A Critique Of:

"Insurance-Based Credit Scores: Impact on Minority and Low-Income Populations in Missouri"

Study by

Brent Kabler, PhD
Missouri Department of Insurance

Critique

by

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Introduction

The authors of this critique have a long-standing interest in the subject of credit-based insurance scores and their applications to underwriting and pricing of property/casualty insurance coverages. As a result of our interest in the subject, it was natural that we should give a careful review to the recently published study by Dr. Kabler entitled "Insurance-Based Credit Scores: Impact on Minority and Low Income Populations in Missouri".

After initiating our review of the Study, we were commissioned by the American Insurance Association, the National Association of Mutual Insurance Companies, and the Property Casualty Insurers Association of America to prepare this report and publish our critique.

Overview of the Study

Dr. Kabler, Research Supervisor of the Missouri Department of Insurance, studied data (i.e., exposure counts and average credit scores by ZIP code) provided by selected automobile and homeowners insurers. He observed that the average scores tended to be worse in areas with high minority concentrations and in areas with low per capita income. After application of three statistical analysis techniques, Dr. Kabler concluded that credit scores are correlated with minority status and income levels on an individual basis.

Summary of This Critique

The Study was titled in a way that will almost certainly mislead readers as to the results of the data analysis. There was no study of the impact of insurance scores on insurance rates, or on the availability of insurance coverage, even though the title declares otherwise.

Despite implications that credit-based insurance scores will negatively impact coverage availability and affordability in certain areas of Missouri, there is not one bit of data in the Study to support such a conclusion.

The Study, inappropriately and without analysis, implies that all minority populations will be affected to the same degree by credit-based insurance scores.

The Study relies on the differences in percentiles in a way that almost certainly overstates the actual differences in scores. Reliance on percentiles automatically implies differences in average scores that may not actually exist.

The Study ignores the fact that the variation of scores between individuals will dwarf any differences among average scores by race, income, or zip code. We expect that an analysis which accounted for the variation of scores among individuals would show virtually no relationship between insurance scores and race or income.

The Study inappropriately assumes that nearly all differences in average scores between the zip codes are a function of geography, race and income. The error of this assumption would have been evident if other important variables would have been included in the analysis. Important variables readily available to Dr. Kabler were not included in his regression analysis. If the missing variables had been included it is likely that the differences ascribed to race and income would have disappeared. Also, insufficient information was included in the Study to determine if the variables used were structured properly.

The Study's data call was structured in such a way as to prevent the removal of any potential biases in the average scores which were in the Study's database.

The Study assumes that all insurance scores are the same and have the same negative impact on minority populations. Yet the analysis results on a company-specific basis are widely different.

The Study chose to highlight the methodology that suggested the greatest differences in scores by race and income. One of the methods produced much smaller differences. In some cases the differences were negligible.

The individual inferences drawn by Dr. Kabler were drawn without access to any data about individuals, thereby eliminating the possibility of determining whether insurance scores really do vary by race or income. Inferences were drawn from statistical models which are at best speculative. This part of the analysis was further harmed by the weaknesses of the regression models.

In our judgment none of the major conclusions in the Study are supported by the data and data analysis described in the Study. There was a failure to control how the average scores were calculated by each participating insurer. There was a failure to call for data necessary to "normalize" the average scores for potential biases arising from non-geographic factors. There are apparent flaws in the regression analyses because of a failure to determine the extent of any non-linear relationships and to further investigate other important variables.

The issues addressed in the Study are important socially and politically and deserve serious scientific study. This study does not further the research. Dr. Kabler delivered highly controversial conclusions and he described the results of some statistical analysis. Unfortunately, there is precious little, if any, connection between the conclusions and the data analysis.

Critique of the Study

Title

The title of the Study will almost certainly mislead most readers. The effect of credit-based insurance scores on minority groups and low-income groups is a serious social and political issue which deserves to be addressed by serious, statistical analysis. The public is not well-served by this study which purports in its title to be an "impact" study, but does not actually study the question of impact. In fact, the data necessary to conduct an "impact" study are not part of the Study's database.

It is reasonable to assume that many users of the Study will go no further than reading the title and the four major conclusions. Without digging deeper, many users will likely be misled to conclude that the Study proves that credit-based insurance scores have a negative impact on the pricing and availability of insurance for minority groups and low-income groups.

