census data, additional information about each community was gathered by interviewing community leaders as well as adolescents.

Census data were used to determine which towns met selection criteria. Because many rural towns consolidate middle and high schools, we determined which communities had schools serving sixth through eighth grade students. The data were stratified in two additional ways, population and proximity from urban areas, resulting in a narrowed list of 360 towns (101 in North Dakota, 108 in South Dakota, 117 in Wisconsin, and 34 in Wyoming). Twenty-two communities were randomly selected from the 360, resulting in seven in North Dakota, seven in Wisconsin, five in South Dakota, and three in Wyoming.

All adolescents from the sixth through eighth grades in each community were asked to participate. The adolescent sample of 1424 6th-8th graders was 47% male and 84% Caucasian, with a mean age of 12.48 years. The response rate was 73%. Data from a randomly-selected 20% of parents of adolescents in these grades were also collected. Parent data were aggregated to serve as a reference group. Parents were asked about perceptions of their community in general, and community attitudes toward adolescent drinking in particular. All sixth through eighth grade teachers in each community were asked to participate. Community leaders in each location also included the following: two law enforcement officers, one principal, one social services coordinator, one mental health counselor, one newspaper editor, one mayor, and three members of the clergy. We identified community leaders by working with community schools and community social service agencies. The adult sample was 98% Caucasian and 42% male, with 70% having children under the age of 18. The average age was 44.03 years, ranging from 20 to 81. 31% of the adult sample were parents, 27% were teachers, and the rest were community leaders.

Data were gathered from all individuals through survey instruments. Adolescents completed the surveys during school time. Adult surveys were administered by telephone, after being informed about the project by letter. For each person (student or adult) who participated, $10.00 was donated to participating schools.

The Data-Generating Processes

Here, in detail, are the five stylized competing models, each of which typifies a standard approach to modeling in the literature we have reviewed thus far in the paper:

Model One: The Kitchen Sink Model. The Quantity-Frequency Index (QFI) index (individual average ounces of alcohol consumed per month, derived from data about beer, wine and spirit consumption, obtained from adolescent surveys following from Armor and Polich, 1982), regressed against the following individual control variables: perceptions of community controls against adolescent drinking through collective efficacy and social cohesion (YCONTROL, a principal-component reduction of ten Likert-scale survey questions developed by Sampson and Raudenbush (1999), with individual responses distanced from the community mean response; internal consistency was .86 in the adult sample (one item deleted to increase reliability), and factor loadings ranged from .57 to .76, averaging .69), perceptions of family economic hardship (YECSTRN, measured through a similar process by a seven-item instrument (Connor-Smith et al., 2000) developed for use with adolescents; internal consistency was .92 in our study, and factor loadings ranged from .77 to .88, averaging .83.), age and gender of adolescent respondent (AGE, GENDER), and (following Sampson et al. 1999 and many others) a number of Census-sourced socio-economic town status variables, entered into the equation as individual control variables. We list these variables in three groupings:[39]

- Concentrated Disadvantage socio-economic status (SES) measures: town-level child poverty rate (CHILDPOV), town family poverty rate (FAMPOV), percent of female-headed households in the town (FEMHOUS), percent of population over 16 with less than high-school education (LESHISCH), percent of population white (PERWHITE), town unemployment rate (UNEMP).
- Housing stability measures: ratio of renter-occupied to owner-occupied housing (ROVOO), change (1990-2000) in proportion of housing that is renter-occupied (CHPROPRO).
- Concentrated Advantage/Affluence measures: percent of town's adults that are high-school graduates (HIGRAD), percent who have at least a bachelor's degree (BACHPLUS), the product of town median income and town family poverty rate (CONCENTY, a standard measure of relative concentration of affluence in the town), and the town's median household income (MEDHINC).

Because of the diversity of units of measurement among these variables, we use unit-variance, zero-mean-standardized measurements for all but age and gender to ease the interpretation of the regression coefficients.

This regression, like those that follow, is a Poisson regression, because the dependent variable consists of count data that are not normally distributed. The regression takes the fixed-effect form

$$Y_{i,j} = \beta_j + \beta_1(YCONTROL_{i,j}) + \beta_2(YECSTRN_{i,j}) + \beta_3(AGE) + \beta_4(GENDER) + \varepsilon_{i,j}$$

$$\beta_j = \sum_{k=1}^{12} \beta_k (\text{SESvariabl e}_k)$$

where k runs from one to twelve, since there are twelve SES explanatory variables. Each of the j towns is allowed to have a unique regression intercept, driven by the socio-economic status variables.

Model Two: The Summed-Variables Model. The same as Model One, except that the town-specific socio-economic status variables are measured as unit-variance zero-mean-standardized variables *and then summed* within each of the three groups of SES variables, following the practice of a subset of the literature we have reviewed. Thus the model becomes

$$Y_{i,j} = \beta_j + \beta_1(YCONTROL_{i,j}) + \beta_2(YECSTRN_{i,j}) + \beta_3(AGE) + \beta_4(GENDER) + \varepsilon_{i,j}$$

$$\beta_j = \sum_{m=1}^{3} \beta_m (\text{sum} - \text{of} - \text{standardized} - \text{SESvariabl es}_m)$$

where *m* runs from one to three, since there are three categories of standardized SES variables over which the model sums: concentrated disadvantage, housing stability, and concentrated advantage.

Model 3: The Principal Components Model. The same as Model One, except that rather than summing within the three categories of SES variables, the data in each group are reduced by principal components analysis (again, following a subset of the literature we have reviewed). We retain in the analysis all components with engenvalues greater than unity. In our case this resulted in two Concentrated Disadvantage components (PC1A1 and PC1A2), a single Housing Stability component (PC1C1), and two Concentrated Advantage components (PC1D1 and PC1D2).[40]

Model 4: The Without-Concentrated-Advantage Model. The same as Model One, with the Concentrated Affluence/Advantage variables removed as a way of evaluating the claims made in some parts of the literature that inclusion of relative advantage is important.

In order to explore an approach that has appeal in some circles but has not been common in the literature, we also include the following model:

Model 5: The History/Expectations Model. Like Model 3, except instead of forming principal components from static, time-blind Census-sourced SES variables, we form principal components for categories of variables that have commonly been used as leading or lagging indicators of SES: *Recent Past SES Stress* (a single component emerged, PC2A1, reflecting % population change, 1990-2000, and % of 2000 housing stock built since 1990[41]), *Current SES situation* (four components, PC2B1-4, reducing median household income, child poverty rate, % female-headed households, % of housing costs in typical family income, % of adults in the labor force, civilian unemployment rate, % of families employed in farming, forestry or fishing, % of adult population with high-school diploma, % of population with at least a bachelor's degree, % of population older than 16 with less than high-school education[42]), *and an index of perceived future SES prospects* in the town (a single principal component, PC2D1, reducing answers by adults to four questions indicating the likely future prospects of the town).[43] We first estimate each of these five models, saving the predicted dependent variable values (YHAT1, YHAT2, …, YHAT5) for use in the bootstrap simulations.[44] The estimation results, which are considered five separate potential data-generating processes in the simulations that follow, are presented as the first element in Tables 1, 2, 3, 4 and 5.

Estimations for the Data-Generating Processes

In most papers, the regressions that we are calling "data-generating-process" regressions would be the main focus of the paper, as they are estimates of the relationship between the dependent variable and various potential independent variables. In this study these regressions are not our principal interest; they form a series of virtual realities, and our main interest is in seeing which of the various model specifications that has been suggested in the literature will do best at correctly identifying the features of each known virtual reality. However, the results in the data-generating-process regressions do merit some review in their own right.[45] First consider the coefficients on the first four variables, reflecting the influence of social control, family economic strain, and adolescent's age and gender. The results across the various models are virtually identical, and the directions of influence are roughly what one would expect. Adolescent drinking is negatively related to social control and positively related to age. Family economic strain has the expected positive association with drinking, though the effect is not statistically significant; the same can be said of the gender-related coefficients.

Now consider the various measures of model goodness-of-fit. The reported R^2 is rather low in all regressions, which we attribute in part to the linear, non-hierarchical simplicity of the models.[46] As a check on the importance of modeling nonlinearity, we conduct a link test for model specification, which all but Models 02 and 03 pass.[47]

Finally, consider the coefficients on the socio-economic status variables. The models that report coefficients for individual variables (Models 01 and 04) tell a consistent story: heavier drinking is associated (by statistically-significant coefficients) with higher child poverty rates, higher unemployment rates, and larger ratios of renter-occupied to owner-occupied housing. Each model reports some association between heavier drinking and *more* educational attainment in the town; Model 01 reports a significant positive coefficient on the proportion with high-school diplomas, and Model 04 reports a negative coefficient on the proportion with less than a high-school diploma. Both models report a significant positive coefficient on the percent of the town that is white, though the coefficient is statistically significant in Model 04 only.

We can compare the effects of the socio-economic variables across the first four models by comparing the reduced-data coefficients of models 02 and 03 to the linear combinations of the underlying coefficients that we have calculated for models 01 and 04. Models 01 and 04 report statistical significance for sums of grouped SES variables only in the case of the concentrated-disadvantage variables. Though Model 02 finds coefficients with the same signs for these grouped influences, the pattern of statistical significance is reversed: only concentrated disadvantage and housing stability are statistically significant. In Model 03, both concentrated-disadvantage components are statistically significant and bear the same sign as the other regressions. The housing-stability coefficient is not statistically significant, and the coefficients on the two concentrated-advantage components are statistically significant *but mutually offsetting*, such that their sum fails a test for a significant difference from zero. Taken together, these results may raise some cautions for researchers who measure relative advantage with a single data-reduced variable, since the estimations that took this approach were the estimations that failed a test for nonlinearity and also appear to fail in reporting underlying significance for concentrated advantage.[48]

We have not yet discussed the SES coefficients from Model 05. They are not directly comparable to the other models since the SES variables are grouped dynamically (past, present and future influences) and contain different underlying variables than the other equations (including survey information about expected future prospects of the towns). But we do note that expectations about the future are statistically significant (with a larger coefficient and more statistical significance than the "past" or "present" measures), with more-positive expectations associated with less adolescent drinking. To the extent that this is an important influence on adolescent drinking, it is measured in the other models only in the most indirect of ways, if at all.

