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An introduction to the general monotone model with application to two problematic datasets.

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Abstract

We argue that the mismatch between data and analytical methods, along with common practices for dealing with "messy" data, can lead to inaccurate conclusions. Specifically, using previously published data on racial bias and culture of honor, we show that manifest effects, and therefore theoretical conclusions, are highly dependent on how researchers decide to handle extreme scores and nonlinearities when data are analyzed with traditional approaches. Within least-squares approaches, statistical effects appeared or disappeared based on the inclusion or exclusion of as little as 1.5% (3/198) of the data, and highly predictive variables were masked by nonlinearities. We then demonstrate a new statistical modeling technique called the General Monotone Model (GeMM; Dougherty & Thomas, 2012), and show that it has a number of desirable properties that may make it more appropriate for modeling messy data: It is more robust to extreme scores, less affected by outlier analyses, and more robust to violations of linearity on both the response and predictor variables compared to a variety of well-established statistical algorithms, and frequently possessed greater statistical power. We argue that using procedures that make fewer assumptions about the data, such as GeMM, can lessen the need for researchers to use data-editing strategies (e.g., apply transformations or engage outlier analyses) on their data to satisfy often unrealistic statistical assumptions, leading to more consistent and accurate conclusions about data than traditional approaches of data analysis.

Keywords: *data editing, monotone regression, maximum rank correlation estimator, culture of honor, racial bias*

1. Introduction

Although recent high-profile cases of fraud have brought unwelcome attention to social sciences, these cases offer an opportunity to reflect on the state of our sciences as well as currently accepted practices (Crocker, 2011; Fang, Steen, & Casadevall, 2012). To be sure, sociologists have been somewhat ahead of the curve in addressing issues related to data quality, reproducibility (Freese, 2007; Hauser, 1987), replicability (King, 1995), and publication bias (Gerber & Malhotra, 2008; Leahey, 2005). Of these, data quality arguably ranks as the foremost problem for social scientists because so much, including reproducibility and replication, depends on having good quality data. Unfortunately, much of the data within the social sciences is messy, and often requires a good amount of editing (e.g., transformation, replacement of missing values, outlier removal, etc.) prior to analysis when used with traditional metric statistics. Data editing, however, enables the researcher to capitalize on chance, a problem that is compounded by the fact that there are not well-accepted (or followed) guidelines for how and when to use particular data editing strategies (Leahey, 2008; Leahey, Entwisle, & Einaudi, 2003; Sana & Weinreb, 2008). The plethora of available strategies, even for something as simple as outlier analysis, can promote flexibility in data analysis. Unfortunately, different approaches to data editing can yield different substantive conclusions, meaning that replications not only depend on the data, but can also depend on the specific choices one makes in data editing.

The use of data editing strategies is just one end of the spectrum of the flexibility afforded to researchers. Modern computers and an ever-expanding toolbox of available statistical algorithms permit researchers to easily explore their data in a variety of different ways under different modeling assumptions prior to settling on the subset of analyses that are to be reported (Ho, Imai, King, & Stuart, 2007). Coupled with methodological issues surrounding the use of data editing, flexibility in analysis techniques has been a major concern within the social sciences leading some to call for open-source documentation of data analysis techniques (Freese, 2007;

Simonsohn, 2013). Although there are many reasons to demand open-source documentation, it does not address the problem of flexibility of analysis: It only makes the use of flexible analysis methods public and open to scrutiny.

The work presented here has two related goals. The first goal is to illustrate the problem with implementing accepted practices on how to deal with messy data, showing just how sensitive substantive conclusions can be to different choices made in data analysis. The second goal is to provide an alternative approach to modeling messy data that reduces or eliminates the need for researchers to make such decisions. With regard to the first goal, using data on racial prejudice (Siegel, Dougherty, & Huber, 2012) and culture of honor (Henry, 2009), we show that the use of LS regression techniques yield inconsistent conclusions across various accepted methods for dealing with messy data. These inconsistencies call into question the validity of statistical conclusions based on LS approaches, and in general render the data less interpretable. We argue that the mismatch between the nature of one's data and standard statistical approaches can deceive researchers into drawing invalid conclusions, no matter how well intentioned or diligent the researchers are.

Turning to the second goal, we introduce a new statistical algorithm, the General Monotone Model (GeMM, Dougherty & Thomas, 2012) that makes weaker assumptions than LS approaches about scale of measurement and the functional relationships among manifest variables. GeMM provides relatively more consistent statistical outcomes across several criteria for inclusion or exclusion of extreme scores and the presence of nonlinearities. We show that GeMM is more robust to extreme scores, unaffected by nonlinear monotone relationships, has superior predictive accuracy and better statistical power in comparison to a variety of procedures based on least-squares. Our application of GeMM in this paper goes beyond previous published applications. Specifically our analyses evaluate the stability or robustness of GeMM relative to alternative modeling techniques under a variety of realistic conditions that might otherwise entice

researchers to make tough decisions about how to handle nonlinear or non-normal data, or the presence of extreme scores. We argue that GeMM provides a promising solution to flexibility in data analysis by greatly reducing both the need for and the impact of data editing.

2. Messy Data and Tough Decisions

Rarely do data neatly conform to the assumptions required for carrying out standard statistical procedures. For instance, it is well recognized that real data typically deviate, often non-trivially, from normality (Micceri, 1989), which can result in violations of assumptions underlying standard statistical techniques. Real data are messy. As researchers, we are taught to be vigilant to aberrations in our data, and even to remove them through the use of transformations or "outlier" analyses. For example, Hayes (1994) states "The data should be inspected for unusually skewed or artificially restricted distributions, missing data, and the presence of unusually deviant cases or outliers … Fortunately, even messy data can often be cleaned up enough to be used, but doing so requires many choices (p 721)" (Hayes, 1994, pg 721).

Many textbooks contain similar advice – advice that instructs researchers to clean their data through transformation and outlier deletion techniques. These techniques, which we refer to collectively as *data editing strategies* (Leahey, 2008; Leahey, et al., 2003), allow researchers to clean and/or re-express the data in a form that more closely conforms to the assumptions of the statistical model. However, the same textbooks that offer advice for how to handle non-normalities and outliers also point out that standard least-squared (LS) estimation procedures and their robust implementations often perform reasonably well even when their assumptions are not met (see Howell, 2002). This type of back-and-forth between prescribing data editing strategies and touting robustness is typical.

The fact that many analysis techniques make strong assumptions about distributional (e.g., multivariate normality) and functional (e.g., linear) forms can present the researcher with a

potentially important dilemma: Should one engage in data editing to bring the data in line with the assumptions of the analytical procedure, recognizing that the statistical conclusions are conditional on the particular data editing strategies employed? Or, should one analyze the data 'as is', recognizing that the statistical conclusions are conditional on potential violations of assumptions? Obviously, the best-case scenario is that statistical conclusions are invariant across various data editing strategies and methodologies. However, there may be cases in which one's statistical, and therefore theoretical, claims depend on *whether* or *how* one has transformed or trimmed the data. Indeed, in investigating Diederik Stapel's infamous body of work for instances of deceptive research practices, an investigatory panel specifically noted how the elimination or inclusion of extreme scores affected the statistical conclusions:

"On the one hand, 'outliers' (extreme scores on usually the dependent variable) were removed from the analysis where no significant results were obtained. This elimination reduces the variance of the dependent variable and makes it more likely that 'statistically significant' findings will emerge ... Conversely, the Committees also observed that extreme scores of one or two experimental subjects were kept in the analysis where their elimination would have changed significant differences into insignificant ones; there was no mention anywhere of the fact that the significance relied on just one or a few subjects" (pg. 49, Levelt Committee, Noort Committee, and Drenth Committee, 2012).

Obviously, it strikes us as problematic when statistical and theoretical conclusions are dependent not on the data per se, but on the creative use (or misuse) of statistical methods and data editing strategies—what Simmons, Nelson, and Simonsohn (2011) have referred to as "experimenter degrees of freedom." Although Stapel may have been guilty of not disclosing his decisions to include or exclude participants (and outright fraud in other cases), the fact that he sometimes engaged in outlier elimination (and other times chose not to) is not inconsistent with standard practices. In fact, the authors of the Stapel report even seem conflicted about whether it

was appropriate to eliminate extreme scores. The bottom line is that decisions about whether or not to engage in data editing that are based on whether the data meet the assumptions of the statistical model leave the researcher in a precarious position: Damned if you do and damned if you don't.

While there have been several documented cases of inappropriate data editing within the psychological literature (e.g., that of Diedrick Stapel), the issue of data editing is clearly of concern across the all of the social sciences including sociology (John, Loewenstein, & Prelec, 2012; Leahey, 2003). The tension surrounding the appropriateness of eliminating outliers was illuminated by an exchange between Kahn and Udry (1986) and Jasso (1986) in *American Sociological Review* regarding an analysis of intercourse frequency amongst married couples: Kahn and Udry criticized Jasso's original analysis by arguing that her inclusion of outliers was inappropriate and biased the statistical results; Jasso countered by arguing that the exclusion of outliers in Kahn and Udry's reanalysis produced "sample truncation bias." This divergence on the inclusion of outliers highlights a common predicament: there is not always a clear solution to the presence of outliers, and decisions to include or exclude them often come down to a judgment call.

The scope of the data-editing problem for statistical inference is difficult to assess from published papers, in part because there is little oversight or consistency in regard to how data editing procedures are carried out (Leahey, 2008), and in part because few articles include serious discussion of how specific data-editing decisions impact statistical conclusions. Nevertheless, it is clear that data editing is a relatively common component of statistical analysis. Notable examples from the literature include the common use of logarithmic transformations for analyses that include estimates of income (e.g., Olsen & Dahl, 2007; Semyonov & Lewin-Epstein, 2011) and homicide rates (Lederman, Loayza & Menéndez, 2002). Although decisions regarding whether to transform variables presumably are based on the need to bring the data inline with modeling

assumptions, these decisions represent an important source of flexibility in data analysis, and one that can be exploited either intentionally or unintentionally (Simmons et al., 2011).

The exploitation of flexible analysis techniques is a problem for science. However, the critical question concerns the precise nature of this problem: Is the problem that people fail to report faithfully the many decisions that ultimately exploit this flexibility? Or, is the problem that there is too much flexibility with data analysis techniques to begin with? Depending on how one perceives the problem, it suggests different solutions. If the problem is that people do not faithfully report the many decisions that exploit the flexibility of available statistical algorithms, then the obvious solution is to require full disclosure of data analysis methods in an open-source forum, as suggested by Freese (2007). However, if the problem is that there is too much flexibility to begin with, then the solution would seem to lie in the development (or use of) procedures that reduce this flexibility (Ho et al., 2007). Thus, while full disclosure is important, we believe that the more fundamental problem lies with the use of standard statistical techniques, which permit, and in some cases demand, that the researcher engage in data editing. Assuming this is the case, then one reasonable approach is to use analysis techniques that are robust to the types of decisions that researchers would otherwise be compelled to make in order to bring their data in line with the modeling assumptions (cf. Beck & Jackman, 1998).

3. The General Monotone Model (GeMM)

Fundamentally, GeMM is an algorithm for detecting and modeling monotone statistical relationships in regression contexts. The primary difference between GeMM and standard least-squares approaches lies in the fitness function. In least-squares regression, the goal is to find the regression coefficients that minimize the sum of the squared differences between the observed and the predicted values. In contrast, in GeMM the goal is to find the regression coefficients that minimize the difference in the ordinal correspondence (i.e., minimize the number of rank-order

inversions) between the observed and predicted values, as defined by Kendall's (1938) tau. In this way, GeMM attempts to find the solution that provides the best *monotonic* (i.e., rank order) fit to the data, as opposed to finding the best *linear* least-squares fit to the data. Thus, GeMM is a variant of the maximum rank correlation estimator (Han, 1987; Cavanagh & Sherman, 1998). As demonstrated below, GeMM has superior statistical power relative to ordinary least-squares (OLS) to detect non-linear but monotone statistical relationships, without requiring the researcher to model the non-linearity directly or engage in data editing. The reason for this is that the rank order correlation tau, on which GeMM is based, is invariant to monotone transformation on the criterion variable. It is also important to note that GeMM suffers little loss in statistical power compared to OLS when the statistical relationship is linear and the data satisfy standard OLS assumptions (Dougherty & Thomas, 2012). Because GeMM is invariant to transformation on the criteria, unaffected by nonlinearities, and should be less sensitive to extreme scores (a property we demonstrate below), it provides a new tool for modeling messy data that would otherwise require editing or more specialized statistical algorithms.