We acknowledge the Study's partial disclaimer in its third paragraph that impact on pricing and availability was "not directly examined in this study". But even that disclaimer is seriously misleading because it implies the Study may have "indirectly" examined the impact of credit-based insurance scores. It did not do so. Perhaps the most egregious, misleading statement is in Finding 4 on page 2. There the author represents that the maps on page 3 "indicate areas in Missouri that are most negatively affected by the use of credit scores". There is nothing in the Study that shows if, or to what extent, credit-based insurance scores affect any geographical area of Missouri.

In our opinion, all copies of this Study should be retrieved and the Study should be reissued with an appropriate title and with appropriate edits to the body of the report. We suggest that a limitation be placed in bold-type on the new title page stating that the Study does not address the impact of credit-based insurance scores on either the availability or the pricing of insurance.

Availability

The impact of credit-based insurance scores on the availability of insurance coverage is an important issue for study. It is an issue which is subject to a scientific study of data.

History is replete with examples of how suppression of rates in the marketplace has inevitably forced insureds to find coverage at higher rates in a state's residual market (i.e., insurer of last resort). If there is concern that the use of credit-based insurance scores has created coverage availability problems in Missouri, then we suggest a study of the relevant data.

There is no reason to accept without study, Dr. Kabler's assumption that a below-average insurance score automatically translates into higher than average rates or a restriction on the availability of coverage for any zip code. It is misleading to readers for Dr. Kabler to make such a suggestion as part of a statistical analysis that does not actually study the issue of impact on availability of coverage.

We offer an equally likely hypothesis, which is also subject to data analysis. Our hypothesis: to the extent that credit-based insurance scores lead to more accurate rates, proportionately more insureds in hard-to-serve markets will find it easier to find insurance in the regular marketplace at rates below those available in the residual market. There is no reason to believe or expect that credit-based insurance scores are the "magic bullet" solution to all availability problems. However, there is every reason to believe there will be a positive impact on problems of insurance availability, brought about by increased accuracy in risk assessment.

Affordability

Dr. Kabler implies that his Study shows that a below-average credit-based insurance score in a specific zip code will lead to a higher than average insurance rate in that area. The impact of credit-based insurance scores on rates is far more complex than Dr. Kabler's simplistic assumption. The relationship between an individual's score and the average score does not translate in a one-to-one proportion to the relationship between an individual's insurance rate and the average insurance rate. Relatively modest differences in actual scores for individual insureds are not likely to have much, if any, impact on rates.

Our own study of the issue shows that a score which is worse (e.g., 10% lower) than the average score, does not represent a propensity for loss that is 10% higher than the average risk of loss and, therefore, will not lead to a rate that is 10% higher. Further, the actual effect on average rates if credit-based insurance scores are introduced into the rate formula are dependent upon the actual rate/discount factors used by individual insurers, not on some hypothetical difference in average scores across the zip codes.

To the extent that the more accurate rates afforded by using credit-based insurance scores encourage low-cost insurers to be more active in hard-to-serve markets and to the extent that more insureds can avoid the higher rates in the residual market, average rates may actually level or decrease in areas with higher than average credit-based insurance scores.

Minority Groups

Dr. Kabler's definition of high-minority zip codes is based on a combination of African-American and Hispanic populations. He apparently conducted a separate analysis of African-Americans and found "no substantive differences" from the results when Hispanics were included in the database.

It is not surprising that the results of a Missouri study of African-Americans would be similar to the results of a study which included Hispanics. In Missouri the African-American population is approximately six times that of the Hispanic population. Inclusion or exclusion of a relatively small population of Hispanics will not significantly change the averages in the Study.

A serious problem with the Study is that it not only misleads readers to believe that it has found different impacts on premiums by racial groups, but that the impacts are negative on all minority groups. We believe a properly structured study would prove Dr. Kabler's generalization about minority populations to be false.

We would hypothesize that if the analysis were extended to measure the impact of credit-based insurance scores on loss propensity, the impact would not be meaningfully different by racial group. If such a study were to find differences in average scores by racial groups, it is just as likely that at least one racial group will be found to have a higher than average score as it is that a racial group will be found with a below average score.

Average Scores versus Percentiles

Participating insurers were requested to submit average scores for each zip code. The Study should make it <u>much</u> clearer to the reader that reference is being made to variations in average score percentiles, and not variations in percentiles at the individual level. The difference is important, and could be missed by those without training in statistics.