The Bootstrap Estimations

Because the dependent variables involve count data that are expected to follow a Poisson distribution, we conduct the simulations as bootstrap estimations, rounding all models' predicted values to non-negative integers before proceeding. We then do bootstrap estimations using each model's predicted values to estimate all of the other models' parameters for each data-generating process.[49] Thus, for example, Table One presents the data-generating process derived from Model One, followed by the four bootstrap simulations in which the other four models were estimated using predictions from Model One as their dependent variable.

As a primer in reading the tables, consider the first two regression reports in Table One. The initial Poisson regression reports that the coefficient on STDYECSTRN, the measure of family economic strain, is 0.0654961 (in the second line of the table's coefficients). The next panel of Table One, titled "Bootstrap results, Model 0102," reports results of a bootstrap simulation using dependent-variable forecasts from Model 01 as the dependent variable when estimating coefficients for Model 02. This simulation resulted in a coefficient on STDYECSTRN of 0.0480802. The 95% confidence interval for this estimate, reported at the right end of the first line of the panel, is (0.0051532 , 0.0910071). Since the true data-generating coefficient of 0.0654961 is captured within that confidence interval, we score a success for Model 2 in estimating this coefficient when it confronts data generated by Model 1. By reviewing all of the possible pairings of true coefficients with estimation confidence intervals, we aim to identify which models are generally the most successful in reporting reliable regression coefficients. If a simulation's 95% confidence interval for a particular coefficient does not contain the true underlying parameter, we score the model a failure for that coefficient, and as a measure of the severity of the failure we will sometimes mention the percentage difference between the true coefficient and the closest endpoint of the simulation's 95% confidence interval.[50]

There is one difficulty in comparing regression coefficients across different models in this way. Some of the models report individual coefficients for a variety of independent variables, and others report fewer coefficients for data-reduced components reflecting groups of influences (relative disadvantage, housing stability, and relative advantage). To make the estimations comparable, after each simulation that reports results for individual variables we present the results of a hypothesis test that sums the individual underlying coefficients into a single reduced coefficient while appropriately computing the true standard deviation for that reduced coefficient. We have labeled these reduced coefficients as DISADVANTAGE, HOUSE STABLE, and ADVANTAGE throughout the tables. Thus we can compare the coefficients on STDYCONTROL, STDYECSTRN, YAGE, YGENDER, DISADVANTAGE, HOUSE STABLE, and ADVANTAGE across models.[51] We present those estimates in **boldface** in each panel. One can still, of course, compare the accuracy of some individual-variable coefficients across some of the models.

Using this approach we aim to identify the models that are generally most successful at reporting accurate coefficient estimates. But there is a second standard by which one model might be judged superior to others: not individual parameter estimates, but overall goodness-of-fit and ability to forecast the dependent variable. We have therefore included several goodness-of-fit measures for comparison across models. Near the top of each panel we report the model's chi-squared statistic, the four-decimal-point probability value for that statistic, the model's pseudo-R^2, the log-likelihood for the estimation, the mean squared error, the mean absolute percentage error, and the probability value for the chi-squared statistic. At the bottom of each table we report the AIC and BIC alternatives to the pseudo-R^2 measure of goodness of fit. Models that fit well and forecast well will generally have larger chi-squared statistics and pseudo-R^2 values; the other reported statistics will be smaller as fit and forecasting ability improve.

We now discuss the estimation results, proceeding through the tables from first to last. In each case we follow the same outline, first discussing the models' goodness of fit and ability to forecast, then the coefficients on the independent variables.

Table One: The Kitchen Sink data-generating process.

We note that Model 04, the Kitchen Sink model less its concentrated disadvantage variables, dominates the other models on goodness-of-fit and forecasting measures. Model 04 (and Model 02) perform well on coefficient estimates for the first four independent variables. But Model 04 runs into serious difficulty in estimating coefficients on the SES independent variables. For example, *family poverty rate* is given a statistically significant incorrect sign; the *less than high school* variable's confidence interval is smaller than the true coefficient by 300%, and *percent white* is over-estimated by nearly 100%. The summed coefficient for the concentrated-disadvantage coefficients is high by over 50%, relative to the same summed coefficient for the data-generating process. It appears that deletion of the data-generating process' concentrated-advantage variables has led to serious omitted-variables bias for the coefficients that remain.

By comparing the coefficient estimates for the other models, we judge that Model 02 outperforms the others, presenting no false-positive or false-negative results, no errors in coefficient signs, and having all confidence interval bounds falling within about 20% deviations from the true underlying coefficients. Though it is difficult to directly compare Model 05 to all elements of the data-generating process, the model certainly is defensible, with goodness-of-fit measures near the other models' findings and very reasonable coefficients for the first four independent variables, which all the models share. Note that only the current variables appear to be statistically significant in this estimation.

Though Model 04 outperforms Model 02 on goodness-of-fit measures, we judge that Model 02 would be the better specification because its goodness-of-fit measures are still defensible and because forecasting is less important in this context than forming policy prescriptions by accurately measuring the importance of various SES influences. We will encounter a similar situation for the *Without Relative Advantage* model data generating process (below); in both cases the standard goodness-of-fit measures appear to be unreliable metrics for choosing a specification, if accurate coefficient estimates are important. Model 05 is again difficult to directly compare to the others, but we do not see an obvious disqualifier in its results.

Table Two: The Summed Variables Model.

In this case, Model 02 is generating the data, and we are fitting the other four models to Model 02's forecasts. We note that Models 01 and 04 are virtually indistinguishable for the best goodness-of-fit measures. All four models do well on estimating coefficients for the first four independent variables. Models 01 and 04 do better than the other options on the remaining SES-variable coefficients, but both models do rather badly, with confidence intervals for concentrated advantage and housing stability that are 100%-450% too large. With none of the simulation specifications performing terribly well, we judge that Model 02's specification would be the safest to choose when faced with data generated by an unknown data-generating process. Model 05 remains a possibility with no obvious disqualifying results.

Table Three: The Principal Components Model.

Here Models 01 and 04 have the best goodness-of-fit measures (though all the models' measures fall in a relatively tight band). All models do well for estimating the first four independent-variable coefficients. For the concentrated disadvantage variables, the best estimations are in Model 01 and 02; for housing stability, Model 04 and 02; for concentrated advantage, Model 04 and 02. Taken together, we judge that Model 04 or Model 02 would be the safest choice for an unknown data-generating process. Model 05 again presents no obvious disqualifications.

Table Four: The Without-Concentrated-Advantage Model.

Here Model 01 performs best on all goodness-of-fit measures, but again presents unreliable SES coefficients, including a "false positive" result for the community's proportion of high-school graduates. Strikingly, the full "kitchen sink" approach of Model 01 is outperformed by Model 02, which reduces the same variables into grouped sums. In the presence of multicollinearity small correlations among variables can lead to large, spurious changes in coefficient estimates, and it appears that in this case data-reduction can outperform models that retain all of the original variables. Model 02 appears to have the most reliable estimates among the data-reduction approaches, and we again judge it to be superior to Model 01. There are again no obvious disqualifications for Model 05.

Table Five: The History/Expectations Model.

Model 01 has the best overall goodness-of-fit measures, though by the BIC standard Models 02 and 03 are better. All models do well at estimating the first four independent-variable coefficients. It is difficult to compare the simulations to Model 05's coefficients for the remaining SES variables, since Model 05 groups those variables so differently than the other models, and includes variables not present elsewhere. Thus we judge the quality of the models to be essentially indistinguishable for part of the competition.

Conclusions

We have suggested that Monte Carlo simulations based on small-town data offer a promising approach as a starting point for resolving some stubbornly difficult issues in the measurement of neighborhood effects. We presented five models that typify the major contending approaches to neighborhood-effects measurement: including a long list of socio-economic status variables, including the same variables as unit-variance zero-mean-standardized variables that are summed within three categories (concentrated disadvantage, housing stability, and concentrated advantage), including the same variables as reduced principal components rather than sums, returning to the first approach but deleting the relative-advantage variables, and forming principal components from variables that measure past, present and expected future SES realities. We then estimated all five models with small-town data, and used forecasts from those estimations to conduct Monte Carlo bootstrap investigations of the reliability of each model when confronting data for which it is known to be mis-specified.

Contrary to our initial expectations, the wisest choice of model specification appears to be the second option, a model that relies upon standardized variables that are summed within categories. In the presence of multicollinearity, common in neighborhood-effects studies, small correlations among variables can lead to large, spurious variability in coefficient estimates; it appears that in our case data-reduction can outperform models that retain all of the original variables, and it appears that a simple summing of standardized variables can be a better approach to data reduction than principal components approaches.

In brief, the approach begins by organizing socio-economic status variables into three categories: concentrated disadvantage, housing stability, and concentrated advantage.[52] The individual variables are then standardized into zero-mean, unit-variance variables, *and then summed* within each of the three groups of SES variables. Thus only three "explanatory SES variables" enter the regression, rather than the host of individual SES variables that the sums represent.

We also find that the last model, involving time-oriented categories of variables, performs well but is different enough from the other models that it is difficult to evaluate them by a common standard. We note that expectations about the future are statistically significant in this model, and that such expectations are measured in the other models very indirectly if at all. When a well-performing model finds statistically-significant influences that other models do not consider, we take it as evidence that this new model should be used in tandem with the summed-variables model that also performed well in our simulations. Together, the two approaches can give a more full-orbed measurement of the effects of neighborhoods.

Our simulations also raise cautions for researchers who do not include relative advantage variables when estimating neighborhood effects, or who measure relative advantage with a single data-reduced variable.[53] More than once the simulations also indicate that standard goodness-of-fit measures like R^2 appear to be unreliable metrics for choosing a neighborhood-effects specification if accurate coefficient estimates are important.

This work is, of course, a limited initial study in the proper measurement of neighborhood effects. Our data consider a limited number of upper-plains communities with a limited representation of minority groups, and similar simulations should be pursued in a variety of other settings. But we argue that these apparent limitations of rural communities have allowed the opening of a methodological door for studying which approaches to measurement of neighborhood effects will normally yield the most reliable results, whether applied to rural or urban situations.

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Endnotes

[1]
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[2] The literature is reviewed by Duncan and Raudenbush (1999); Jencks and Mayer (1989); Leventhal and Brooks-Gunn (2000); Pebley and Sastry (2004); Sampson, Morenoff, and Gannon-Rowley (2002).