In its simplest form, GeMM consists of a one-parameter model (i.e., one predictor), which is used to predict the criterion variable[1] of interest. In this context, GeMM is actually identical to Kendall's (1938) tau correlation coefficient, but expressed in a model form. Rather than expressing the relationship between X and Y directly, we substitute $\hat{Y}$ for X to show the model-form equivalence of tau for a single predictor*:*

$$\hat{Y} = \beta X \tag{1}$$

In equation 1, one wishes to find a value for β that minimizes the *incorrectly* predicted paired comparisons, as defined by equations 2 – 6,

$$\tau(\hat{Y}, Y) = (C\text{-}D) \,/\, \mathrm{sqrt}[(\mathrm{Pairs} - T_p)*(\mathrm{Pairs} - T_c)] \tag{2}$$

$$C = Prop(Y_i > Y_j \cap \hat{Y}_i > \hat{Y}_j) + Prop(Y_i < Y_j \cap \hat{Y}_i < \hat{Y}_j) \tag{3}$$

$$D = Prop(Y_i > Y_j \cap \hat{Y}_i < \hat{Y}_j) + Prop(Y_i < Y_j \cap \hat{Y}_i > \hat{Y}_j) \quad (4)$$

$$T_p = Prop(Y_i \geq Y_j \cap \hat{Y}_i = \hat{Y}_j) + Prop(Y_i \leq Y_j \cap \hat{Y}_i = \hat{Y}_j) \quad (5)$$

$$T_c = Prop(Y_i = Y_j \cap \hat{Y}_i \leq \hat{Y}_j) + Prop(Y_i = Y_j \cap \hat{Y}_i \geq \hat{Y}_j) \quad (6)$$

where Pairs = N(N-1)/2, the number of unique paired comparisons, C= the number of concordant paired comparisons, D=the number of disconcordant pairs, T_p=the number of ties on the predictor, and T_c=the number of ties on the criterion. With only one predictor, only the sign of β matters, which provides the direction of the relationship between $\hat{Y}$ and Y. Thus, for the one-predictor case, the specific value of the β is irrelevant, and the strength of the predictor is defined by the value of tau. Note that there is no intercept parameter in Eq 1 because it is not necessary for predicting the ordered relationship.

Equation 1 can be generalized to the multiple predictor case,

$$\hat{Y} = \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \quad (7)$$

In equation 7, the different coefficients are estimated to maximize model fit and can therefore take on any real number, which allows the variables to differentially contribute to the overall fit between the data, Y, and the model estimates, $\hat{Y}$. In this context, the magnitudes of the βs are interpreted as the *relative* contribution of each predictor for predicting the ordinal values of Y. In contexts in which predictors are uncorrelated, the β weights can be viewed as the relative importance of each variable for characterizing the ordinal values of Y.

Parameter estimation is achieved computationally, rather than analytically, as there are no currently available methods for deriving optimal weights to maximize the rank order correspondence between a model and the data. In the present analyses, we used a genetic algorithm to search the parameter space for the best-fit parameter estimates. Prior work (Dougherty & Thomas, 2012) illustrated that genetic search works well for estimating the optimal

weights for simulated data with known parameters.

In the analyses that follow, we fit data within the context of minimizing model complexity. This was achieved by using a variant of the Bayesian Information Criterion (BIC). Raftery (1995) showed that the BIC could be estimated from

$$\text{BIC} = N \log(1 - R^2) + k \log(N) \qquad (8)$$

where N is the sample size, R^2 is the squared multiple correlation, and k is the number of parameters. One problem with applying Eq 8 directly is that GeMM is designed to predict rank orders. However, Kendall and Gibbon (1990) showed that under bivariate normality[2], Pearson's *r* could be estimated from tau using

$$r\text{-tau} = \sin(\text{pi}/2\tau) \qquad (9)$$

Substituting equation 9 for the value of R^2 in (8) yields equation 10:

$$\text{BIC}_r = N \log(1 - (sin[pi/2\tau])^2) + k \log(N). \qquad (10)$$

Equation 10 is the value of the BIC estimated from the tau-to-*r* transformation. However, because the value of r_r shows greater variability than *r* (Rupinski & Dunlap, 1996) we use an adjusted form of r_r based on sample size and the number of predictors used in the regression. Specifically, we define r_r' as,

$$r_r' = sin[pi/2\tau\omega], \qquad (11)$$

where

$$\omega = (N-P-1)/N. \qquad (12)$$

where ω is a weighting function based on the number predictors, P, used in the regression and sample size, N. ω serves to de-weight the value of tau for smaller sample sizes, and therefore

reduces the variance of the tau-to-*r* transformation. Because ω goes to 1.0 as N increases, the asymptotic value of the tau-to-*r* transformation is preserved. Substituting r_τ' into equation 12 gives

$$BIC_\tau' = N \log(1 - r_\tau'^{\,2}) + k \log(N). \qquad (13)$$

Model selection based on equation 13 (BIC_τ') is assessed on the fit of the model to the data as given by the degree of monotonic relationship expressed by the tau-to-*r* transformation, adjusted for model complexity. Dougherty and Thomas (2012) showed that model fitting based on r^2_τ' is invariant to monotone transformation on y, whereas model fit based on the linear r^2 can suffer from considerable loss of power when statistical relations deviate from strict linearity. Further, Dougherty and Thomas (2012) illustrated that GeMM's estimated parameters approximated the metric population values, and were unaffected by nonlinearities. This later result occurs for the same reason that ordinal multidimensional scaling solutions approximate metric properties of the data: The number of constraints on the rank-order solution increases exponentially as sample size increases (Dougherty & Thomas, 2012; see also Shepard, 1962, 1966).

The base GeMM algorithm described above and in Dougherty and Thomas (2012) searches the parameter space to find coefficients that maximize the value of tau. However, a simple modification to this process involves maximizing the linear fit (R^2), conditional on the optimal ordinal fit. This can be achieved in GeMM by sorting all models with equivalent (maximal) ordinal fit by their corresponding values of R^2. This yields the vector of beta's that optimize the *linear* fit, conditional on the set of coefficients that maximize ordinal fit. Note that the coefficients derived from this process are scale independent and are not directly comparable to coefficients derived from ordinary least-squares, as there is an infinite number of parameter values that will yield an equivalent solution. This is because GeMM lacks an intercept term and because the fit statistic, tau, is invariant to monotone transformation. However, one may obtain a

comparable least-squares model, one that is conditioned on maximizing tau, by regressing the criterion value Y on the predicted values of Y obtained from GeMM. In other words, we can use the ordinary least-squares machinery to rescale the GeMM fitted weights to the least-squares solution that simultaneously maximizes the rank-order correspondence between the criterion and fitted values. We refer to this procedure as order constrained least-squared optimization (OCLO, Tidwell, Dougherty, Chrabaszcz, & Thomas, 2014). In principle, the OCLO solution is a special case of the base GeMM model in which weights are rescaled to minimize the sum of squared errors, conditional on the optimized ordinal fit. The end result of applying OCLO is a set of beta coefficients that are directly comparable to those obtained via ordinary least-squares regression.

4. Reducing flexibility in analysis: An illustration of GeMM on two datasets

Flexibility in data analysis presents an appreciable challenge when different analysis techniques or data editing decisions change the substantive conclusions. Here, we argue that GeMM offers a promising approach for reducing this flexibility. GeMM assumes that the predictors are interval scale, permitting the model to take the traditional additive form, but treats the criterion variable as ordinal--allowing ordinal, interval, ratio, and even nominal (in some cases) scale variables to serve as the criterion. A key feature of GeMM is that it is designed to model the monotone relations of the data. This feature means that GeMM is invariant to transformation on Y, and should be relatively robust to extreme scores, or outliers, compared to LS procedures. Consequently, GeMM's solution should be relatively stable across different methods for identifying and eliminating extreme scores. In contrast, because LS procedures seek to maximize linear fit, extreme scores can exert undue influence on LS solutions, even when only a small number of scores are extreme. Below, we demonstrate that a small number of extreme scores can sometimes drive manifest effects, and other times hide effects when data are analyzed using LS procedures. In addition, we illustrate that different methods for identifying and eliminating extreme scores and nonlinearities can lead to inconsistent statistical conclusions when

analyzed with LS approaches. In contrast, GeMM provides more consistent statistical conclusions across multiple data editing strategies in our demonstrations.

4.1 When extreme scores drive effects: The case of racial bias

What is the relationship between explicit measures of racial bias, implicit measures of racial bias, and motivation to control prejudice? Prior work on this topic suggests that explicit measures of racial bias capture some element of one's true underlying attitude, but that they are subject to response biases on the part of the participant (e.g., Dunton & Fazio, 1997; Fazio et al., 1995). For example, how people respond on the Attitudes Toward Blacks (ATB) scale appears to be moderated by people's motivation to control prejudice (Plant & Devine, 1998). Plant and Devine (1998) identified two separate forms of such motivation: An internal motivational factor and an external motivational factor. The internal factor tests for motivations stemming from the belief that stereotypes are morally wrong or personally unacceptable. The external factor tests for motivations stemming from the desire to avoid social censure—in other words, the belief that *other people* believe stereotypes are morally wrong or unacceptable. Either type of motivation could lead to similar self-censoring of socially unpopular attitudes, but that similarity belies the important differences between people who are driven by one versus the other motive type.

Partly to deal with this problem of self-censoring, considerable research has validated the use of implicit measures of racial bias. Perhaps the most well known implicit measure is the implicit association test (Greenwald, McGhee, & Schwartz, 1998), a measure that uses response times to assess the difficulty respondents have classifying White or Black faces simultaneous to categorizing other stimuli as good or bad. More recently, other implicit measures have been developed that do not rely on response times. For example, Payne and colleagues (Payne, Cheng, Govorun, & Stewart, 2005; Payne, Burkley, & Stokes, 2008) developed the affect misattribution procedure (AMP), which involves showing people a stimulus word or picture that they are told to

ignore, followed by a Chinese pictograph. Participants are instructed to rate how pleasant the pictograph is, ignoring the stimulus that precedes it. However, the affect associated with the first stimulus is expected to "bleed over" to the pictograph, revealing how positively or negatively respondents *actually* feel about that *first* stimulus that they are supposed to be ignoring. Payne and colleagues showed that scores on the AMP reflect subtle ingroup preferences among both White and Black respondents, and that this ingroup bias occurs whether or not participants are warned to avoid being biased on the measure (an external motivation to control prejudice). In contrast, participants who reported strong *internal* desires to avoid prejudice appeared to modify their *explicit* racial attitudes. Consequently, the self-reported attitudes of these participants hardly correlated at all with their scores on the AMP. Among participants who reported weaker internal desires to avoid prejudice, AMP scores were highly correlated with explicit prejudice.