One of the outputs of regression analysis is a statistic called the "R-Squared". This value ranges between 0% and 100%, and represents how much of the variation in one variable (the dependent variable) is described by another variable (the independent variable). Typically, if there is a statistically significant correlation between these variables at the <u>individual</u> level, the R-Squared statistic should show that the independent variable describes a meaningful percentage of variation that exists in the dependent variable.

When the same variables are studied at an aggregated level, the R-Squared values are typically much higher that those at the individual level. The R-Squared values shown on pages 21 through 23 of the Study, are much closer to 0% than to 100%. Given these relatively low values at the aggregate level, we seriously doubt that analysis done properly, at the individual level, would validate the results shown in the Study.

The independent variable in the study is the percentage of minority population within a zip code, or per capita income within a zip code.

It was determined that zip codes with a high concentration of minority population were on average in the 18.4 percentile of all zip codes. Zip codes with a high concentration of non-minority population were on average in the 57.3 percentile. It was this 38.9 difference in the percentile rankings which was the basis for the finding that "On average, residents of areas with high minority concentrations tend to have significantly worse credit scores than individuals who reside elsewhere." Even if Dr. Kabler intended to use the word "significantly" in its statistical sense, this finding is dangerously misleading to any reader of the report who is not a statistical theoretician.

To understand one of the traps in Dr. Kabler's statistical analysis method, consider the hypothetical situation where a participating insurer submitted average scores for 1,000 zip codes. Assume there were 800 zip codes with 100% non-minority population and the average score in each of the 800 zip codes was exactly 750. Further assume there were 200 zip codes with a 100% minority population and the average score in each of the 200 zip codes was exactly 749.

As was done in the Study, Dr. Kabler's analysis method would not reveal the actual average scores to the readers. Dr. Kabler's analysis method would lead him to tell the readers of his Study that the high-minority zip codes (with scores of 749) generated an average percentile of 2.0 and that the non-minority zip codes (with scores of 750) generated an average percentile of 69.0. The difference in the percentile rankings would be a remarkable 67.0 points and the reader would be led to conclude there were significantly worse credit scores in the group of 200 minority zip codes, as compared to the average credit scores in the group of 800 non-minority zip codes.

> *Note:* In this example, the overall average score is 749.8. The 100% minority zip code average score is 2.0 standard deviations below, and the 0% minority zip code average score is 0.5 standard deviations above that average. The percentiles would be found by looking up the standard deviation figures in a standard-normal table.

Dr. Kabler's regression analysis would produce a perfect fit to this hypothetical data. There would be a dramatic difference in the percentile rankings of minority and non-minority zip codes. His results would be statistically significant, but have no practical meaning in the real world.

Despite the statistical tests of significance, the fact is that while there would be a difference of 67 percentiles in the hypothesized average scores, there would be only a one point difference in the actual scores. Our hypothetical scores were virtually identical and that one point difference would have had no impact on insurance rates. Dr. Kabler's assumptions would lead the reader to conclude otherwise.

Neither the average scores nor the distribution of the average scores are shown in the Study. Only the percentiles are shown. Proper interpretation of any modeled differences in percentiles can only be made in context with the average scores themselves, the distribution of the scores and their standard deviation. Based on the low R-Squared we suspect that the actual score distributions would not validate the regression results published by Dr. Kabler. Publishing differences in percentiles almost certainly exaggerates any practical difference in the average scores.

Our experience in studying credit-based insurance scores leads us to expect that the average score of the lowest three quintiles in each zip code will be much closer to the overall average score for each zip code than is suggested by Dr. Kabler's differences in percentiles. Until the average scores in the Study are available for review, there can be no valid conclusions drawn as to the importance of any differences which may exist in the average scores across all zip codes.

Calculation of Average Scores

We can find nothing in the Study's data call which defines how the participating insurers were to calculate the average scores for each zip code. If one or more of the participating insurers calculated an average score based on an exposure count, rather than on the basis of a household count, differences in average scores between zip codes could be exaggerated.

To better understand the potential distortions in the average scores used in the Study, assume the following:

a) Insurance Score = 730 for all named insureds in a single-car household.
b) Insurance Score = 770 for all named insureds in a two-car household.
c) ZIP A contains two households, both of which are single-car households.
d) ZIP B contains two households, one is single-car and one is two-car.