[3] The issues is reviewed by Burton and Jarrett (2000) and Coulton (1997:372-373).

[4] For examples, see Baumer et al. (2003); Bellair, Roscigno, and McNulty (2003); Booth and Crouter (2001); Brooks-Gunn et al. (1993); Bursik and Webb (1982); Caughy, O'Campo, and Muntaner (2003); Cotterell (1986); Coulton, Korbin, and Su (1996); Cubbin et al. (2005); English et al. (2003); Kubrin and Herting (2003); Morenoff and Sampson (1997); Perez-Smith, Spirito, and Boergers (2000); Simons et al. (2002); Smart, Adalf, and Walsh (1994); South, Baumer, and Lutz (2003); Wooldredge and Thistlethwaite (2003). Rankin and Quane (2002) also include questionnaire results to form a measure of collective efficacy. Wen, Browning, and Cagney (2003) use census tracts and larger "neighborhood clusters." Culton, Korbin, and Su (1999) use Census block-groups.

[5] Observational approaches are reviewed by Pebley and Sastry (2004:126ff); encouraged by Duncan and Raudenbush (1999:38); employed by Mauke and Fried (2000).

[6] Sampson, Morenoff, and Earls (1999) take a survey approach to intergenerational closure, reciprocal exchange and social control; additional examples include Bowen, Bowen, and Ware (2002); Brook, Nomura, and Cohen (1989); Cantillon (2006); Chaiken (2000); Coulton, Korbin, and Su (1996***)***; Jackson (2003); Moore (2003); Pebley and Sastry (2004:125); Pretty, Rapley, and Bramston (2002). Jang and Johnson (2001) also include structural and observational measures; Sampson et al. (1999) also include structural Census variables; Browning and Cagney (2003) combine survey results with Census variables to measure collective efficacy.

[7] See Pebley and Sastry (2004:126) for a review; see also Sampson and Lauritsen (1994:78-79).

[8] For example, Duncan and Raudenbush (1999:29).

[9] For examples, see Bayer and Ross 2006; Duncan and Raudenbush 1999:29-30, 36; Harding 2003; Jencks and Mayer 1989:126, 119; Pebley and Sastry 2004:129; Tienda 1991:245, 247, 255.

[10] Cotterell (1986) and Terluin (2003) are exceptions.

[11] Jencks and Mayer 1989:123-124, 178.

[12] Coulton 1997:373; Furstenberg and Hughes 1997: 353, 365; Jencks and Mayer 1989:179; Pebley and Sastry 2004:123, 126.Even studies that try to get beyond structural measures are in some sense built on the structural measures. Basic structural studies have identified the relationships between neighborhood attributes and behavioral outcomes; these are then plumbed by explorations of social realities that mediate neighborhoods' influences.

[13] Furstenberg and Hughes 1997:356.

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[14] Jencks and Mayer 1989:121-122, 177-178.

[15] See Booth and Crouter 2001:17; Duncan et al. 1998:406-407; Duncan and Raudenbush 1999:31; Furstenberg and Hughes 1997:357-358; Jencks and Mayer 1989:119-120; Pebley and Sastry 2004:130; Reiss 1995; Tienda 1991:252. Bellair et al. (2003) use county-level census data to mitigate selection effects; Harding (2003) uses propensity score matching with sensitivity analysis. The "Moving To Opportunity" voucher system has also allowed some quasi-experimental estimations of neighborhood effects; see e.g. Goering (2003) and Kling, Liebman, and Katz (2005).

[16] For examples, see Bellair et al. 2003:20ff ; Browning and Cagney 2003; Cho, Gimpel, and Dyck 2006; Coulton et al.1999; Duncan and Raudenbush 1999:34; Lee and Bryk 1989; Leventhal and Brooks-Gunn 2000; Rankin and Quane 2002; Sampson et al.1999; Simons et al. 2002; Wen et al.2003. Bowen et al. (2002) use structural-equations modeling; Brook et al. (1989) include canonical correlation analysis with their hierarchical modeling.

[17] Coulton 1997:374-375, 381; Leventhal and Brooks-Gunn 2000; Leventhal and Brooks-Gunn 2003a, 2003b:28; Pebley and Sastry 2004:127-33; Sampson et al. 1999.

[18] Browning and Cagney 2003; Furstenberg and Hughes 1997:346, 354; Harding 2003; Pebley and Sastry 2004:132.

[19] Nechyba, McEwan, and Older-Aguilar 1999:7.2.2; Sampson and Lauritsen 1994:65.

[20] For example, Booth and Crouter 2001; Wen et al. 2003.

[21] Brooks-Gunn et al.1993; Cotterell 1986; Smart et al. 1994. Moore (2003) includes Likert-scale measures of perceptions with Census SES measures in logistic regression.

[22] Baumer and South (2001), Rankin and Quane (2002), and South et al. (2003) sum standardized variables; Simons et al. (2002) form “community clusters” via cluster analysis, sum four Census proportion measures with per-capita income for each block group in each cluster, then find a weighted average of block-group results to measure the cluster’s community disadvantage; Caughy et al. (2003) average standardized variables to generate Census block-group factor scores, citing Korbin and Coulton (1997); Smart et al. (1994) use cluster analysis of z-scored Census variables; Sampson et al. (1999) average standardized variables, but also use principal-components analysis independently.

[23] Brook et al. 1989; Browning and Cagney 2003; Kubrin and Herting 2003; Lee and Bryk 1989; Morenoff and Sampson 1997; Perez-Smith et al. 2002; Sampson and Lauritsen 1994:67. Rankin and Quane (2002) employ factor analysis, but also simply sum Census variables for some measures; Bowen et al. (2002) reduce survey scales via factor analysis before their structural-equations modeling.

[24] Baumer et al. 2003; Sampson and Lauritsen 1994:48; Sampson, Raudenbush, and Earls 1997; Wooldredge and Thistlethwaite 2003. See also Booth and Crouter (2001), who combine principle-components analysis with two of the previous methods, all in the same regressions. Bickel and McDonough (1997) employ principal components analysis, and also include individual Census variables in the same regressions.

[25] Booth and Crouter 2001; Sampson et al. 1997; Sampson et al.1999. See Kennedy (2003:211-212) for a principled argument in favor of this approach. In its pure form, this approach requires that the variables in the principal component analysis also be measured in common units, or at least be standardized to have unit variance, a requirement often

overlooked in this literature. In any event, principal components analysis still inevitably requires that presumed information about relationships among the estimated parameters is being brought into the estimations, very often with no justification; it also is theoretically weakened by the fact that there is no necessary relationship between the order of the principal components and the extent to which they are correlated with the dependent variable (Kennedy 2003:215; Maddala 1992:289, 285). Because principal components are by definition orthogonal, a rotation of components to aid in interpretation, though sometimes reported in the literature, makes no sense.

[26] Their work involves both Census variables and self-reported impressions of neighborhood characteristics and boundaries.

[27] Sampson et al.1999: 640.

[28] Sampson and Lauritsen 1994:78-79.

[29] See Sampson and Lauritsen (1994) 86 for a discussion of the importance of this possibility. Goux and Maurin (2006) take an approach that is in some ways similar, arguing that several institutional features of France enable a clever resolution of the neighborhood-choice and arbitrary-size-of-administratively-defined-measurement-area problems.

[30] Since this appears to be the first use of Monte Carlo simulations in this literature, we provide a brief primer in Appendix One.

[31] Some variables appear in more than one component. Factor loadings are constrained to be stable over time. The authors still retain several additional independent variables not included in the principal components reduction.

[32] Kennedy 2003:211-212.

[33] Judge et al. 1980:470.

[34] Kennedy 2003:215.

[35] Kennedy 2003:211-212.

[36] These five represent stylized versions of the main families of models we have encountered in the literature review presented earlier in this paper. We have not considered hierarchical models, nor the more exotic suggestions for addressing mluticollinearity, considering them to be worthy of a paper in their own right since they can not be appropriately addressed until some of the basic issues taken up in this paper are resolved. Creating Monte Carlo data for multicollinearity studies is not straightforward, and even afterward ridge regression/Stein estimators are not subject to hypothesis testing (Kennedy 2003:215-16).

[37] We use bootstrap estimates rather than Monte Carlo estimates from multiple randomly-generated data sets because the bootstrap is preferred when errors can not be presumed to be normally distributed. Since our dependent variable measures ounces of alcohol (derived from data about beer, wine and spirit consumption) ingested per month per person, we expect a Poisson distribution.

[38] Because of the number of individual, family, and community-level variables, it was important to hold aspects of the broader context as constant as possible. Hence our use of relatively similar northern-plains states.

[39] In later estimations we will reduce the number of variables within each grouping by summing or conducting principal component analysis.

[40] The relative-disadvantage variables are (unit-variance, zero-mean standardized in all cases): child poverty rate, family poverty rate, proportion of female-headed households,

proportion with less than high-school education, proportion non-minority, and unemployment rate. PC1a1 has an eigenvalue of 2.49, and loads these variables with coefficients of 0.42, 0.32, 0.50, -0.42, -0.27, and 0.46. PC1a2 has an eigenvalue of 1.72, and factor loadings of -0.39, 0.58, 0.18, -0.39, 0.46, and -0.33. PC1c1 has an eigenvalue of 1.01, and factor loadings of -0.70 (STDROVOO) and 0.71 (STDCHPROPRO). PC1D1 and PC1D2 have eigenvalues of 2.42 and 1.22, and the following factor loadings: proportion high-school graduates, 0.30 and 0.74; percent with more than bachelor degree, 0.36 and -0.67; measure of concentrated income, 0.63 and 0.01; median household income, 0.62 and 0.02.

[41] Eigenvalue 1.73, scoring coefficients 0.707 and 0.707.

[42] Eigenvalues 2.98, 2.55, 1.20 and 1.05. Scoring coefficients: First component: .36, .05, .33, .20, .38, .25, -.01, .38, .27, -.53. Second: -.31, .58, .26, -.17, -.11, .43, .39, .20, -.28, .04. Third: -.07, -.04, .03, -.40, .26, -.05, .55, -.44, .51, -.11. Fourth: -.35, .14, .03, .67, -.28, .20, -.05, -.36, .38, -.12.