An important question regarding the measurement of racial attitudes is the degree to which explicit measures of racial attitudes capture one's true attitude and the degree to which they are subject to people's motivation to control their expression of their attitude. This problem is reflected in the results found by Payne and colleagues (2005), as well as by many other researchers (e.g., Devine, Plant, Amodio, Harmon-Jones, & Vance, 2002; Dunton & Fazio, 1997; Plant & Devine, 1998; Plant, Devine, & Blazy, 2003). Theoretically, a case can be made for both the inclusion and exclusion of external and internal motivation to control prejudice as predictors of racial attitudes. On the one hand, it makes sense that one would wish to avoid social censure (an external motivation) as a consequence of openly admitting that one is racially biased. For this reason, it is clear that explicit motivations should play an important role in how people respond on the ATB and other such explicit attitude measures. On the other hand, the belief that racism is morally wrong (an internal motivation) might lead one to explicitly state more positive attitudes toward Blacks than one actually holds. Either way, researchers who want to know people's *true*

attitudes would seem to do well by accounting for these types of motivations in studies of prejudice or other socially sensitive topics.

4.1.1. Data and Analyses

We re-analyzed data initially published by Siegel, Dougherty, and Huber (2012). The original sample included 213 University of Maryland undergraduate students (128 females). Of these, 15 participants were missing data on one or more measures and were therefore excluded from the analysis. Each participant was measured on 10 variables, including 3 measures of racial attitudes—the Attitudes Toward Blacks (ATB) scale, the Race Attitude Misattribution Procedure (Race-AMP), and the Racism Implicit Association Test (Race-IAT); the motivation to control prejudice subscales (the External Motivation Scale, EMS, and the Internal Motivation Scale, IMS); two measures of cognitive control (the Stroop Test and the Stop Signal Task); and three measures of political attitudes—explicit political attitudes (EPA), a Political AMP (Pol-AMP), and a Political IAT (Pol-IAT). Additional details of the study, including how the various tasks were constructed, administered, and scored are provided in Siegel et al. (2012).[3]

Siegel et al. (2012) were primarily concerned with understanding the relationship between the IAT and the measures of cognitive control. Using factor analyses, they showed that both the Political-IAT and the Race-IAT loaded on two factors: their respective attitude factor, and a cognitive control factor. That is, performance on the IAT appeared to be predicted best by a model that assumed that the IAT measures both the target attitude and cognitive control. While the Race-IAT was unrelated to the explicit ATB, it was highly related to the Race-AMP. Moreover, the ATB was correlated with the Race-AMP and both the EMS and IMS. This pattern of correlations suggests that scores on the ATB are dependent on an (implicit) attitude factor and both forms of motivation to control prejudice. However, Siegel et al. (2012) did not explore these relationships in depth. Thus, the substantive goal of our reanalysis was to identify the best

predictors of scores on the ATB from the collection of variables included in Siegel et al.'s study. The methodological goals were to (a) demonstrate that the substantive conclusions could change depending on how extreme scores were identified and treated, and (b) test whether GeMM was less sensitive to the treatment of outliers.

Using LS regression, we tested the hypothesis that both internal and external motivations to control prejudice were negatively related to participants' self-reported (explicit) racial biases, as measured by the ATB scale, independent of participants' implicit racial bias, as measured by the Race-AMP. Using the classical Null Hypothesis Significance Testing (NHST) approach with alpha = .05, we found the predicted relationship: The ATB was significantly and positively related to the Race-AMP, and the ATB was negatively related to both the EMS and IMS. Summary statistics for this analysis are presented in the top row of Tables 1 and 2 in the row labeled "Full data". Overall, these three variables accounted for 13.2% of the variance in ATB scores, with the rank order correlation between the predicted and the actual values of the ATB yielding a value of tau = 0.239. Thus, on the basis of this analysis, it seems that we are justified in supporting the theory that self-reported (explicit) racial bias is a function of people's implicit racial bias, their internal motivations to control racial bias, and their external motivations to avoid being seen as racially biased. Or are we?

Figure 1 plots the histograms for all 10 variables in the study, and Figure 2 provides the bivariate scattergrams for each predictor (x-axis) plotted against the ATB. Two findings should be evident from inspection of the graphs. First, the relationships identified by linear regression are not easily discernible from the bivariate plots, although by itself this fact might not be terribly concerning—subtle associations do not always yield their secrets to the naked eye. Second, many of the predictors are poorly distributed, which is somewhat more concerning, given the assumptions underlying LS regression. And third, there appears to be a small number of extreme scores (outliers?) in the distribution of the ATB scale, which could prove to be especially

problematic for standard regression techniques and might even "require" data editing prior to analyzing the data with OLS.

Given the presence of extreme scores and the non-normality of the distributions, we conducted a series of follow-up analyses to determine the robustness of the conclusions to different methods for reducing the influence of violations of the assumptions of linear-LS regression. The first approach was to conduct outlier analyses to identify and eliminate potentially problematic data points. There are a variety of outlier detection methods, but we confined ourselves to three techniques: Univariate outlier analysis, Cook's D, and DFFITS[4]. Application of these three approaches to the dataset resulted in the identification of 3, 13, and 8 extreme scores, respectively. After trimming these data points out of the sample, we re-analyzed the data, again using OLS with an alpha of 0.05.

The results of the analyses after eliminating these extreme data points are also presented in Tables 1 and 2. As can be seen, two approaches to eliminating extreme scores revealed that two predictors were significant, and one approach revealed three significant predictors. Surprisingly, the elimination of a mere 1.5% of the data (3 data points) was sufficient to knock out internal motivation as a significant predictor. This was not just a matter of the p-value hovering around 0.05 and bouncing back and forth over the threshold, as the p-value for IMS was 0.02 for the full dataset, but jumped to nearly 0.12 after eliminating only 3 data points. Thus, the decision to exclude IMS for the univariate trimmed data is not an inconvenient by-product of the conventional, yet arbitrary, value of alpha=0.05. Combined with the analyses using the full data set, there appears to be no clear "winner" regarding which statistical conclusions are most appropriate.

The fact that different methods for dealing with extreme scores resulted in different statistical models is problematic for the purposes of theory testing. Therefore, we conducted a

series of analyses using three variations on robust LS regression and ordinal logistic regression. Robust statistics are designed to de-weight extreme scores based on their distance from the mean, and therefore are purported to have better statistical properties when distributional assumptions are violated. The methods used here are the Huber, Bi-square, and Hampel methods, which were implemented again using NHST. Ordinal logistic regression treats the criterion variable as an ordered category, and estimates thresholds for each category. For our purposes, we modeled the raw data rather than creating binned responses.[5] In addition, we also re-analyzed the full and trimmed datasets using the Bayesian Information Criterion (BIC) as a model selection method. The BIC model selection method has the advantage of not relying on the arbitrary 0.05 threshold for statistical significance.

The results of the Robust, BIC model selected, and ordinal regression analyses are presented in the middle portions of Tables 1 and 2. Once again, the results are inconclusive, with two of the robust approaches (Huber and Bi-square) yielding two significant predictors and one approach (Hampel) yielding three significant predictors. Model selection using the BIC to select predictors was even more inconsistent, as it yielded *two different* 2-predictor models, as well as a 3-predictor model. The results of the ordinal logistic model are a bit more complicated. This model fits the ordinal properties of the data, but to do so it estimates thresholds for each of the ordered categories using the full model with all predictors. As can be seen, this model fits the ordinal properties quite well, but at the expense of a considerable increase in model complexity due to the need to estimate the threshold parameters. Even so, this method also produced different models between the full data set and the univariate trimmed dataset in which only 3 observations were eliminated: Three predictors were significant on the full dataset, but only two were significant on the reduced (univariate trimmed) dataset.

The inconsistency across outlier and data analysis methods is undesirable for many reasons, but principally *because it allows the researcher the freedom to choose which theoretical*

conclusions to draw from the data, rather than forcing theoretical conclusions to be constrained by the data—a principle at the heart of basic science. Given these inconsistencies, we reanalyzed the data using GeMM. In contrast to traditional LS approaches, GeMM models data at the level of paired comparisons, as we explained earlier. Because GeMM does not model data using a distance metric and makes less stringent assumptions of the data, it should be more robust to the presence of extreme scores and nonlinearities.

The results using GeMM are presented at the bottom of Tables 1 and 2[6]. As can be seen, GeMM resulted in a 2-parameter solution when applied to the full dataset, and this solution was consistent for both the univariate and DFFITS methods for eliminating outliers. Note that the two-predictor solutions include the same predictors (EMS and Race AMP) identified as significant by the Huber and Bi-square procedures. GeMM was not completely insensitive to outlier deletion methods, as it identified a 3-predictor solution when the 13 observations were trimmed using Cooks D. However, the fact that it was stable for both the univariate and DFFITS methods (which required deleting only 3 and 8 observations) suggests that it is relatively more robust than OLS. In fact, further analyses on these data indicated that the OLS solution changed from a 3 to a 2-predictor model even after eliminating just one data point, the single most extreme value on the ATB (attitudes towards blacks) scale. This pattern of analyses suggests that GeMM has a much greater tolerance for extreme scores than OLS. Coincidentally, the robust regression procedures also resulted in a 3-predictor model when applied to the Cooks-D trimmed data.

Considering the full-dataset, is the 2-parameter GeMM solution preferable to the 3-predictor LS solutions, and are we justified in accepting the 2-parameter model over one that includes three predictors? There are two ways to address this question: (a) Compare the fit indices for GeMM with those of OLS, and (b) conduct cross-validation analyses. We consider both in turn.

4.1.2 Comparing fit and cross validation

Inspection of the fit indices indicates that the 2-parameter GeMM solution actually provides a better fit to the data in terms of accurately capturing the ordinal properties of the data than all of the other approaches except ordinal regression, even the models that included 3 parameters, as shown by the values for BICt' and tau. Although the LS solutions fit the data better when evaluated in terms of the multiple *R* and BIC, these indices are highly suspect because they require the assumption of linearity: Inasmuch as the linear (LS) solution is relatively poor at capturing the monotonic relations of the data (as given by the tau and BICt'), one must be wary of interpreting a solution that makes the stronger assumptions of normality and linearity. While ordinal logistic regression had a higher value of tau, this came with considerable increase in model complexity. As we show below, this increase in model complexity can lead to overfitting.

One interesting aspect of these fit indices is that although the LS versions (ordinary and robust regression) provide better fit to the data in terms of the R^2, this fit comes at a cost of accurately capturing the ordinal properties of the data. For instance, for the full sample, OLS accounts for 13.2% of the variance (R^2=0.132), but has a rank order correlation of only 0.239. In contrast, when GeMM is applied to the same data it accounts for only 8.0% of the variance (R^2=0.080), but is better able to account for the ordinal properties of the data, with a rank order correlation of 0.251. This pattern also holds for all three methods for trimming outliers.

We used split half cross-validation to evaluate out-of-sample prediction: Which statistical algorithm provides the best predictive accuracy when the estimated parameters are used to predict new observations. This approach has the advantage that it directly addresses the problem of over fitting, in which statistical models tend to show poorer accuracy (i.e., shrinkage) at predicting new observations compared to the fit to the original estimation sample. The cross-validation

approach has the added benefit, however, of allowing one to evaluate statistical power, or the probability that each of the predictor variables will be identified as a 'significant' predictor (or included in the selected model). We conducted a split-half cross-validation using the full data set (N = 198), in which one-half of the data were randomly sampled and used to estimate model parameters. The remaining one-half of the data were used as the hold-out sample. For each 'replication' of this procedure, we recorded for each algorithm which parameters were recovered, fit indices, and beta weights. For methods using NHST, a parameter was classified as recovered if it was significant at the 0.05 level using a t-test on the regression coefficient. Out-of-sample predictive accuracy was assessed by applying the recovered statistical model to the holdout sample (i.e., the beta weights for non-significant predictors were set to 0). We computed the multiple R, tau, and the corresponding values of BIC and BICt'. This procedure was repeated 500 times for each statistical model.

The results of the cross-validation analyses are presented in Tables 3 and 4. Table 3 shows the probability of recovering each predictor when each algorithm is provided half of the data. Recall that on the full sample, OLS recovered a three-predictor model consisting of the Race AMP, the IMS and the EMS, whereas GeMM recovered a two-predictor model consisting of the Race AMP and the EMS. Overall, GeMM was more likely to recover both the AMP and the EMS than OLS, indicating that GeMM had more power to detect these effects. The remaining models are less straightforward, but on balance GeMM showed recovery rates that were either approximately equal to (RLS-Huber, Ordinal Logistic) or better than the other alternatives.

Perhaps more instructive are the fit statistics provided in Table 3, which illustrate the average fit (top half) and average cross-validation accuracy (bottom half). GeMM provided better out-of-sample predictive accuracy than all of the alternatives in terms of tau, and even outperformed many of the alternatives in terms of the multiple R. Note that logistic regression showed the poorest out of sample prediction in terms of R and second worst in terms of tau,

despite the fact that it showed the best performance in terms tau (and second best in term of R) on the estimation sample.

To summarize, based on the statistical fit and predictive accuracy of the various statistical models, it is clear that the best and most defensible conclusion to draw from the data is that responses on the Attitudes Toward Blacks scale in the Siegel et al. (2012) study are best accounted for by both implicit racial prejudices (as measured by the race AMP) and external motivations to control prejudice (EMS), but not internal motivation to control prejudice (IMS). However, the bigger point to be made from these analyses is that statistical conclusions based on LS approaches proved to be highly suspect, and often due to a very small number of observations. Removing merely 3 of the 198 data points was sufficient to change one's statistical conclusions, and the use of robust procedures only muddled the picture. The main problem, as we see it, is that the labile nature of LS procedures and their sensitivity to the removal or de-weighting of extreme scores *licenses the researcher to choose which theory to support via the selection of a data-analytic strategy*. Thus, rather than the data constraining the theory, the theory can constrain the data in the name of making sure the data adhere to statistical assumptions. GeMM appears to be more resistant to outliers, which means it will be less affected by decisions to eliminate them.

4.2 When nonlinearities mask effects: The case of homicide rates and the culture of honor

A recent topic of interest in social psychological research concerns cultures of honor, which are societies in which defense of reputation is a central organizing theme (Nisbett, 1993; Nisbett & Cohen, 1996). Such societies are especially common, according to Nisbett and colleagues, where scarce resources are highly portable (hence, easily stolen) and where the rule of law is weak or altogether absent (see also Brown & Osterman, 2012). Nisbett (1993) argued that this combination is quite common in societies whose economies are based on herding rather than agriculture or industry, as herding societies tend to be resource-poor, their resources are quite portable, and they tend to be poorly managed by law enforcement, the latter due in part to the fact

that herders are, by necessity, spread out. Under such conditions, people are especially vulnerable to social predation, both from within (via internal competition for scarce resources) and from without (via attack from other groups). This vulnerability, over long periods of time, has a tendency to breed the beliefs, values, and social norms that characterize honor cultures, such as a hyper-vigilance to reputational threats and aggressive responses to perceived honor violations.

Honor cultures tend to stress strength and toughness as primary qualities of value for men, and loyalty and purity as primary qualities of value for women (Nisbett & Cohen, 1996; Vandello & Cohen, 2003). These qualities are pursued vigorously by men and women in such societies, as they help to protect people from their key sources of vulnerability. For instance, men who are known to be strong and brave are not men who are likely to be targeted for attack, as long as there are other targets available. Arguably, a man does not have to be *absolutely* strong and brave to protect himself or his family—he only has to be known as being *relatively* stronger and braver than other men, as someone who should not be disturbed or "messed with." As long as he maintains his reputation for pugnacity, he can reduce the odds of predation from his neighbors and from hostile outgroups. Because of this combination of an extreme emphasis on reputation management and the types of reputations that are idealized for men and women, honor cultures tend to exhibit higher-than-average rates of argument-based homicides (Nisbett & Cohen, 1996). In addition, research has shown that states in the US classified as "honor states" (in the South and West) display higher levels of school violence (Brown, Osterman, & Barnes, 2009), higher rates of suicide (Osterman & Brown, 2011), and excessive levels of risk-taking that lead to higher rates of accidental deaths (Barnes, Brown, & Tamborski, 2012), compared to "non-honor states."

In a series of studies, Henry (2009) argued that one of the reasons that herding cultures tend to develop honor norms (as Nisbett & Cohen, 1996, suggested they do) is that such cultures tend to be characterized by strong status disparities. When a society has a large status hierarchy, with relatively few people controlling a relatively large amount of that society's resources, people

at the bottom of the status hierarchy may feel especially vulnerable to social devaluation and be prone to hyper-vigilance and hyper-reactance to status threats (see also Daly & Wilson, 2010). Aggression in the face of insults is one prime example of the type of reaction that might be especially prevalent in members of low status groups in such unequal societies. Henry (2009) tested this notion in part by showing that homicide rates were higher in cultures whose economies tended to be based heavily on herding, where (theory suggests) honor-related beliefs and values will tend to proliferate. Importantly, Henry showed that elevated homicide rates in herding-oriented countries were statistically accounted for by levels of social *wealth disparity* within those countries, independent of a country's overall level of wealth. Henry (2009) also expected to replicate past findings that overall wealth would independently predict homicide rates, which he showed in Study 1 (at the county level) but failed to show in Study 2 (at the country level).

4.2.1 Data and Analyses

We reanalyzed the data used for Study 2 of Henry (2009). Our use of this dataset was a matter of convenience and motivated by his failure to replicate the association between overall wealth and homicide rates obtained in his study 1 and other prior work (Nisbett & Cohen, 1996). Using ordinary LS regression, we were able to reproduce his international results: Countries with larger proportions of their lands devoted to uncultivated pastures and meadows appropriate to herding (hereafter *pastureland*) tended to exhibit higher homicide rates, but this association was largely accounted for by within-country levels of wealth disparity (as indexed by the Gini coefficient of income inequality, hereafter *Gini*), independent of overall levels of wealth across those countries (as indexed by gross domestic product per capita, adjusted for purchasing power parity, hereafter simply *GDP*). Replicating Henry (2009), GDP was not a significant predictor ($p = 0.36$), which remains as surprising to us as it did to Henry (2009). However, are our statistical conclusions robust?

Figures 3a and 4 show the bivariate scattergrams and histograms for the four variables: Homicide rates, % pastureland, Gini, and GDP. As is clear, the data are poorly distributed, yet there is obvious structure in the bivariate scattergrams. In particular, there appears to be a monotone but nonlinear relationship between GDP and homicide rates. Indeed, in terms of Kendall's tau, the strength of the relationship between Gini and homicide (tau = +0.39) is virtually identical to the strength of the relationship between GDP and homicide (tau = -0.36). In contrast, the pattern of correlations obtained using Pearson's *r* yields a much stronger relation between the Gini and homicide (r = +0.50) compared to GDP and homicide (r = -0.30). Not only does there appear to be substantial nonlinearity in the data, but there also are a small number of extreme scores and substantial non-normality.

Given the obvious violations of assumptions for the linear model, it is likely that OLS regression is ill equipped to model these data accurately.[7] But, how *should* the data be modeled? Henry (2009) modeled homicide rates in their raw form using OLS, but other researchers interested in understanding factors contributing to homicide rates have used different approaches. For example, in testing the social capital theory of cross-national homicide rates, Lederman, Loayza & Menéndez (2002) modeled the natural logarithm of homicide. In a replication of Lederman et al., Robbins and Pettinicchio (2012) used negative binomial regression, which they argue more accurately captures the modeled distribution. As well, because the data are transformations on count data (homicides per 100,000), both Poisson and quasi-Poisson regression are logical alternatives as well. The fact that there are multiple potential analysis techniques raises two questions: (a) which method is 'most' appropriate?, and (b) do the different methods yield different substantive conclusions? The question of which method is most appropriate is debatable, though addressing the second question seems straightforward. To start, we reanalyzed the data using two reasonable and common transformations: natural logarithm and square root. We used these transformations in two ways: First where only the criterion variable

(homicide rate) was transformed, and again where all of the variables were transformed. As an illustrative example, Figure 3b plots the bivariate scattergram after applying the log transformation to homicide rate. As can be seen, the non-linear relationships in the raw data are mostly linearized after the transformation.

Table 5 provides the results of the analyses using LS regression and GeMM both on the original (raw) data and on the transformed data. As should be evident, only GeMM provided a consistent model form across the various transformations. In particular, both versions of LS regression (OLS-NHST, OLS-BIC) recovered a one-predictor model consisting of Gini when applied to the raw data, but a two-predictor model consisting of Gini and GDP when the criterion variable was log-transformed (p's < 0.001 across method for both Gini and GDP). When all of the variables were transformed, however, both OLS-NHST and OLS-BIC again recovered the single-predictor model consisting of Gini. The square-root transformation also yielded inconsistent findings across methods. GeMM recovered a two-parameter model (Gini and GDP), and this was consistent across all of the transformations. Also included in Table 5 are the results from using three variants from the Generalized Linear Models family. Poisson regression identified all three predictors as significant, whereas both quasi-Poisson and negative binomial regression identified both Gini and GDP as significant.

Arguably, given the distributions presented in Figure 4, the data could legitimately be transformed to remove the skew prior to using traditional least-square regression. However, whether the transformation should apply only to the criterion variable (homicide rate) or to all variables is a matter of debate and an existing "researcher degree of freedom" under traditional analysis methods. Although explicit transformations are unnecessary for negative binomial and the two Poisson regressions, they are implicitly carried out via the link function within GLM, of which researchers have many options. In contrast, with GeMM there is no need to transform the criterion variable because the rank-order correlation, tau, is invariant to monotone transformation.

Thus, whether homicide rate is transformed by taking the logarithm, square root, or any other monotonic function, or left untransformed is immaterial for GeMM's solution and therefore removes this potentially important researcher degree of freedom.

The analyses presented above indicate that LS regression procedures are sensitive to decisions about whether (and how) the data are transformed. This should not be too surprising, because LS procedures fit distance information and because the distance information changes under different transformations. But, just how distorted can it get? To explore this sensitivity, we analyzed the data again, but this time after adding a constant before applying the logarithmic transformation. The need to add a constant to the data prior to taking the logarithm arises when responses take on the value of '0' or are negative. Negative values are likewise problematic for the square root transformation, but so are positive values less than 1 (as a square-root transformation on values between 0 and 1 will *increase* these values, while simultaneously *decreasing* all values greater than 1; adding a constant to raise all raw values to a number greater than 1 eliminates this transformation disequilibrium). Using OLS-NHST, adding any constant between 0.2 and 1.4 leads to both Gini and GDP identified as significant. Adding any constant above 1.4 or below 0.2 resulted in only Gini as statistically significant. The LS models yield different models with different additive constants; GeMM does not. The use of the negative binomial and Poisson regression models from the generalized linear model family do not really solve the underlying issue: For these models, whether you conceptualize the number of homicides in each country as a count or rate problem can actually change the form of the statistical model. Further, if homicides are interpreted as a rate (number of homicides per unit of population), the model form can also depend on the choice of scaling constant. For example, both the Pearson r and rank order correlation (tau) between the fitted values and the data varies depending on whether the homicide variable is expressed per 1,000, per 100,000 or per 10,000,000. How likely

is it that researchers are aware of these sources of variation when they choose to add or divide by a constant as part of their data-transformation routine?

As mentioned above, GeMM provides a 2-predictor model regardless of transformation. But how well does this solution compare when evaluated in terms of fit indices and cross-validation?

4.2.2 Comparing fit and cross validation

A comparison of the relative fit indices favors the solution identified by GeMM. First, consider the results of the OLS. The one-predictor solution on the raw data has the highest value for R amongst the various procedures. However, despite having the best *metric* fit, this model is much poorer at capturing the ordinal properties of the data compared to GeMM and the GLM models. That is, in order to fit the ordinal properties of the data, it is necessary to give up a little accuracy in predicting the metric properties. Both GeMM and the GLM models do just this. Comparing GeMM to the GLM models, however, also reveals that GeMM performs favorably in terms of tau and BICtau'. GeMM's fit to the metric properties is somewhat poorer than the GLM models.