[43] Questions for the measurement of future prospects of each town, each on a five-point Likert scale from “strongly disagree” to “strongly agree:” 1. I think in ten years this community will be bigger and better than it is now. 2. Sometimes I worry about the future of this community, in terms of how it is doing economically. 3. I sometimes wonder if this community will even be around in the future. 4. The problems and challenges facing this community can be solved. Eigenvalue for component: 2.25. Component scores: .56, .48, .55, .38.

[44] We do not include a set of bootstrap simulations that directly evaluate claims about the importance of specifying models as nonlinear, as this is unimportant in our case (in which

we will *know* the true data-generating process in our simulations) and would add a level of complexity that could cloud the main goal of our work. But we do note in passing that, in our estimations of the five basic models from the actual town-level data, we conducted an omitted-variables test that regresses the dependent variable on the regression residuals and the squared residuals, a common test for omitted non-linearity. The estimations of the majority of models (Models One, Four and Five) indicate that non-linearity is not an issue. That non-linearity issues only emerge in the models that reduce individual variables by summing or finding principal components (Models Two and Three) may indicate that data reduction creates a need to think more carefully about modeling non-linearity.

[45] Because our models are quite diverse, it is difficult to draw their data-generating estimations together into a single table as would be common in non-Monte-Carlo studies. We therefore will draw the results together, from across the first panels of Tables 1 through 5, in prose.

[46] Since these are the data-generating processes for later simulations, the estimations' R^2 statistics are not particularly important; the low R^2 values are also tempered by the fact that all models easily pass Chi-squared goodness-of-fit tests, with probability values of zero to the fourth decimal place, and report AIC and BIC goodness-of-fit measures that are very similar.

[47] Some of the data that we have collected for these towns offer stronger correlations to adolescent drinking, but we have not included these variables in an attempt to conform to the rest of the literature on neighborhood effects. For example, our measure of parental

closeness to the adolescent reports r=-0.16, and our measure of the adolescents' perception that other teens are drinking yields r=0.20.

[48] For this reason, in the simulations that follow we retain all of the components in Model 03 when creating the dependent variable for the bootstrap simulations, rather than reducing the components to single indexes of concentrated advantage and concentrated disadvantage.

[49] Because we estimate statistics and coefficients with variances that may be a function of the parameter of interest, we present *bias-corrected and accelerated* bootstrap estimates, whose confidence intervals are expected to have better coverage probability than percentile, normal, or simple bias-corrected estimates in such a circumstance.

[50] One might also report a "false positive" if a simulation reports a statistically-significant coefficient on a variable that was statistically insignificant in the data-generating regression, and a "false negative" if the simulation reports no statistical significance for a coefficient that was statistically significant in the data generating process regression.

[51] Since Model 5 does not use the disadvantage-housing stability-advantage groupings of variables, we can only use the first four coefficients in comparisons involving Model 5.

[52] Standard underlying disadvantage variables would include child poverty rate, family poverty rate, percent of female-headed households, percent of population over 16 with less than high-school education, percent of population white, and unemployment rate. Housing stability measures include ratio of renter-occupied to owner-occupied housing, and changes in the proportion of housing that is renter-occupied. Concentrated Advantage/Affluence measures include percent of town's adults that are high-school graduates, percent who have at least a bachelor's degree, the product of town median

income and town family poverty rate (a standard measure of relative concentration of affluence in the town), and the town's median household income.

[53] The estimations that took this approach were the estimations that failed a test for nonlinearity, and they also appear to fail in reporting underlying significance for concentrated advantage.

Table One

Poisson regression		Number of obs	= 594
		LR chi2(16)	= 253.65
		Prob > chi2	= 0.0000
Log likelihood = -1222.127		Pseudo R2	= 0.0940

Y30DUSE2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
STDYCONTRL	**-.1958132**	**.0439464**	**-4.46**	**0.000**	**-.2819467**	**-.1096798**
STDYECSTRN	**.0654961**	**.0418565**	**1.56**	**0.118**	**-.0165412**	**.1475334**
YAGE	**.264866**	**.0477374**	**5.55**	**0.000**	**.1713023**	**.3584297**
YGENDER	**.0783191**	**.0877134**	**0.89**	**0.372**	**-.093596**	**.2502342**
STDCHILDPOV	.6440694	.1489471	4.32	0.000	.3521385	.9360003
STDFAMPOV	-.0483271	.4264156	-0.11	0.910	-.8840862	.7874321
STDFEMHOUS	-.1275209	.0962098	-1.33	0.185	-.3160887	.0610469
STDLESHISCH	-.0943051	.1673381	-0.56	0.573	-.4222817	.2336716
STDPERWHITE	.2604457	.1494198	1.74	0.081	-.0324117	.553303
STDUNEMP	-.476424	.0826108	-5.77	0.000	-.6383382	-.3145098
STDROVOO	.1521673	.0619579	2.46	0.014	.0307321	.2736025
STDCHPROPRO	-.025701	.0729721	-0.35	0.725	-.1687237	.1173217
STDHIGRAD	.3367808	.1133031	2.97	0.003	.1147108	.5588509
STDBACHPLUS	.1944857	.1351461	1.44	0.150	-.0703958	.4593671
STDCONCENTY	.4665657	1.352155	0.35	0.730	-2.183609	3.116741
STDMEDHINC	-.3685751	1.217789	-0.30	0.762	-2.755399	2.018248
_cons	-3.927228	.6375171	-6.16	0.000	-5.176738	-2.677717
DISADVANTAGE	**.157938**	**.5738291**	**0.28**	**0.783**	**-.9667464**	**1.282622**
HOUSE STABLE	**.1264663**	**.1025523**	**1.23**	**0.218**	**-.0745324**	**.327465**
ADVANTAGE	**.6292571**	**.2945594**	**2.14**	**0.033**	**.0519313**	**1.206583**

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-1348.95	-1222.127	577	2478.254	2552.831

Bootstrap results, Model 0102		Number of obs	= 594
		Replications	= 1200
		Wald chi2(7)	= 371.09
		Prob > chi2	= 0.0000
Log likelihood = -598.64526		Pseudo R2	= 0.1402
mse0102 = .39243074	mape0102 = .44671643	signif0102 = 3.760e-76	

YHAT1	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2642396**	**.032254**	**-8.19**	**0.000**	**-.3274563**	**-.201023**
STDYECSTRN	**.0480802**	**.0219019**	**2.20**	**0.028**	**.0051532**	**.0910071**
YAGE	**.3197367**	**.0280401**	**11.40**	**0.000**	**.2647792**	**.3746942**
YGENDER	**.0808276**	**.0594253**	**1.36**	**0.174**	**-.0356438**	**.1972989**
DISADVANTAGE	**.1037239**	**.0094419**	**10.99**	**0.000**	**.0852181**	**.1222296**
HOUSE STABLE	**.1893666**	**.0206872**	**9.15**	**0.000**	**.1488205**	**.2299128**
ADVANTAGE	**.0130448**	**.0081448**	**1.60**	**0.109**	**-.0029188**	**.0290083**
_cons	-4.547276	.3790466	-12.00	0.000	-5.290194	-3.804358

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-696.2359	-598.6453	586	1213.291	1248.386

Bootstrap results, Model 0103

```
                                                    Number of obs    =        594
                                                    Replications     =       1200
                                                    Wald chi2(9)     =     386.13
                                                    Prob > chi2      =     0.0000
Log likelihood = -590.60978                         Pseudo R2        =     0.1517
mse0103 =  .37459636       mape0103 =  .43884432     signif0103 =  1.248e-77
```

YHAT1	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2722228**	**.0306592**	**-8.88**	**0.000**	**-.3323138**	**-.2121318**
STDYECSTRN	**.0568277**	**.0227166**	**2.50**	**0.012**	**.0123039**	**.1013515**
YAGE	**.3218233**	**.0281686**	**11.42**	**0.000**	**.2666139**	**.3770327**
YGENDER	**.0963222**	**.0567226**	**1.70**	**0.089**	**-.0148522**	**.2074965**
STDPC1A1	.1932929	.0182986	10.56	0.000	.1574284	.2291574
STDPC1A2	.3260428	.0360283	9.05	0.000	.2554286	.3966571
HOUSE STABLE	**-.0889709**	**.0326017**	**-2.73**	**0.006**	**-.152869**	**-.0250728**
STDPC1D1	-.2084539	.0243369	-8.57	0.000	-.2561533	-.1607544
STDPC1D2	.1783865	.0346437	5.15	0.000	.1104861	.2462869
_cons	-4.660956	.3844424	-12.12	0.000	-5.41445	-3.907463
DISADVANTAGE	**.5193357**	**.0427006**	**12.16**	**0.000**	**.435644**	**.6030274**
ADVANTAGE	**-.0300673**	**.0368346**	**-0.82**	**0.414**	**-.1022619**	**.0421272**

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-696.2359	-590.6098	584	1201.22	1245.088

Bootstrap results, Model 0104

```
                                                    Number of obs    =        594
                                                    Replications     =       1200
                                                    Wald chi2(12)    =    1175.60
                                                    Prob > chi2      =     0.0000
Log likelihood = -541.15482                         Pseudo R2        =     0.2227
mse0104 =  .13380933        mape0104 =  .30048019    signif0104 =  3.11e-244
```

YHAT1	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2223826**	**.0181841**	**-12.23**	**0.000**	**-.2580228**	**-.1867425**
STDYECSTRN	**.1013612**	**.0161468**	**6.28**	**0.000**	**.0697141**	**.1330084**
YAGE	**.3180566**	**.0202297**	**15.72**	**0.000**	**.2784071**	**.3577061**
YGENDER	**.1159798**	**.0340413**	**3.41**	**0.001**	**.04926**	**.1826997**
STDCHILDPOV	.8175167	.0455842	17.93	0.000	.7281733	.9068602
STDFAMPOV	.1214542	.0485076	2.50	0.012	.0263811	.2165272
STDFEMHOUS	-.0103673	.0356902	-0.29	0.771	-.0803187	.0595842
STDLESHISCH	-.4525606	.055783	-8.11	0.000	-.5618933	-.3432279
STDPERWHITE	.6662937	.0904841	7.36	0.000	.4889481	.8436393
STDUNEMP	-.5641789	.0325725	-17.32	0.000	-.6280198	-.500338
STDROVOO	.1914116	.0302188	6.33	0.000	.1321839	.2506394
STDCHPROPRO	-.0690548	.0249231	-2.77	0.006	-.1179032	-.0202064
_cons	-4.839989	.2752549	-17.58	0.000	-5.379479	-4.3005
DISADVANTAGE	**.5781578**	**.1580861**	**3.66**	**0.000**	**.2683147**	**.8880009**
HOUSE STABLE	**.1223568**	**.0344102**	**3.56**	**0.000**	**.0549142**	**.1897995**