Using the same split-half methodology described in the discussion of the racial bias data, we evaluated the predictive accuracy and statistical power of GeMM relative to the various LS procedures. Figure 5a plots the probability of recovering each predictor using N/2 for raw and transformed data for OLS-NHST, OLS-BIC, and GeMM. Table 6 provides the fit and out of sample predictive accuracy for all of the models. As is strikingly clear, GeMM recovers each of the two predictors (Gini and GDP) identified in the full sample on approximately 95% of runs, with statistical power remaining high across the various transformations. For comparison, for the full data set all three procedures recovered Gini and GDP when homicides were log transformed, but note that GeMM substantially outperforms both versions of OLS in terms of recovering these

predictors when provided half the data, in particular for GDP. Thus, not only does GeMM accurately recover GDP on the full dataset, it does so with much higher power compared to OLS, even under conditions in which the data are transformed to make them more suitable for OLS.

Given the relatively poor showing of the LS procedures in recovering the predictors identified on the full dataset, it should not be surprising that GeMM substantially out-performed its LS competitors in out-of-sample prediction. Indeed, even if we restrict our analyses to only the subset of non-null models identified by the LS procedures, which we have done here in Table 6, it is clear that GeMM is the hands-down winner of the cross-validation contest. GeMM uniformly out-performs OLS and OLS-BIC in terms of predicting the rank order of homicide rates across nations, and in some cases even out-predicts OLS in terms of the Pearson's R (e.g., sqrt(homicides), and log(homicides)).

Comparison of GeMM to the GLM models is a bit more complicated. GeMM clearly outperforms quasi Poisson in probability of recovery (Figure 5b) and out of sample predictive accuracy (Table 6). Standard Poisson regression recovered both Gini and GDP at the approximate level of GeMM, but also recovered percent pastureland over 50% of the time. The inclusion of percent pastureland in the model is particular problematic here, since adding it to the model actually decreases ordinal predictive accuracy. Negative binomial regression performed nearly identical to GeMM across the board, with GeMM having a modest advantage in probability of recovery and a small (0.015) advantage in terms of tau. Thus, overall GeMM performed better than all three of the models from the GLM family.

To summarize, we argue that homicide rates across the 92 countries analyzed in this dataset are best accounted for by both wealth disparity and a country's overall wealth per capita. Although the finding was tangential to Henry's main theoretical conclusions, it nevertheless explains a failure to replicate a classic finding in one of his studies, that of the relationship

between GDP and murder rates. This finding is consistent with Henry's (2009) original prediction, which presumably was masked by the substantial nonlinearity present in the data. GeMM was able to accurately capture both Gini and GDP as important predictors of homicide rates without transformation and without requiring specific assumptions about the form of the underlying distribution of homicides. In contrast, within OLS the decision to include GDP in the statistical model was conditional on how the data were transformed, and within GLM it was contingent on which distribution was assumed.

5. General Discussion

The analyses presented in this paper identified two important problems faced by behavioral and social scientists in their use of standard and robust LS procedures, and a possible solution to these problems. First, LS regression procedures are highly sensitive to violations of assumptions and the presence of extreme scores. In our re-analysis of the racial bias data, we illustrated that a small number of extreme scores was sufficient to drive or mask statistical effects. Eliminating a mere 1.5% of the data was sufficient to render internal motivation to control prejudice as unnecessary to predict explicit attitudes toward blacks. In contrast, for the culture of honor data, violations of the linearity assumption and/or the presence of extreme scores resulted in the failure of LS regression to identify expected patterns for which there was structure in the data. Taken together, these results suggest that nuances within one's data can either drive effects or mask them when using LS procedures. The fact that violations of assumptions and messy (which is to say, real) data can undermine statistical conclusions is not a new insight, of course. What is new, we believe, is that accepted procedures for dealing with messy data offer no real solutions to the problem – which leads to the second finding.

The second finding identified by our analyses is that accepted methods for dealing with messy data do not uniformly converge on a consistent statistical, and therefore theoretical,

conclusion. This is especially problematic because the failure to find consistency across methods leaves too much decision-making power in the hands of the scientist. Unfortunately, scientists are not always unbiased observers of their data, and are probably most likely to use the data editing strategies that result in an outcome supportive of their theory, although they might not be aware that they are doing so. Thus, standard practices for dealing with messy data increase the number of researcher degrees of freedom (cf. Simmons et al., 2011), which we argue can undermine the search for valid scientific conclusions and hamper scientific progress.

Our solution to these two problems is to advocate for statistical procedures that reduce or eliminate the need for conducting outlier analyses and data transformations. As we showed throughout this paper, GeMM provides a promising new approach that maximizes fit at the ordinal level. To illustrate the fundamental importance of modeling the ordinal level of data, imagine that a new scoring system were proposed for use at the Olympics. This scoring system, statisticians show, does a good job of accounting for variance in athletes' past scores (analogous to a high R^2), although it does not do particularly well at recovering ordinal outcomes—in other words, in post-dicting who came in first, second, or third place. We cannot imagine that such a scoring system would ever see the light of day, and whoever proposed it would be laughed out of a career in statistics. Nonetheless, that is essentially what the present two studies suggest is happening with LS procedures when it comes to modeling ordinary, messy data in the behavioral sciences. As we have shown, GeMM's solution was relatively more robust across a variety of reasonable methods for identifying and eliminating extreme and influential scores. This is a major advantage of GeMM, as it removes some of the degrees of freedom that researchers have to make the results "turn out" in favor of their hypotheses (Simmons et al., 2011).

As a side note, it is interesting to comment on what constitutes an outlier in the traditional sense. Outliers are typically identified by their distance from the center-point of a distribution of scores, or how much influence they have on the fit of a regression model. Measures of influence,

such as Cook's D and DFFITS, are defined within a least-squares function and provide a metric for how influential a particular data point is on the overall least-squares fit of a model. Thus, the more extreme an observation is, the more influence it exerts on the LS solution. In contrast, within the GeMM framework, a score that is 3 standard deviations from the mean is treated as no different than a score that is 100 standard deviations from the mean. Indeed, the only influence an extreme score has on the overall fit of the model is gauged by how many inversions it creates in the predicted rank orders when included in the dataset. This implies a need for influence statistics that operate in ordinal, rather than metric space. Because GeMM models data on an ordinal level, it has a higher bar in terms of what constitutes an outlier.

Reconceptualizing one's data through the lens of ordinality redefines the meaning of outliers as those observations that have undue influence on the rank order fit of the model. These observations may be true aberrations – data points that represent illegitimate responses given the measurement instruments (e.g., a response of 12, when the scale is bounded at 10) – or may be real observations. For example there are many cases in which extreme scores might be produced by data-entry errors, distracted subjects, or other processes external to an experiment. However, in the great majority of cases there is no ground-truth by which one can determine whether an extreme score is a legitimate member of the population distribution or an aberration due to an external factor. The uncertainty surrounding the cause of an extreme score is problematic for justifying its exclusion. If the decision to exclude is based on the need to meet the assumptions of a statistical algorithm, this strikes us as a poor justification and is tantamount to forcing a round peg into a square hole.

Obviously there are a number of alternative regression procedures not included in our modeling competition, and one might take issue with our focus on least-squares regression. However, we believe that this focus is warranted given the widespread use of the ordinary least squares (and its robust implementations) across the social sciences. Still it is quite possible that

other models might perform better than GeMM, though the appropriate candidates for the two datasets presented here (ordinal logistic, negative binomial, Poisson and quasi-Poisson regressions) did not offer any performance advantages over GeMM, and in most cases underperformed relative to GeMM.

At the same time, one might argue that decisions regarding whether or not to transform one's data should be based on sound justification and the need to do so prior to engaging in data analysis. We agree, of course, but also argue that transformation for the purpose of analyzing a particular dataset seems potentially opportunistic. Hence, we suggest that decisions to transform a dataset in a particular way should be based on an understanding of the population distribution and driven by theory, not based merely on characteristics of the sample distribution. In the absence of theoretically justified reasons for transformation, we suggest that procedures such as GeMM are more appropriate for handling data where there are even slight departures from linearity, except where the form of the non-linearity is of theoretical interest.[8]

Substantively, the findings based on GeMM for the racial bias and culture of honor data were at odds with what were found using traditional LS approaches. First, analysis of the race data suggests that responses on the ATB scale are a function of two variables: an unconscious racial attitude, as measured subtly by the AMP, and an external motivation to control prejudice. The AMP was positively predictive of people's responses on the ATB scale, whereas external motivation to control prejudice was negatively related to people's responses on the ATB. This pattern supports the idea that individuals are motivated to conceal their racial attitudes because they know that racial prejudice is socially unacceptable.

The fact that internal motivation to control prejudice was not included in the GeMM model contradicts the conclusions drawn by Plant and Devine (1998) and more recent findings of Payne et al. (2005). There are many possible reasons that our findings are at odds with these prior

studies, including the fact that racial attitudes likely differ across geographical regions (i.e., attitudes toward Blacks may differ across different subject populations) and change over time (i.e., the data collected by Plant and Devine are at least 15 years old). We therefore do not question the validity of these prior findings. Rather, the critical point for the present purposes is that *the statistical, and therefore theoretical, conclusions drawn from our data were heavily dependent on decisions about how to deal with its messiness*.

Second, for the culture of honor data, we showed that homicide rates are predicted by both wealth disparity (Gini) and overall country wealth (GDP). Wealthier countries experience fewer homicides, whereas countries with greater *wealth disparity* experience *more* homicides. These variables are theoretically independent of one another, as a country could be poor but exhibit complete social equality in its distribution of its few resources (not likely, but theoretically possible), or a country could be wealthy and exhibit a similar degree of social equality. Indeed, developed nations with high GDPs per capita differ widely in terms of how their overall wealth is distributed across their people. This potential independence of GDP and Gini, however, is largely theoretical, as overall wealth and wealth disparity are, in fact, negatively correlated in analyses at the level of nations, states, and even counties within states (e.g., Henry, 2009). In poorer countries, resources are more likely to be controlled by a few powerful people, compared to the more abundant resources of wealthier countries. Because of this typical association, researchers studying wealth or wealth disparities must consider both of these variables if they want to avoid confounding one with the other.

According to the analyses presented here, *how* a researcher decides to handle messy data can have an enormous impact on whether or to what extent variables (e.g., GDP, internal motivations to control prejudice) reveal their influences. Because of both nonlinear patterns and the influence of extreme scores, traditional LS analyses will sometimes overestimate a variable's influence, as in the case of internal motivations to control prejudice as a predictor of racial

attitudes. Traditional LS analyses can also *underestimate* a variable's influence, as is the case in the association between a country's wealth and homicide rates, due to non-linear relations and extreme scores in the data.

5.1 What are the practical advantages of GeMM?

These substantive issues aside, what might compel one to use GeMM in lieu of traditional least-squares regression? As with other regression techniques, GeMM is a tool for prediction, inference, and data mining/exploration, though we believe that it offers some practical advantages over standard least-squared techniques. We articulate these next.

5.1.1 GeMM as a tool for prediction.

As demonstrated with the two datasets presented in this paper, GeMM provides a computational algorithm for optimizing rank order prediction that can outperform more complex algorithms based on least-squares. The tradeoff, of course, is that GeMM is not guaranteed (and likely will not) optimize prediction of metric values. However, we believe that this trade-off is warranted in many contexts. For example, consider any task that entails a selection decision on the criterion or outcome variable, such as selecting among job applications, choosing graduate applicants (if you are a faculty member), or choosing graduate programs (if you're a student). In all of these cases, the goal of the decision maker is to predict the relative ordering on the criterion, rather than to predict a specific quantitative value. As should be clear from the two example data sets presented here, GeMM generally showed greater accuracy for out of sample prediction when assessed in terms of predicting the ordinal values. Inasmuch as one of the principle goals of the social and health sciences is to predict real-world behaviors, having statistical models that can, first and foremost, accurately predict ordered relations is important: What good is a statistical model with a high R-square if it does poorly in predicting the relative ordering of the criterion variable?