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-696.2359	-541.1548	581	1108.31	1165.339

Bootstrap results, Model 0105

Number of obs = 594
Replications = 1200
Wald chi2(10) = 366.10
Prob > chi2 = 0.0000
Log likelihood = -610.50896
Pseudo R2 = 0.1231
mse0105 = .40492312   mape0105 = .45858391   signif0105 = 1.519e-72

YHAT1	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2923398**	**.0312155**	**-9.37**	**0.000**	**-.3535211**	**-.2311586**
STDYECSTRN	**.0600596**	**.0225291**	**2.67**	**0.008**	**.0159035**	**.1042158**
YAGE	**.3410641**	**.0294667**	**11.57**	**0.000**	**.2833104**	**.3988178**
YGENDER	**.1095933**	**.0587804**	**1.86**	**0.062**	**-.0056141**	**.2248007**
STDPC2A1	.0655211	.0739317	0.89	0.375	-.0793825	.2104246
STDPC2B1	.0928789	.0265891	3.49	0.000	.0407652	.1449926
STDPC2B2	.099611	.0221102	4.51	0.000	.0562758	.1429462
STDPC2B3	-.1388323	.0272572	-5.09	0.000	-.1922554	-.0854092
STDPC2B4	.0623813	.0373493	1.67	0.095	-.0108221	.1355846
STDNPC2D1	-.1063356	.0860521	-1.24	0.217	-.2749946	.0623233
_cons	-4.84324	.4029136	-12.02	0.000	-5.632936	-4.053543
_nl_1	.1160388	.0521806	2.22	0.026	.0137667	.218311

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-696.2359	-610.509	583	1243.018	1291.274

Table Two

Poisson regression		Number of obs	=	594
		LR chi2(7)	=	154.92
		Prob > chi2	=	0.0000
Log likelihood = -1271.4908		Pseudo R2	=	0.0574

Y30DUSE2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
STDYCONTRL	**-.2349154**	**.0432855**	**-5.43**	**0.000**	**-.3197536**	**-.1500773**
STDYECSTRN	**.0218326**	**.0406865**	**0.54**	**0.592**	**-.0579116**	**.1015767**
YAGE	**.2686829**	**.0465428**	**5.77**	**0.000**	**.1774606**	**.3599051**
YGENDER	**.0369673**	**.0869452**	**0.43**	**0.671**	**-.1334421**	**.2073768**
DISADVANTAGE	**.1003042**	**.017032**	**5.89**	**0.000**	**.066922**	**.1336863**
HOUSE STABLE	**.1664831**	**.034401**	**4.84**	**0.000**	**.0990585**	**.2339078**
ADVANTAGE	**.0194864**	**.0164338**	**1.19**	**0.236**	**-.0127233**	**.051696**
_cons	-3.800487	.6218272	-6.11	0.000	-5.019246	-2.581728

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-1348.95	-1271.491	586	2558.982	2594.077

Bootstrap results, Model 0201		Number of obs	=	594
		Replications	=	1200
		Wald chi2(16)	=	921.64
		Prob > chi2	=	0.0000
Log likelihood = -560.76864		Pseudo R2	=	0.1455
mse0201 = .10407854	mape0201 = .28548756	signif0201 =		6.57e-186

YHAT2	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2395621**	**.0171518**	**-13.97**	**0.000**	**-.273179**	**-.2059452**
STDYECSTRN	**.0447944**	**.0138932**	**3.22**	**0.001**	**.0175643**	**.0720245**
YAGE	**.3272055**	**.0186766**	**17.52**	**0.000**	**.2906001**	**.3638109**
YGENDER	**.040426**	**.0296247**	**1.36**	**0.172**	**-.0176373**	**.0984894**
STDCHILDPOV	.1032582	.0474888	2.17	0.030	.0101819	.1963344
STDFAMPOV	.4983876	.1534991	3.25	0.001	.1975348	.7992403
STDFEMHOUS	.1085606	.0376231	2.89	0.004	.0348208	.1823005
STDLESHISCH	.0210616	.0643061	0.33	0.743	-.104976	.1470992
STDPERWHITE	.0931995	.0574422	1.62	0.105	-.0193852	.2057843
STDUNEMP	.111971	.0263646	4.25	0.000	.0602973	.1636446
STDROVOO	.2075592	.0254076	8.17	0.000	.1577613	.2573571
STDCHPROPRO	.2477605	.0326575	7.59	0.000	.183753	.3117681
STDHIGRAD	-.0681468	.0406325	-1.68	0.094	-.1477851	.0114914
STDBACHPLUS	-.0749225	.0496188	-1.51	0.131	-.1721736	.0223286
STDCONCENTY	-1.217359	.5071811	-2.40	0.016	-2.211416	-.2233022
STDMEDHINC	1.12684	.457295	2.46	0.014	.2305585	2.023122
_cons	-4.586096	.2534135	-18.10	0.000	-5.082778	-4.089415
DISADVANTAGE	**.9364385**	**.1897809**	**4.93**	**0.000**	**.5644747**	**1.308402**
HOUSE STABLE	**.4553197**	**.0484543**	**9.40**	**0.000**	**.3603511**	**.5502884**
ADVANTAGE	**-.233588**	**.1194655**	**-1.96**	**0.051**	**-.467736**	**.00056**

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-656.2398	-560.7686	577	1155.537	1230.114

Bootstrap results, Model 0203

Number of obs = 594
Replications = 1200
Wald chi2(9) = 653.60
Prob > chi2 = 0.0000
Log likelihood = -575.66367
Pseudo R2 = 0.1228
mse0203 = .13432176 mape0203 = .31532008 signif0203 = 6.49e-135

YHAT2	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2443767**	**.0184627**	**-13.24**	**0.000**	**-.280563**	**-.2081904**
STDYECSTRN	**.0446489**	**.0141527**	**3.15**	**0.002**	**.0169102**	**.0723876**
YAGE	**.3300112**	**.0206508**	**15.98**	**0.000**	**.2895364**	**.370486**
YGENDER	**.0505496**	**.03279**	**1.54**	**0.123**	**-.0137175**	**.1148168**
STDPC1A1	.1965752	.0138826	14.16	0.000	.1693659	.2237846
STDPC1A2	.117719	.0222581	5.29	0.000	.0740939	.161344
HOUSE STABLE	**.0377457**	**.0191069**	**1.98**	**0.048**	**.0002969**	**.0751946**
STDPC1D1	-.1295761	.0176616	-7.34	0.000	-.1641922	-.09496
STDPC1D2	-.0283678	.0159679	-1.78	0.076	-.0596643	.0029287
_cons	-4.591093	.2811014	-16.33	0.000	-5.142042	-4.040145
DISADVANTAGE	**.3142942**	**.0297743**	**10.56**	**0.000**	**.2559377**	**.3726507**
ADVANTAGE	**-.1579439**	**.024778**	**-6.37**	**0.000**	**-.2065078**	**-.10938**

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-656.2398	-575.6637	584	1171.327	1215.196

Bootstrap results, Model 0204

Number of obs = 594
Replications = 1200
Wald chi2(12) = 931.86
Prob > chi2 = 0.0000
Log likelihood = -561.45303
Pseudo R2 = 0.1444
mse0204 = .10496339 mape0204 = .28706291 signif0204 = 8.24e-192

YHAT2	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.240402**	**.0169889**	**-14.15**	**0.000**	**-.2736996**	**-.2071044**
STDYECSTRN	**.0439845**	**.0136041**	**3.23**	**0.001**	**.0173209**	**.0706481**
YAGE	**.333956**	**.0181817**	**18.37**	**0.000**	**.2983205**	**.3695916**
YGENDER	**.0473036**	**.0293325**	**1.61**	**0.107**	**-.0101869**	**.1047942**
STDCHILDPOV	.0810618	.0310007	2.61	0.009	.0203016	.1418221
STDFAMPOV	.1113257	.0375873	2.96	0.003	.0376559	.1849955
STDFEMHOUS	.0928814	.029382	3.16	0.002	.0352938	.150469
STDLESHISCH	.0437409	.0407918	1.07	0.284	-.0362095	.1236914
STDPERWHITE	.1114456	.0440737	2.53	0.011	.0250628	.1978285
STDUNEMP	.1116728	.0250756	4.45	0.000	.0625256	.16082
STDROVOO	.1839165	.0206057	8.93	0.000	.1435302	.2243029
STDCHPROPRO	.2104548	.0253334	8.31	0.000	.1608022	.2601074
_cons	-4.668406	.2491781	-18.74	0.000	-5.156786	-4.180026
DISADVANTAGE	**.5521284**	**.0760305**	**7.26**	**0.000**	**.4031114**	**.7011454**
HOUSE STABLE	**.3943713**	**.0355404**	**11.10**	**0.000**	**.3247133**	**.4640293**

```
------------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |    594   -656.2398    -561.453    581     1148.906    1205.935

Bootstrap results, Model 0205                    Number of obs   =        594
                                                  Replications    =       1200
                                                  Wald chi2(10)   =     581.72
                                                  Prob > chi2     =     0.0000
Log likelihood = -579.03975                       Pseudo R2       =     0.1176
mse0205 =  .14834105       mape0205 =  .33168399     signif0205 =  1.45e-118

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
       YHAT2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  STDYCONTRL |  -.2748176   .0201813   -13.62   0.000    -.3143723   -.2352629
  STDYECSTRN |   .0519557   .0149564     3.47   0.001     .0226417    .0812697
        YAGE |   .3365677   .0212634    15.83   0.000     .2948922    .3782432
     YGENDER |   .0469259    .035883     1.31   0.191    -.0234036    .1172554
    STDPC2A1 |  -.1269614   .0397825    -3.19   0.001    -.2049337   -.0489891
    STDPC2B1 |   .0911233   .0172013     5.30   0.000     .0574094    .1248372
    STDPC2B2 |   .0775292   .0146848     5.28   0.000     .0487476    .1063108
    STDPC2B3 |   -.019988   .0212194    -0.94   0.346    -.0615773    .0216012
    STDPC2B4 |   .1796035   .0221655     8.10   0.000       .13616     .223047
   STDNPC2D1 |   .0884698   .0379526     2.33   0.020     .0140841    .1628554
       _cons |  -4.673269   .2929688   -15.95   0.000    -5.247478   -4.099061
-------------+----------------------------------------------------------------
       _nl_1 |    .328268    .035256     9.31   0.000     .2591674    .3973685
------------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |    594   -656.2398   -579.0398    583      1180.08    1228.335
```