5.1.2 GeMM as tool for inference.

In an ideal world, inferences drawn from data should be invariant across data-editing strategies. The problem, of course, is that there is theoretically an infinite number of ways in which data can be transformed, and numerous justified ways of identifying outliers. Though it is certainly possible to explore a variety of potential data-editing strategies to assess the robustness of the conclusions, it would be virtually impossible to explore all possible transformations and outlier deletion methods. In this respect, GeMM offers many practical advantages over standard techniques: (1) it is invariant to transformation on the criterion variable, (2) more robust to transformation on the predictors, and (3) more robust to outliers. These advantages follow from the use of tau as the fit metric, which, unlike Pearson's r, is invariant to monotone transformation. Because transformation on the predictors can affect the additive form of the predicted values, GeMM can still be affected by transforming the predictors, but only if the transformation results in changes in the ordinal properties of the additive model. In contrast, the use of transformation on the predictors is *guaranteed* to affect the least squares fit. In other words, many of the decisions that could be exploited for analysis based on least-squares approaches are unnecessary for analyses based on GeMM. Further, unlike linear least squares, GeMM does not lose statistical power under deviations from linearity.

As an example, consider our analysis of the culture-of-honor data. In this analysis, we illustrated that GeMM was relatively insensitive to transformation, and had higher statistical power than linear least squares. Thus, making fewer assumptions about one's data can payoff in an increased likelihood of detecting effects and more robust conclusions that are not conditional on having met specific model assumptions or on particular data editing strategies. Importantly, the conditions in which one is most inclined to engage in data editing are precisely those conditions in which the data are unlikely to satisfy metric statistical assumptions.

On the flip side, GeMM's strength as a method for identifying monotone relationships limits the specificity of the inferences that can be drawn from the data. Though it can identify any nonlinear monotone relationship with equal probability without the need to transform the data, it cannot characterize the nature of those relationships. Thus, if one were interested in modeling the specific functional relationship between a set of variables, then GeMM would not be an appropriate tool. Yet, note that the application of GeMM does not preclude one from further exploring these functional relationships with nonlinear least squares methods, if one is comfortable drawing conclusions that go beyond the ordinal properties.

5.1.3 GeMM as a tool for exploration.

Just like with traditional least-squares methods, GeMM can also be used in the context of data exploration. Note, however, that in this context the fact that GeMM relaxes assumptions about functional form can be advantageous. Consider, for example, a data set in which one has no a priori hypotheses about which variables should be related to the criterion. In these cases, it is even less likely that the researcher has any a priori guess about the form of the functional relationships that might exist therein. The problem with using traditional least-squares regression approaches in these contexts is that they require either that one commit to modeling specific functional forms, engage in a great deal of data editing, or explore various alternative modeling approaches. With GeMM, identifying potentially interesting statistical relations can be accomplished with minimal data editing and without loss of power when those relations are nonlinear.

5.2 Interpreting the output of regression coefficients within GeMM

The most straightforward interpretation of GeMM is in its model form, wherein the GeMM returns the model that best accounts for the rank-ordered properties of the criterion. The regression coefficients derived from GeMM have the exact same interpretation as those obtained

from ordinary least-squares once the Order Constrained Least-Squared Optimized (OCLO) solution is obtained, with one caveat. The OLS solution minimizes least squares, whereas the rescaled OCLO-GeMM weights minimize least-squares conditional on maximizing ordinal fit.

While in many cases, the actual parameter values derived from GeMM may be close in magnitude to those obtained from other statistical procedures, there may be cases in which the relative magnitudes of the parameters differ in important ways. For example, for the homicide data set, the standardized regression coefficients derived from OLS yielded $|B_{Gini}|>|B_{GDP}|$ (0.42 versus -0.09) but the GeMM solution yielded $|B_{Gini}|<|B_{GDP}|$ (0.25 versus -0.29). This is informative because it tells one that the relative contribution of GDP and Gini is different if one is interested in using these variables to predict the rank order of homicide rates (GeMM) versus predicting the metric values of homicide rates (OLS). The implications of the GeMM solution compared to the OLS solution could be rather important. For example, a policy maker who wishes to reduce homicide rates would make different policy decisions if using OLS as the basis of that decision than if GeMM were used as the basis of that decision: The OLS solution implies that efforts at reducing homicide rates should focus primarily on decreasing wealth disparity (Gini), whereas the GeMM solution implies both that wealth disparity should be decreased and overall wealth (GDP) is increased. This is not to suggest that GDP or wealth disparity cause homicides, but rather to highlight the two very different policies that could result from using OLS versus GeMM.

5.3 Availability and extensions

The bulk of this paper has focused on the application of GeMM in contexts in which one must deal with messy data in one way or another. To facilitate the use of GeMM, we have developed versions in Matlab, Mathematica, SAS, and R. Matlab code and an accompanying user's guide is available from the first author's website

(http://www.damlab.umd.edu/gemm.html); Mathematica and SAS code is available upon request. The development version of the GeMM package for R, and associated code and data used in this article, are available freely from the authors. The R package will be posted to Cran when completed. In its present form, the R package automatically produces the OCLO solution proposed in Tidwell et al. (2014).

We have a number of active lines of work aimed at extending the GeMM framework. A key limitation of GeMM thus far is that it is constrained to modeling monotonic relationships, and therefore is not applicable to datasets that include non-monotonic relationships. To address this, we have begun developing a version of GeMM that permits inflection points between the criterion and the modeled data, where an inflection point implies a change in the direction (sign) of the modeled relationship (Lawrence, Thomas, & Dougherty, 2014).

A second area of work motivated by GeMM involves the development of leverage or influence statistics that identify outliers in ordinal space. Although GeMM should in principle be more robust to many different types of extreme scores, it will still be sensitive to extreme scores that create a large number of rank-order inversions. This is likely the reason that GeMM showed some sensitivity to the outlier deletion in racial bias dataset. Although these types of extreme scores might be identifiable with traditional leverage statistics such as Cooks D, we imagine that alternative methods for identifying highly influential scores in ordinal space will be required.

6. Summary

The existence of "uncooperative" and messy data poses a major challenge for behavioral and social science researchers. Unfortunately, within the standard approaches, traditional methods for handling non-linearities, non-normalities, and outliers provide the data analyst with a great deal of freedom for reconditioning the data to remove these properties – a freedom that can be exploited, intentionally or otherwise, to tell the preferred story. The more freedom allotted to the

data analyst to make decisions that are not well justified, the more likely it is that the stories that get told are little more than myths. The goal of discovering fundamental facts about nature shouldn't lead one to treat data and data analysis as if it were fine art requiring delicate hands. Rather, it should compel us to approach data analysis the way an engineer approaches the development of a new jetliner, which is to ensure that the plane flies even under non-ideal conditions. As a public good that informs social and health policy, we argue that the same standard should operate for scientific claims. GeMM provides a new tool that we believe can help ensure that scientific claims are robust and invariant to data editing strategies.

Table 1. Fit indices from the various models

	BICt'	BIC	tau	R	k
OLS-NHST					
Full data (N=198)	-9.905	-12.283	0.239	0.364	3
Univariate (N=195)	-12.837	-6.282	0.23	0.288	2
DFFITS (N=191)	-15.321	-10.142	0.245	0.321	2
Cooks D (N=185)	-22.196	-24.986	0.299	0.444	3
Robust Regression					
Huber	-15.651	-8.965	0.241	0.307	2
Bisquare	-15.005	-9.132	0.238	0.308	2
Hampel	-10.646	-11.886	0.243	0.362	3
OLS-BIC					
Full data (N=198)	-9.242	-12.445	0.236	0.365	3
Univariate (N=195)	-11.472	-6.551	0.223	0.29	2
DFFITS (N=191)	-10.982	-11.093	0.224	0.328	2
Cooks D (N=185)	-21.074	-25.253	0.295	0.445	3
Ordered Logistic					
Full data (N=198)	162.602	166.442	0.277	0.3	35
Univariate (N=195)	153.567	157.535	0.266	0.285	33
DFFITS (N=191)	147.438	150.248	0.268	0.298	32
Cooks D (N=185)	132.55	131.86	0.377	0.443	33
GeMM					
Full data (N=198)	-17.835	-5.878	0.251	0.282	2
Univariate (N=195)	-15.389	-3.89	0.242	0.267	2
DFFITS (N=191)	-17.348	-7.524	0.254	0.301	2
Cooks D (N=185)	-23.914	-24.109	0.306	0.44	3

Note: K is the number of significant or retained parameters. For Ordered Logistic, k includes the number of significant threshold parameters. Thus, for k=35, there are 3 significant predictors (EMS, Race AMP, and IMS) and 32 significant threshold parameters.

Table 2. Standardized regression coefficients revealed for each model.

OLS-NHST	P-EXP	P-IAT	P-AMP	R-AMP	EMS	IMS	R-IAT	Stroop	StopSig
	-0.054	-0.083	0.016	**0.17***	**-0.217***	**-0.172***	0.016	0.03	-0.027
Full data (N=198)	(.074)	(.092)	(.081)	**(.073)**	**(.069)**	**(.074)**	(.082)	(.086)	(.074)
	-0.059	-0.076	0.028	**0.152***	**-0.194***	-0.11	0.009	0.035	-0.034
Univariate (N=195)	(.070)	(.088)	(.077)	**(.070)**	**(.067)**	(.070)	(.072)	(.081)	(.069)
	-0.103	-0.017	0.081	**0.147***	**-0.199***	-0.127	0.025	0.014	-0.02
DFFITS (N=191)	(.068)	(.083)	(.073)	**(.070)**	**(.063)**	(.069)	(.073)	(.079)	(.067)
	-0.04	-0.054	0.007	**0.167***	**-0.244***	**-0.17***	0.049	0.045	-0.039
Cooks D (N=185)	(.066)	(.079)	(.070)	**(.067)**	**(.064)**	**(.068)**	(.072)	(.077)	(.064)
Robust Regression									
	-0.059	-0.078	0.018	**0.19***	**-0.229***	-0.13	0.034	0.05	-0.049
Huber (N=198)	(.071)	(.088)	(.078)	**(.070)**	**(.066)**	(.070)	(.078)	(.082)	(.070)
	-0.064	-0.076	0.02	**0.201***	**-0.222***	-0.125	0.025	0.047	-0.044
Bisquare (N=198)	(.074)	(.092)	(.081)	**(.081)**	**(.073)**	(.073)	(.081)	(.085)	(.073)
	-0.063	-0.078	0.023	**0.177***	**-0.21***	**-0.144***	0.025	0.034	-0.036
Hampel (N=198)	(.073)	(.090)	(.080)	**(.072)**	**(.068)**	**(.072)**	(.080)	(.084)	(.072)
OLS-BIC									
				0.168*	**-0.213***	**-0.200***			
Full data (N=198)	-	-	-	**(.070)**	**(.068)**	**(.069)**	-	-	-
				0.181*	**-0.172***				
Univariate (N=195)	-	-	-	**(.066)**	**(.065)**	-	-	-	-
					-0.233*	**-0.196***			
DFFITS (N=191)	-	-	-	-	**(.061)**	**(.063)**	-	-	-
				0.168*	**-0.241***	**-0.206***			
Cooks D (N=185)	-	-	-	**(.063)**	**(.062)**	**(.063)**	-	-	-
Ordered Logistic									
Full data (N=198)	-0.098	-0.15	0.032	**0.383***	**-0.447***	**-0.292***	0.05	0.071	-0.061
	(.138)	(.161)	(.144)	**(.142)**	**(.141)**	**(.144)**	(.155)	(.158)	(.135)
	-0.108	-0.141	0.048	**0.375***	**-0.431***	-0.230	0.043	0.078	-0.07
Univariate (N=195)	(.139)	(.162)	(.145)	**(.144)**	**(.142)**	(.145)	(.156)	(.159)	(.137)
	-0.187	-0.052	0.147	**0.338***	**-0.466***	**-0.326***	0.058	0.031	-0.024
DFFITS (N=191)	(.144)	(.165)	(.148)	**(.148)**	**(.145)**	**(.151)**	(.160)	(.164)	(.141)
	-0.058	-0.136	0.005	**0.436***	**-0.573***	**-0.409***	0.067	0.107	-0.046
Cooks D (N=185)	(.144)	(.167)	(.150)	**(.150)**	**(.150)**	**(.155)**	(.164)	(.168)	(.142)
GeMM									
				0.133*	**-0.236***				
Full data (N=198)	-	-	-	**(0.077)**	**(0.085)**	-	-	-	-
				0.113*	**-0.217***				
Univariate (N=195)	-	-	-	**(0.071)**	**(0.084)**	-	-	-	-
				0.112*	**-0.224***				
DFFITS (N=191)	-	-	-	**(0.067)**	**(0.074)**	-	-	-	-
				0.146*	**-0.270***	**-0.147***			
Cooks D (N=185)	-	-	-	**(0.076)**	**(0.079)**	**(0.098)**	-	-	-

Note: *= predictor retained by the model using BIC (OLS-BIC and GeMM) or predictor was significant with p<=0.05 (OLS-NHST, Robust regression, Ordered Logit). Dashes indicate that the predictor variable was not included in the model. Coefficients and SE's listed for GeMM were computed based on 1000 bootstrap runs.

Table 3. Probability of recovering each model coefficient given half (N/2) the full sample, for each algorithm.

	P-EXP	P-IAT	P-AMP	R-AMP	EMS	IMS	R-IAT	Stroop	StopSig
GeMM	0.062	0.028	0.014	**0.336**	**0.716**	0.198	0.02	0.000	0.008
OLS-NHST	0.024	0.016	0.002	**0.306**	**0.596**	**0.368**	0.032	0.006	0.008
OLS-BIC	0.068	0.068	0.008	**0.402**	**0.566**	**0.486**	0.036	0.012	0.004
RLS-Bisquare	0.028	0.012	0.002	**0.458**	**0.576**	0.164	0.014	0.012	0.010
RLS-Huber	0.034	0.016	0.004	**0.422**	**0.642**	0.214	0.016	0.012	0.010
RLS-Hampel	0.032	0.012	0.000	**0.336**	**0.572**	**0.268**	0.028	0.010	0.010
Ord. Logistic	0.030	0.020	0.004	**0.432**	**0.636**	**0.266**	0.026	0.012	0.018

Note: P = political, R=race, AMP = affect misattribution procedure, IAT = implicit association test, IMS = internal motivation scale, EMS=external motivation scale, P-EXP = explicit political attitude, Stop Sig= Stop signal. Bolded values correspond to predictors that were recovered on the full sample as indicated in Table 2.

Table 4. Cross-validation results for analyses predicting attitudes toward blacks.

	Cross validation using Selected (Best fit) Models				
	BICt'	BIC	tau	R	k
Estimation					
GeMM	-7.847	-4.881	0.259	0.314	1.397
OLS-BIC	-5.293	-7.321	0.245	0.363	1.647
Bisquare	-6.686	-5.787	0.255	0.337	1.542
Huber	-6.796	-6.041	0.259	0.344	1.604
Hampel	-6.864	-6.755	0.255	0.348	1.513
OLS	-6.209	-6.894	0.251	0.352	1.559
Ordered Logit	120.919	114.465	0.299	0.354	28.042
Crossvalidation					
GeMM			0.155	0.18	
OLS-BIC			0.134	0.178	
Bisquare			0.145	0.18	
Huber			0.149	0.183	
Hampel			0.141	0.169	
OLS			0.147	0.179	
Ordered Logit			0.137	0.157	

Table 5. Fit indices for models. In all cases where k = 1, the predictor included in the model (or identified as significant) was GINI. In call cases where k=2, the predictors included in the model or identified as significant were both GINI and GDP.

Transformation	BICt'	BIC	tau	R	k
OLS-NHST					
None	-29.332	-22.289	0.391	0.503	1
Sqrt (Homicide)	-41.419	-30.888	0.471	0.593	2
Sqrt (All)	-29.332	-30.682	0.391	0.564	1
Log (Homicide)	-42.672	-32.096	0.476	0.6	2
Log (All)	-29.332	-28.687	0.391	0.55	1
OLS-BIC					
None	-32.709	-22.289	0.391	0.503	1
Sqrt (Homicide)	-32.709	-31.062	0.391	0.566	1
Sqrt (All)	-32.709	-30.682	0.391	0.564	1
Log (Homicide)	-46.769	-32.129	0.471	0.601	2
Log (All)	-32.709	-28.687	0.391	0.55	1
GeMM					
None	-45.712	-13.636	0.488	0.467	2
Sqrt (Homicide)	-45.712	-27.531	0.488	0.573	2
Sqrt (All)	-42.328	-26.307	0.475	0.565	2
Log (Homicide)	-45.712	-30.677	0.488	0.592	2
Log (All)	-38.647	-25.71	0.459	0.561	2
Generalized Linear Model					
Poisson	-35.999	-12.302	0.467	0.495	3
Quasi Poisson	-40.521	-16.824	0.467	0.495	2
Negative Binomial	-40.298	-16.267	0.466	0.49	2

Table 6. Estimation and Cross-validation analyses for the culture of honor data using various transformations.

Estimation

Transform	Model	BICtau'	BIC	Tau	R	Mean k
None	GeMM	-18.626	-4.903	0.495	0.48	1.952
None	OLS	-12.554	-11.398	0.4	0.527	1.051
None	OLS-BIC	-12.344	-10.501	0.397	0.512	1.05
None	Poisson	-14.289	-8	0.473	0.54	2.416
None	Quasi Poisson	-19.113	-13.078	0.474	0.546	1.197
None	Negative Binomial	-17.556	-8.458	0.481	0.513	1.806
Sqrt(Homicide)	GeMM	-18.616	-11.686	0.495	0.578	1.936
Sqrt(Homicide)	OLS	-13.771	-15.292	0.418	0.585	1.202
Sqrt(Homicide)	OLS-BIC	-13.736	-15.184	0.421	0.587	1.268
Sqrt(All)	GeMM	-17.356	-11.472	0.482	0.573	1.9
Sqrt(All)	OLS	-13.533	-14.895	0.413	0.578	1.129
Sqrt(All)	OLS-BIC	-13.463	-14.732	0.415	0.579	1.186
Log(Homicide)	GeMM	-18.619	-14.427	0.495	0.603	1.94
Log(Homicide)	OLS	-16.088	-16.689	0.452	0.608	1.474
Log(Homicide)	OLS-BIC	-15.702	-16.321	0.449	0.605	1.528
Log(All)	GeMM	-15.673	-12.401	0.459	0.568	1.712
Log(All)	OLS	-13.541	-14.623	0.418	0.576	1.248
Log(All)	OLS-BIC	-13.566	-14.547	0.419	0.576	1.278

Cross Validation

Transform	Model	Tau	R
None	GeMM	0.453	0.463
None	OLS	0.379	0.48
None	OLS-BIC	0.382	0.487
None	Poisson	0.442	0.428
None	Quasi Poisson	0.373	0.405
None	Negative Binomial	0.438	0.436
Sqrt(Homicide)	GeMM	0.452	0.554
Sqrt(Homicide)	OLS	0.382	0.532
Sqrt(Homicide)	OLS-BIC	0.393	0.545
Sqrt(All)	GeMM	0.44	0.547
Sqrt(All)	OLS	0.385	0.536
Sqrt(All)	OLS-BIC	0.391	0.543
Log(Homicide)	GeMM	0.453	0.567
Log(Homicide)	OLS	0.402	0.526
Log(Homicide)	OLS-BIC	0.416	0.541
Log(All)	GeMM	0.406	0.516

Log(All)	OLS	0.392	0.529
Log(All)	OLS-BIC	0.395	0.531

Figure 1. Scattergram plotting Attitudes Toward Blacks (y-axis) against 9 predictor variables. Pol = political, AMP = affect misattribution procedure, IAT= implicit association test, Int Mot = internal motivation to control prejudice, Ext Mot =external motivation to control prejudice, Pol Att = explicit political attitude.

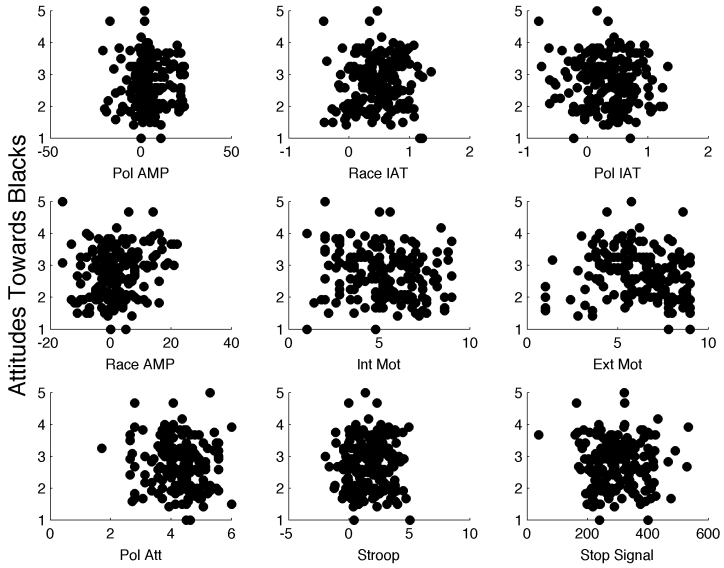


Figure 2. Histograms for the 10 variables reported in Siegel et al. (2012). Pol = political , AMP = affect misattribution procedure, IAT = implicit association test, Mot = Motivation, Int = internal, Ext = external, Pol Att = explicit political attitude.

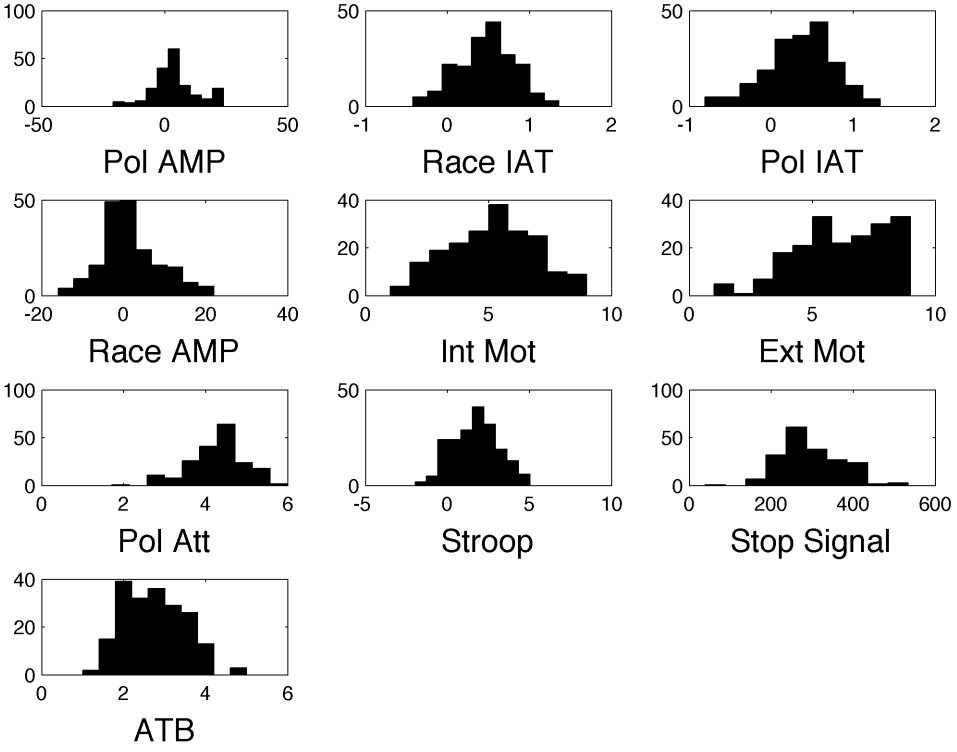
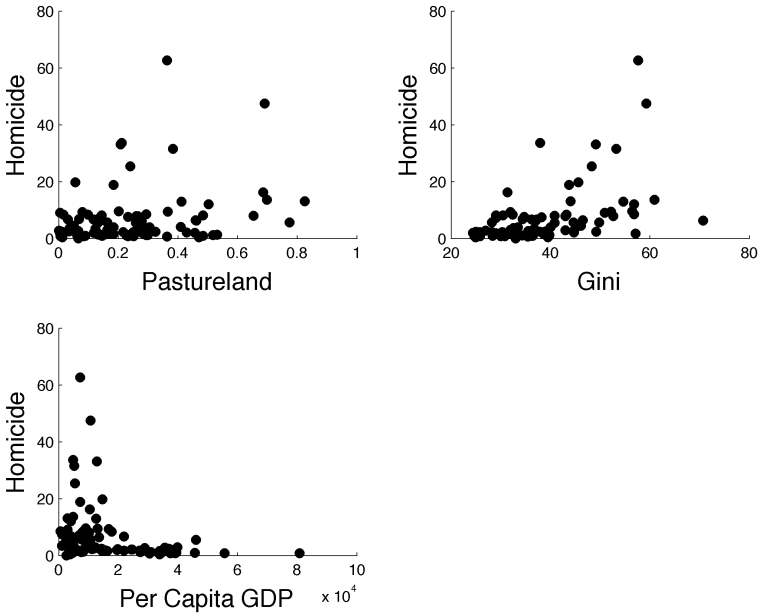