Table Three

Poisson regression — Number of obs = 594; LR chi2(9) = 157.39; Prob > chi2 = 0.0000; Pseudo R2 = 0.0583

Log likelihood = -1270.2526

Y30DUSE2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
STDYCONTRL	**-.2395823**	**.0432864**	**-5.53**	**0.000**	**-.3244221**	**-.1547424**
STDYECSTRN	**.0307899**	**.0414511**	**0.74**	**0.458**	**-.0504527**	**.1120325**
YAGE	**.2682811**	**.0458881**	**5.85**	**0.000**	**.1783421**	**.3582202**
YGENDER	**.0451804**	**.0869555**	**0.52**	**0.603**	**-.1252492**	**.2156099**
STDPC1A1	.1733711	.0327894	5.29	0.000	.109105	.2376372
STDPC1A2	.2424099	.0521713	4.65	0.000	.1401561	.3446637
HOUSE STABLE	**-.0522675**	**.0460616**	**-1.13**	**0.256**	**-.1425466**	**.0380116**
STDPC1D1	-.1541491	.0419892	-3.67	0.000	-.2364463	-.0718518
STDPC1D2	.1517185	.0417154	3.64	0.000	.0699577	.2334793
_cons	-3.838319	.6158114	-6.23	0.000	-5.045287	-2.63135
DISADVANTAGE	**.415781**	**.0706828**	**5.88**	**0.000**	**.2772452**	**.5543168**
ADVANTAGE	**-.0024306**	**.0598688**	**-0.04**	**0.968**	**-.1197712**	**.1149101**

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-1348.95	-1270.253	584	2560.505	2604.374

Bootstrap results, Model 0301 — Number of obs = 594; Replications = 1200; Wald chi2(16) = 892.81; Prob > chi2 = 0.0000; Pseudo R2 = 0.1634

Log likelihood = -547.84652

mse0301 = .09544008 mape0301 = .26314646 signif0301 = 9.56e-180

YHAT3	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2356946**	**.0159595**	**-14.77**	**0.000**	**-.2669747**	**-.2044145**
STDYECSTRN	**.0344673**	**.0146157**	**2.36**	**0.018**	**.0058209**	**.0631136**
YAGE	**.2619322**	**.0183466**	**14.28**	**0.000**	**.2259736**	**.2978909**
YGENDER	**.1076602**	**.0308426**	**3.49**	**0.000**	**.0472098**	**.1681106**
STDCHILDPOV	.1924329	.0774154	2.49	0.013	.0407015	.3441643
STDFAMPOV	.34615	.1904275	1.82	0.069	-.0270811	.7193811
STDFEMHOUS	.1553944	.0458505	3.39	0.001	.0655291	.2452598
STDLESHISCH	-.3705054	.0598225	-6.19	0.000	-.4877554	-.2532555
STDPERWHITE	.471323	.0993218	4.75	0.000	.2766558	.6659902
STDUNEMP	-.0742614	.0326027	-2.28	0.023	-.1381616	-.0103612
STDROVOO	.124526	.0327719	3.80	0.000	.0602942	.1887578
STDCHPROPRO	-.0634254	.0268413	-2.36	0.018	-.1160335	-.0108174
STDHIGRAD	-.1039096	.0518075	-2.01	0.045	-.2054503	-.0023688
STDBACHPLUS	-.3030802	.0556206	-5.45	0.000	-.4120947	-.1940657
STDCONCENTY	-.280866	.6268574	-0.45	0.654	-1.509484	.9477519
STDMEDHINC	.2181956	.562086	0.39	0.698	-.8834727	1.319864
_cons	-4.01478	.2534903	-15.84	0.000	-4.511612	-3.517948
DISADVANTAGE	**.7205335**	**.2906224**	**2.48**	**0.013**	**.1509241**	**1.290143**
HOUSE STABLE	**.0611006**	**.0442176**	**1.38**	**0.167**	**-.0255643**	**.1477655**
ADVANTAGE	**-.4696601**	**.1372867**	**-3.42**	**0.001**	**-.738737**	**-.2005832**

```
-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |    594   -654.8695   -547.8465    577     1129.693     1204.27
```

```
Bootstrap results, Model 0302                    Number of obs   =        594
                                                  Replications    =       1200
                                                  Wald chi2(7)    =     600.22
                                                  Prob > chi2     =     0.0000
Log likelihood = -582.89049                       Pseudo R2       =     0.1099
mse0302 =  .15966742       mape0302 =  .34069782     signif0302 =  2.18e-125

-----------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
      YHAT3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+---------------------------------------------------------------
  STDYCONTRL |  -.2462472    .019869   -12.39   0.000    -.2851898   -.2073046
  STDYECSTRN |   .0271281   .0145248     1.87   0.062    -.0013399    .0555962
        YAGE |   .2544864   .0214957    11.84   0.000     .2123555    .2966173
     YGENDER |   .0939832   .0365263     2.57   0.010      .022393    .1655735
DISADVANTAGE |   .1096207   .0072831    15.05   0.000     .0953461    .1238954
HOUSE STABLE |  -.0086188   .0127216    -0.68   0.498    -.0335527    .0163152
ADVANTAGE    |   .0076678   .0078106     0.98   0.326    -.0076408    .0229763
       _cons |  -3.686878    .294835   -12.50   0.000    -4.264744   -3.109012
-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |    594   -654.8695   -582.8905    586     1181.781    1216.876
```

```
Bootstrap results, Model 0304                    Number of obs   =        594
                                                  Replications    =       1200
                                                  Wald chi2(12)   =     824.36
                                                  Prob > chi2     =     0.0000
Log likelihood = -551.07479                       Pseudo R2       =     0.1585
mse0304 =  .10149228       mape0304 =  .26895217     signif0304 =  9.86e-169

-----------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
      YHAT3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+---------------------------------------------------------------
  STDYCONTRL |  -.2408345   .0163411   -14.74   0.000    -.2728626   -.2088064
  STDYECSTRN |   .0298855   .0143986     2.08   0.038     .0016648    .0581063
        YAGE |   .2613673   .0181649    14.39   0.000     .2257647    .2969699
     YGENDER |   .1103029   .0313071     3.52   0.000     .0489421    .1716637
 STDCHILDPOV |   .3961979   .0445022     8.90   0.000     .3089753    .4834206
   STDFAMPOV |   .2947848   .0414442     7.11   0.000     .2135557     .376014
  STDFEMHOUS |   .0314533   .0246938     1.27   0.203    -.0169456    .0798521
 STDLESHISCH |  -.1573552   .0481185    -3.27   0.001    -.2516657   -.0630448
 STDPERWHITE |    .740823   .0836434     8.86   0.000     .5768849    .9047611
    STDUNEMP |  -.0748299   .0299819    -2.50   0.013    -.1335934   -.0160663
    STDROVOO |   .0919492   .0220768     4.16   0.000     .0486796    .1352189
 STDCHPROPRO |  -.1293597   .0198349    -6.52   0.000    -.1682354    -.090484
       _cons |  -4.025198   .2553806   -15.76   0.000    -4.525735   -3.524662
DISADVANTAGE |   1.231074   .1326606     9.28   0.000      .971064    1.491084
HOUSE STABLE |  -.0374105   .0248422    -1.51   0.132    -.0861002    .0112793
-----------------------------------------------------------------------------
       Model |    Obs    ll(null)   ll(model)     df          AIC         BIC
-------------+---------------------------------------------------------------
           . |    594   -654.8695   -551.0748    581      1128.15    1185.179
```

Bootstrap results, Model 0305

Number of obs	= 594
Replications	= 1200
Wald chi2(10)	= 629.52
Prob > chi2	= 0.0000
Pseudo R2	= 0.1164

Log likelihood = -578.64762

mse0305 = .14059991 mape0305 = .32208259 signif0305 = 8.31e-129

YHAT3	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2712678**	**.0184844**	**-14.68**	**0.000**	**-.3074965**	**-.235039**
STDYECSTRN	**.0292183**	**.0138936**	**2.10**	**0.035**	**.0019874**	**.0564493**
YAGE	**.2671378**	**.0213365**	**12.52**	**0.000**	**.225319**	**.3089566**
YGENDER	**.104977**	**.0354453**	**2.96**	**0.003**	**.0355056**	**.1744485**
STDPC2A1	.0604781	.0447358	1.35	0.176	-.0272025	.1481587
STDPC2B1	.115853	.0237747	4.87	0.000	.0692554	.1624506
STDPC2B2	.1232617	.0164842	7.48	0.000	.0909531	.1555702
STDPC2B3	-.0765739	.0232006	-3.30	0.001	-.1220462	-.0311015
STDPC2B4	.0158474	.0178454	0.89	0.375	-.0191289	.0508238
STDNPC2D1	.0615095	.0416069	1.48	0.139	-.0200386	.1430575
_cons	-3.921953	.2996795	-13.09	0.000	-4.509314	-3.334592
_nl_1	.1783882	.0323295	5.52	0.000	.1150235	.2417529

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-654.8695	-578.6476	583	1179.295	1227.551

Table Four

Poisson regression

Number of obs	= 594
LR chi2(12)	= 232.63
Prob > chi2	= 0.0000
Pseudo R2	= 0.0862

Log likelihood = -1232.6329

Y30DUSE2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
STDYCONTRL	**-.1997626**	**.0442964**	**-4.51**	**0.000**	**-.2865819**	**-.1129433**
STDYECSTRN	**.0665526**	**.0417343**	**1.59**	**0.111**	**-.0152451**	**.1483503**
YAGE	**.2622703**	**.046836**	**5.60**	**0.000**	**.1704735**	**.3540671**
YGENDER	**.0630384**	**.0873908**	**0.72**	**0.471**	**-.1082445**	**.2343213**
STDCHILDPOV	.653518	.0971389	6.73	0.000	.4631292	.8439067
STDFAMPOV	.095011	.0991978	0.96	0.338	-.0994132	.2894352
STDFEMHOUS	.009475	.0837765	0.11	0.910	-.1547239	.1736738
STDLESHISCH	-.3124371	.1267276	-2.47	0.014	-.5608186	-.0640557
STDPERWHITE	.2597548	.1243159	2.09	0.037	.0161001	.5034095
STDUNEMP	-.4732834	.0802065	-5.90	0.000	-.6304853	-.3160815
STDROVOO	.1374327	.0544372	2.52	0.012	.0307377	.2441276
STDCHPROPRO	-.0641474	.0581803	-1.10	0.270	-.1781786	.0498838
_cons	-3.887018	.6256253	-6.21	0.000	-5.113221	-2.660815
DISADVANTAGE	**.2320382**	**.2436987**	**0.95**	**0.341**	**-.2456024**	**.7096788**
HOUSE STABLE	**.0732853**	**.0769357**	**0.95**	**0.341**	**-.0775059**	**.2240765**

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-1348.95	-1232.633	581	2491.266	2548.295

Bootstrap results, Model 0401

Number of obs	= 594
Replications	= 1200
Wald chi2(16)	= 1697.64
Prob > chi2	= 0.0000
Pseudo R2	= 0.2178

Log likelihood = -530.26921

mse0401 = .09801967 mape0401 = .26059485 signif0401 = 0

YHAT4	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.1911014**	**.0155031**	**-12.33**	**0.000**	**-.221487**	**-.1607159**
STDYECSTRN	**.1012226**	**.0141932**	**7.13**	**0.000**	**.0734044**	**.1290408**
YAGE	**.2848863**	**.0192084**	**14.83**	**0.000**	**.2472385**	**.322534**
YGENDER	**.0654064**	**.0293266**	**2.23**	**0.026**	**.0079274**	**.1228854**
STDCHILDPOV	.9194609	.0751797	12.23	0.000	.7721115	1.06681
STDFAMPOV	.6255854	.2349764	2.66	0.008	.1650402	1.086131
STDFEMHOUS	.0849336	.0559852	1.52	0.129	-.0247954	.1946625
STDLESHISCH	-.381958	.0597281	-6.39	0.000	-.4990229	-.2648932
STDPERWHITE	.7582894	.1216736	6.23	0.000	.5198136	.9967653
STDUNEMP	-.5298599	.0327122	-16.20	0.000	-.5939747	-.4657451
STDROVOO	.2721761	.0448804	6.06	0.000	.1842121	.3601401
STDCHPROPRO	-.1358642	.0345495	-3.93	0.000	-.2035801	-.0681484
STDHIGRAD	-.1988627	.0598156	-3.32	0.001	-.316099	-.0816263
STDBACHPLUS	-.0996684	.0695814	-1.43	0.152	-.2360454	.0367087
STDCONCENTY	-1.236912	.7633801	-1.62	0.105	-2.73311	.2592855
STDMEDHINC	1.226359	.6859188	1.79	0.074	-.1180168	2.570735
_cons	-4.417948	.256053	-17.25	0.000	-4.919803	-3.916094
DISADVANTAGE	**1.476451**	**.3709057**	**3.98**	**0.000**	**.7494897**	**2.203413**
HOUSE STABLE	**.1363119**	**.0602036**	**2.26**	**0.024**	**.018315**	**.2543087**
ADVANTAGE	**-.3090837**	**.1675704**	**-1.84**	**0.065**	**-.6375157**	**.0193483**

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-677.938	-530.2692	577	1094.538	1169.115

Bootstrap results, Model 0402

Number of obs = 594
Replications = 1200
Wald chi2(7) = 400.37
Prob > chi2 = 0.0000
Log likelihood = -590.31656
Pseudo R2 = 0.1292
mse0402 = .27147913 mape0402 = .40894864 signif0402 = 1.990e-82

YHAT4	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2419875**	**.0254323**	**-9.51**	**0.000**	**-.2918339**	**-.192141**
STDYECSTRN	**.0668997**	**.0200035**	**3.34**	**0.001**	**.0276937**	**.1061058**
YAGE	**.2997786**	**.0260065**	**11.53**	**0.000**	**.2488067**	**.3507505**
YGENDER	**.0297077**	**.0477834**	**0.62**	**0.534**	**-.063946**	**.1233615**
DISADVANTAGE	**.1068297**	**.008821**	**12.11**	**0.000**	**.0895409**	**.1241185**
HOUSE STABLE	**.1698872**	**.0213241**	**7.97**	**0.000**	**.1280928**	**.2116817**
ADVANTAGE	**-.0132359**	**.0073136**	**-1.81**	**0.070**	**-.0275702**	**.0010984**
_cons	-4.205838	.3485052	-12.07	0.000	-4.888895	-3.52278

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-677.938	-590.3166	586	1196.633	1231.728

Bootstrap results, Model 0403

Number of obs = 594
Replications = 1200
Wald chi2(9) = 479.40
Prob > chi2 = 0.0000
Log likelihood = -572.4552
Pseudo R2 = 0.1556
mse0403 = .27707904 mape0403 = .38322989 signif0403 = 1.475e-97

YHAT4	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2521939**	**.0259181**	**-9.73**	**0.000**	**-.3029924**	**-.2013953**
STDYECSTRN	**.068136**	**.0195999**	**3.48**	**0.001**	**.0297209**	**.1065511**
YAGE	**.3078509**	**.0238815**	**12.89**	**0.000**	**.2610441**	**.3546578**
YGENDER	**.0455904**	**.0492815**	**0.93**	**0.355**	**-.0509996**	**.1421803**
STDPC1A1	.2583757	.0178048	14.51	0.000	.2234789	.2932724
STDPC1A2	.3501793	.0344273	10.17	0.000	.282703	.4176556
HOUSE STABLE	**-.1403677**	**.0285304**	**-4.92**	**0.000**	**-.1962863**	**-.084449**
STDPC1D1	-.3068252	.0235576	-13.02	0.000	-.3529972	-.2606531
STDPC1D2	.0550298	.0298537	1.84	0.065	-.0034824	.113542
_cons	-4.433837	.3243316	-13.67	0.000	-5.069515	-3.798159
DISADVANTAGE	**.608555**	**.0422402**	**14.41**	**0.000**	**.5257656**	**.6913443**
ADVANTAGE	**-.2517954**	**.0338843**	**-7.43**	**0.000**	**-.3182074**	**-.1853834**

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-677.938	-572.4552	584	1164.91	1208.779

Bootstrap results, Model 0405

Number of obs	= 594
Replications	= 1200
Wald chi2(10)	= 366.51
Prob > chi2	= 0.0000
Pseudo R2	= 0.1053

Log likelihood = -606.55134

mse0405 = .32788083 mape0405 = .43977672 signif0405 = 1.245e-72

YHAT4	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2601656**	**.0273051**	**-9.53**	**0.000**	**-.3136826**	**-.2066486**
STDYECSTRN	**.0706831**	**.0217927**	**3.24**	**0.001**	**.0279703**	**.1133959**
YAGE	**.3165715**	**.0277449**	**11.41**	**0.000**	**.2621926**	**.3709505**
YGENDER	**.0587132**	**.0527925**	**1.11**	**0.266**	**-.0447581**	**.1621845**
STDPC2A1	.1423132	.0659044	2.16	0.031	.0131429	.2714835
STDPC2B1	.0442155	.0266697	1.66	0.097	-.0080561	.0964872
STDPC2B2	.1383439	.0217331	6.37	0.000	.0957478	.18094
STDPC2B3	.0007244	.0302679	0.02	0.981	-.0585996	.0600485
STDPC2B4	.115652	.0319452	3.62	0.000	.0530406	.1782634
STDNPC2D1	-.136255	.068188	-2.00	0.046	-.269901	-.0026089
_cons	-4.425776	.3723859	-11.88	0.000	-5.155639	-3.695913
_nl_1	.2989359	.0477822	6.26	0.000	.2052845	.3925873

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-677.938	-606.5513	583	1235.103	1283.358

Table Five

Poisson regression

	Number of obs	=	594
	LR chi2(10)	=	145.18
	Prob > chi2	=	0.0000
Log likelihood = -1276.3606	Pseudo R2	=	0.0538

Y30DUSE2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
STDYCONTRL	**-.2412273**	**.0433223**	**-5.57**	**0.000**	**-.3261375**	**-.1563171**
STDYECSTRN	**.040072**	**.0410429**	**0.98**	**0.329**	**-.0403706**	**.1205146**
YAGE	**.295426**	**.0469371**	**6.29**	**0.000**	**.203431**	**.3874211**
YGENDER	**.0761335**	**.0873668**	**0.87**	**0.384**	**-.0951022**	**.2473692**
STDPC2A1	.152219	.0888985	1.71	0.087	-.0220188	.3264569
STDPC2B1	.102938	.0396106	2.60	0.009	.0253027	.1805734
STDPC2B2	.1045182	.0359189	2.91	0.004	.0341184	.1749179
STDPC2B3	-.1170954	.0533019	-2.20	0.028	-.2215652	-.0126256
STDPC2B4	.0369747	.0483384	0.76	0.444	-.0577668	.1317162
STDNPC2D1	-.2763301	.0830491	-3.33	0.001	-.4391034	-.1135568
_cons	-4.165021	.6316916	-6.59	0.000	-5.403114	-2.926928
_nl_1	.1273355	.07707	1.65	0.098	-.023719	.27839

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-1348.95	-1276.361	583	2574.721	2622.977