Figure 3. Scatter graph showing homicide rates (y-axis) plotted against three predictor variables used in Henry (2009). Panel A plots untransformed data. Panel B plots data after applying the log transformation to homicide rate (homicides per 100,000 residents).

Panel A



Panel B.

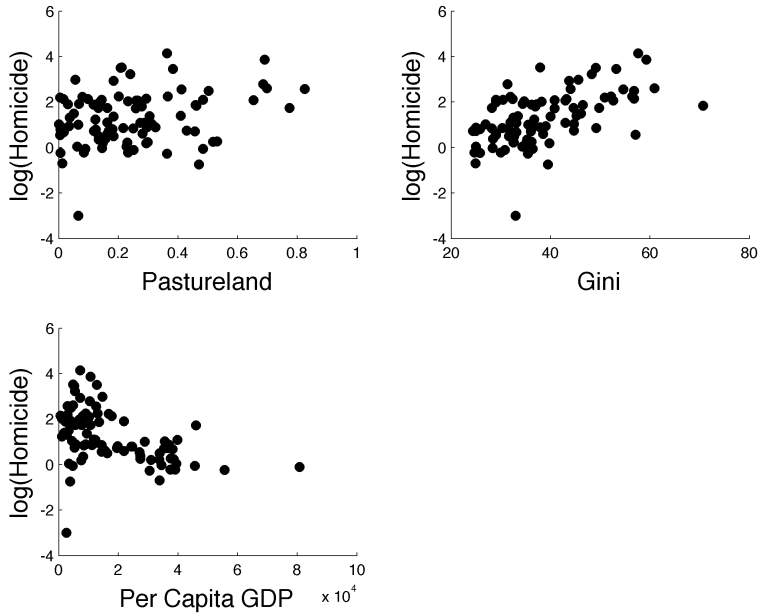


Figure 4. Histograms for three predictor variables and the criterion used in Henry (2009).

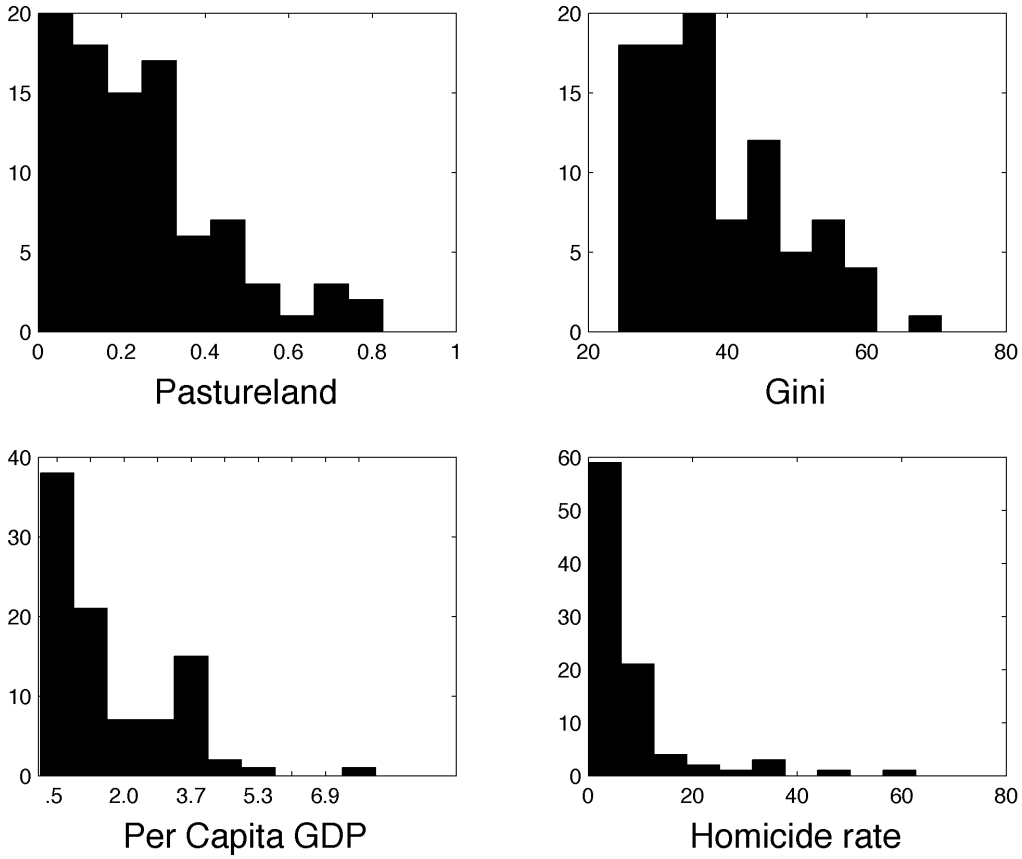
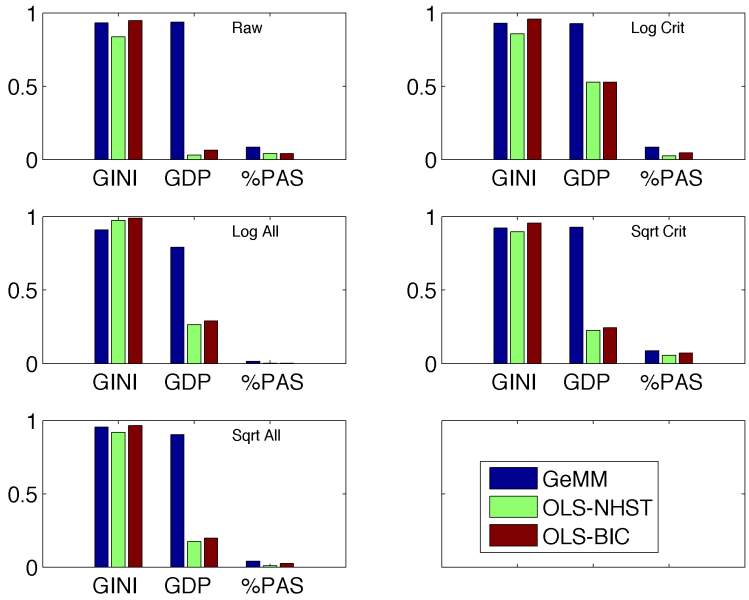
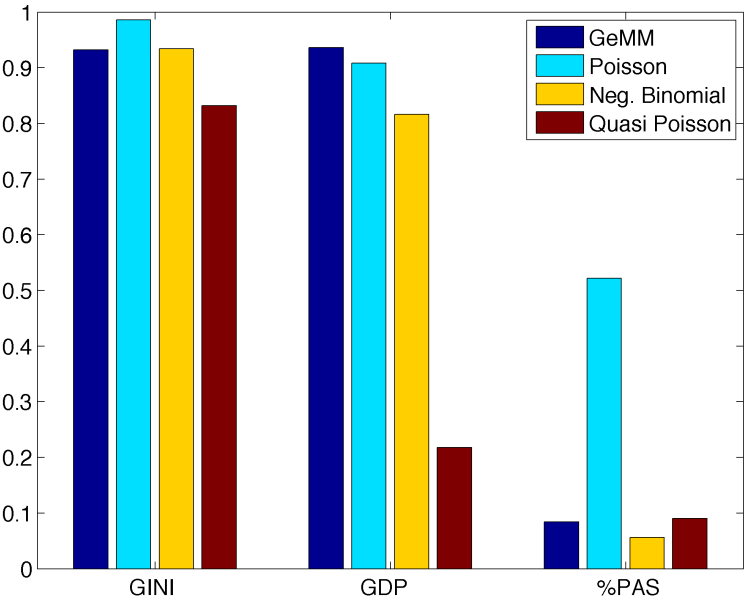


Figure 5. Probability of recovering each predictor on half the total sample (%PAS = Percent pastureland; GINI = wealth disparity index; GDP=gross domestic product). Panel A. Comparison with LS procedures across various transformations. Panel B. Comparison with various forms of GLM.

Panel A.



Panel B



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8. End Notes

[1] We use the term criterion variable to refer to the outcome or dependent variable.

[2] The assumption of bivariate normality is not crucial for the operation of GeMM. One way to conceptualize the tau to r transformation is that it allows one to estimate the value of r under any order preserving transformation of the data, without actually needing to transform the data. When assumptions of bivariate normality and linearity are met, then the tau to r transformation should closely approximate the value of r on the untransformed data.

[3] Siegel et al (2012) used structural equation modeling to examine the factor structure of the various measures of attitude and cognitive ability. For that analysis, the absolute (unsigned) scores were used.

[4] The univariate outliers were identified by observations +/- 3 standard deviations from the mean. Cook's D and DFFITS are standard leverage statistics, which quantify the influence of each individual point on the regression solution. Observations were trimmed from the dataset if the value of Cook's D exceeded 4/N and if the value of DFFITS exceeded 2sqrt(p/N), where P is the number predictors in the regression.

[5] Based on the full sample there are 37 distinct response categories, for which ordered logistic regression must fit 36 threshold parameters. For the full sample, only 32 of these thresholds were statistically significant at $p<0.05$.

[6] Model fitting for GeMM consisted of a two-step process in which we first fit GeMM to the full sample to find the subset of predictors that minimized BICt'. We then ran 1000 bootstrap samples to estimate the standard errors of the coefficients. The coefficients listed in Table 2 correspond to the mean coefficients (and corresponding SEs) from the 1000 bootstrap samples. Model fits listed in Table 1 are based on the analysis of the full sample.

[7] Both the Henze-Zirkler and Mardia tests of multivariate normality revealed significant departures from multivariate normality, a finding that held both for the untransformed and transformed data.

[8] However, we suggest that in most cases in the social sciences theories are not specified in such detail, and instead are expressed largely as ordinal predictions (see also Cliff, 1996).

9. Biographies

Michael R. Dougherty is a professor of psychology at the University of Maryland, College Park. His areas of interest include research methods, computational and mathematical modeling, cognitive decision theory, and memory theory.

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Jeffrey S. Chrabaszcz is a PhD student at the University of Maryland. His research focuses on research methods, computational and mathematical modeling, judgment and decision making, and anxiety.

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