Bootstrap results, Model 0501

	Number of obs	=	594
	Replications	=	1200
	Wald chi2(16)	=	909.26
	Prob > chi2	=	0.0000
Log likelihood = -568.54652	Pseudo R2	=	0.1339

mse0501 = .10698768
mape0501 = .2852852
signif0501 = 2.91e-183

YHAT5	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.249644**	**.0150322**	**-16.61**	**0.000**	**-.2791065**	**-.2201814**
STDYECSTRN	**.0578376**	**.0131278**	**4.41**	**0.000**	**.0321076**	**.0835676**
YAGE	**.326622**	**.0192197**	**16.99**	**0.000**	**.2889522**	**.3642919**
YGENDER	**.104723**	**.0296364**	**3.53**	**0.000**	**.0466367**	**.1628093**
STDCHILDPOV	-.2231302	.0645424	-3.46	0.001	-.3496309	-.0966294
STDFAMPOV	-1.283593	.1589951	-8.07	0.000	-1.595218	-.9719688
STDFEMHOUS	.2113953	.0413542	5.11	0.000	.1303426	.2924481
STDLESHISCH	-.3088264	.0814023	-3.79	0.000	-.4683721	-.1492808
STDPERWHITE	-.2893252	.0485639	-5.96	0.000	-.3845087	-.1941418
STDUNEMP	-.0201247	.0277891	-0.72	0.469	-.0745904	.0343409
STDROVOO	.0160071	.0282664	0.57	0.571	-.0393939	.0714082
STDCHPROPRO	-.0894645	.0352877	-2.54	0.011	-.1586272	-.0203018
STDHIGRAD	.2583752	.05359	4.82	0.000	.1533407	.3634098
STDBACHPLUS	-.1152938	.0659433	-1.75	0.080	-.2445402	.0139527
STDCONCENTY	3.631265	.523706	6.93	0.000	2.60482	4.657709
STDMEDHINC	-3.393253	.4846486	-7.00	0.000	-4.343147	-2.443359
_cons	-4.61255	.2654323	-17.38	0.000	-5.132788	-4.092312
DISADVANTAGE	-1.913605	.2172103	-8.81	0.000	-2.339329	-1.48788
HOUSE STABLE	-.0734573	.0423547	-1.73	0.083	-.156471	.0095563
ADVANTAGE	.3810928	.1304377	2.92	0.003	.1254397	.6367459

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-656.4376	-568.5465	577	1171.093	1245.67

Bootstrap results, Model 0502

Number of obs	=	594
Replications	=	1200
Wald chi2(7)	=	490.58
Prob > chi2	=	0.0000
Pseudo R2	=	0.1010

Log likelihood = -590.13583
mse0502 = .16689946
mape0502 = .34594114
signif0502 = 8.48e-102

YHAT5	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2621482**	**.0189542**	**-13.83**	**0.000**	**-.2992978**	**-.2249987**
STDYECSTRN	**.0240108**	**.0143147**	**1.68**	**0.093**	**-.0040455**	**.052067**
YAGE	**.3007543**	**.0219777**	**13.68**	**0.000**	**.2576789**	**.3438297**
YGENDER	**.0761399**	**.036695**	**2.07**	**0.038**	**.0042191**	**.1480607**
DISADVANTAGE	.072456	.0069323	10.45	0.000	.0588688	.0860431
HOUSE STABLE	-.0148165	.0111967	-1.32	0.186	-.0367616	.0071286
ADVANTAGE	.0262472	.006994	3.75	0.000	.0125392	.0399552
_cons	-4.212214	.3000259	-14.04	0.000	-4.800254	-3.624174

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-656.4376	-590.1358	586	1196.272	1231.367

Bootstrap results, Model 0503

Number of obs	=	594
Replications	=	1200
Wald chi2(9)	=	612.38
Prob > chi2	=	0.0000
Pseudo R2	=	0.1197

Log likelihood = -577.87893
mse0503 = .14279649
mape0503 = .32054062
signif0503 = 4.62e-126

YHAT5	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.263981**	**.0169307**	**-15.59**	**0.000**	**-.2971645**	**-.2307975**
STDYECSTRN	**.0485682**	**.014419**	**3.37**	**0.001**	**.0203074**	**.076829**
YAGE	**.2973065**	**.0204744**	**14.52**	**0.000**	**.2571775**	**.3374356**
YGENDER	**.0683889**	**.0342969**	**1.99**	**0.046**	**.0011681**	**.1356096**
STDPC1A1	.1189428	.0133762	8.89	0.000	.092726	.1451597
STDPC1A2	-.0620599	.0172163	-3.60	0.000	-.0958032	-.0283166
HOUSE STABLE	-.0937745	.0221398	-4.24	0.000	-.1371677	-.0503813
STDPC1D1	.0549398	.0178943	3.07	0.002	.0198676	.0900119
STDPC1D2	.0921538	.0156068	5.90	0.000	.061565	.1227426
_cons	-4.214249	.2835678	-14.86	0.000	-4.770031	-3.658466
DISADVANTAGE	.0568829	.0217531	2.61	0.009	.0142477	.0995181
_nl_2	.1470935	.0248545	5.92	0.000	.0983796	.1958075

Model	Obs	ll(null)	ll(model)	df	AIC	BIC

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-656.4376	-577.8789	584	1175.758	1219.627

Bootstrap results, Model 0504

Number of obs = 594
Replications = 1200
Wald chi2(12) = 611.78
Prob > chi2 = 0.0000
Pseudo R2 = 0.1187

Log likelihood = -578.53585
mse0504 = .14611047
mape0504 = .32233979
signif0504 = 3.22e-123

YHAT5	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
STDYCONTRL	**-.2526351**	**.0178392**	**-14.16**	**0.000**	**-.2875993**	**-.2176709**
STDYECSTRN	**.0549704**	**.0148907**	**3.69**	**0.000**	**.0257851**	**.0841557**
YAGE	**.2987856**	**.0208663**	**14.32**	**0.000**	**.2578883**	**.3396829**
YGENDER	**.081153**	**.0342003**	**2.37**	**0.018**	**.0141216**	**.1481844**
STDCHILDPOV	.0657278	.0347912	1.89	0.059	-.0024616	.1339172
STDFAMPOV	-.1369717	.04447	-3.08	0.002	-.2241312	-.0498121
STDFEMHOUS	.1839504	.0364808	5.04	0.000	.1124494	.2554514
STDLESHISCH	-.14504	.0540944	-2.68	0.007	-.2510631	-.0390168
STDPERWHITE	-.1090288	.0368394	-2.96	0.003	-.1812327	-.036825
STDUNEMP	.0503337	.0369706	1.36	0.173	-.0221275	.1227948
STDROVOO	.0600144	.0216315	2.77	0.006	.0176174	.1024114
STDCHPROPRO	-.1021634	.0251551	-4.06	0.000	-.1514665	-.0528603
_cons	-4.246984	.2866006	-14.82	0.000	-4.808711	-3.685257
DISADVANTAGE	-.0910286	.0926519	-0.98	0.326	-.2726229	.0905657
HOUSE STABLE	-.042149	.0287102	-1.47	0.142	-.0984199	.0141219

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	594	-656.4376	-578.5358	581	1183.072	1240.101

Appendix One: Primer on Monte Carlo Estimations

Thor is concerned about the math grades of his teenage son, Chris. Thor has collected his son's daily math quiz scores for the last seven months, and notices that the grades tended to fall just after his son purchased a car, fell even more during basketball season, and rose slightly whenever Chris was in bed by 10:00 the previous night. To check Thor's instincts, he uses his data to statistically estimate the parameters of the model

$$GRADE_i = \beta_0 + \beta_1(CAR) + \beta_2(BASKETBALL) + \beta_3(BEDTIME_i) + \varepsilon_i,$$

where *GRADE* measures the daily quiz grade, *CAR* is equal to 1 for all days on which the son had access to the car (and equal to zero otherwise), *BASKETBALL* is equal to 1 for quizzes given during the basketball season (and equal to zero otherwise), and *BEDTIME* records Chris' bedtime the night before each quiz. Sure enough, the β slope parameters turn out to be negative and statistically significant—cars, sports and late nights appear to be pulling down Chris' grades. Thor tells Chris that he must give up recreational use of his car, be in bed by 10:00, and not attend any more sports events.

Chris has also been collecting some data, and presents an alternative model. He bought the car in order to be able to drive to the new job his father insisted he accept, and he believes it's the study time sacrificed to work that initially pulled down his grades. His math teacher is also the basletball coach, and Chris reasons that it's the coach's inferior class preparation during basketball season that further harmed his grades. And as for bedtime, he obviously gets to bed later on the nights when he must work, and when he is working he can't prepare for the next day's math quiz. Chris therefore proposes the following model:

$$GRADE_i = \alpha_0 + \alpha_1(STUDYTIME) + \alpha_2(TEACHPREP) + \delta_i,$$

where *STUDYTIME* measures the number of after-school hours not spent at his job on the day before a quiz, and *TEACHPREP* measures the number of minutes his math teacher spent preparing the lesson plan for the material covered in each quiz. Sure enough, the α slope parameters turn out to be *positive* and statistically significant. Chris proposes that he be allowed to quit his job, switch to a different math teacher, and retain his other privileges.

How shall Thor and Chris resolve their dispute? They can not directly observe the process that gives rise to the observed math grades. Given the data to which they have access, it will be very hard to disentangle the unique effects of teacher preparation and basketball season, since these two variables tend to move together. But they could conduct a Monte Carlo simulation to consider which model best imitates a *known* data-generating process that they control themselves, and this would help them decide which model can best be trusted with the real data they don't control. They could generate sets of new, artificial but reasonable grades, using equations and a random-number generator. For example, they might create three sets of artificial grades representing three different virtual realities, using the following equations (where ζ is a normally-distributed random number between, say, -.1 and +.1):

Model I:

$$GRADE_i = 3.0 - .8(CAR) - .9(BASKETBALL) - .8(BEDTIME_i) + .03(LEISURE) + .02(TEACHPREP) + \zeta_i,$$

Model II:

$$GRADE_i = 3.0 - .01(CAR) - .02(BASKETBALL) - .04(BEDTIME_i) + .8(LEISURE) + .9(TEACHPREP) + \zeta_i,$$

Model III:

$$GRADE_i = 3.0 - .15(CAR) - .19(BASKETBALL) - .14(BEDTIME_i) + .16(LEISURE) + .17(TEACHPREP) + \zeta_i,$$

The first equation represents Thor's vision of reality, with large coefficients on *CAR, FOOTBALL* and *BEDTIME* but small coefficients on the other two variables. The second equation encodes Chris' view of the situation, and the third model presents an equation in which all influences matter in roughly equal ways.

Let's say that Thor and Chris create 1000 grade forecasts using Model I, the data they have collected, and a random number generator. They could then use this 1000-observation data set to statistically estimate the coefficients of *the other two models*. By repeating this process through all the possible permutations, they can investigate which (if either) of their proposed models does a good job of correctly measuring the parameters that they know to be generating these artificially-created grades. By documenting which models tend to generate false-positive and false-negative conclusions about parameters, they can draw some conclusions about which models tend to perform well over a range of different conditions. Those models can therefore be considered relatively more dependable when confronting data whose structure is not known in advance by the investigator.