		Single-Car Household				**Two-Car Household**				**Average Scores**	
Zip Code		***# Cars***	***# Houses***	***Avg. Score***		***# Cars***	***# Houses***	***Avg. Score***		***Exposure***	***Household***
A		2	2	730		0	0	—		730	730
B		1	1	730		2	1	770		757	750

Using the above hypothetical as an illustration, we can make the following observations about the average insurance scores used in the Study.

1) In the above hypothetical example, the differences in average scores between the zip codes increased from 20 points to 27 points due solely to how the average was calculated. This hypothetical illustrates that how the average scores were calculated is crucial to judging the reliability of any differences in average scores across all zip codes as presented in the Study.

   If exposure counts were used to calculate the averages, there is a high potential that the differences in average scores were exaggerated because multi-car households would have been over-represented in those averages. This potential problem would be further exaggerated if the auto and homeowners data were combined. In that case, households with multiple policies would be over-represented and cause a distortion in the average scores and an inaccuracy in the calculations shown for each individual company.

2) Given that the average scores can be materially different if calculated on the basis of exposure counts rather than on the basis of household counts, it becomes crucial to determine exactly how each participating insurer in the Study calculated its average scores for each zip code. The differences in the average scores between the zip codes appear to be inconsistent from insurer to insurer in the Study. It is quite possible that this inconsistency is at least partially explained by inconsistent ways of calculating the average scores, rather than telling us anything about the true differences in scores from one zip code to the next.

3) In the above hypothetical example, the average scores in ZIP A and ZIP B were 730 and 750, respectively (calculated based on household counts). This 20 point difference was entirely due to a difference in scores between single-car and multi-car households. The 20 point difference had nothing to do with geography, race, income, or any other factor. Dr. Kabler incorrectly assumed in the Study that nearly all differences in the average scores were related to geography, race and income.

Data Call

We know from our experience working with insurance score data that there are some differences in average scores between age groups, driving records, tenure with the current insurer, multi-car versus single-car policies, and multi-policy households versus single-policy households. We also know there is surprisingly little difference in average scores from low density population areas to high population density areas.

Dr. Kabler constructed a data call which prevented obtaining data that would have allowed him to "normalize" the average scores by zip codes so that the averages reflected a constant mix of insureds by age, driving record, tenure of coverage, and etc.

Because of the way the data call was constructed, there was no way for Dr. Kabler to adjust the average scores for potential biases, so he forged ahead and ascribed nearly all differences in the average scores to the racial composition and income level of each zip code.

While the Study's data call did require the submission of data concerning the age and gender of the insureds, such data were requested in a separate file. The two files of data could not be merged, making it impossible to adjust the average scores for any age or gender biases. The data call did not even attempt to gather data on all the other factors, which could potentially lead to distorted average scores across the zip codes (i.e., multi-car, driving record, etc.).

Regression Analysis

Regression analysis is based on a number of assumptions about the data being analyzed. If some of these assumptions are violated, the estimates and conclusions drawn may be incorrect. However, the Study provides no information that will allow the reader to judge whether the required assumptions hold. One of the assumptions that regression analysis makes is that the dependent variable has a linear relationship to one or more independent variables.

A series of graphs of the errors (residuals) versus predicted results, would have allowed the reader to understand whether any relationship between the insurance score and percentage minority was linear and whether the spread of the error term appeared to be constant, especially at the extremes of the percent minority range. The graphs would have allowed the reader to judge the extent to which a few extreme values may have been distorting the results. This is particularly important given the significance the Study places on predicted values for 100% minority zip codes. The "100% minority zip codes" were a theoretical result of the regression model; they do not actually exist in Missouri; and if the regression results are wrong, the foundation crumbles for Dr. Kabler's conclusions.

Two additional requirements of regression must be addressed: that no important explanatory (independent) variable is missing from the equation and that multiple independent variables are not highly correlated among themselves. Both need to be considered in the context of the Study's attempt to review other socio-economic factors. On Page 24, the Study does refer to the possibility that relevant variables may have been omitted, but as important as that is, the statement is unlikely to be understood or noticed by most readers.

Missing and Poorly Structured Variables

When important variables are missing from a regression model two significant problems arise. One of those problems is obvious with the Study. If Dr. Kabler had considered variables known to be related to insurance losses (i.e., population density, age, miles driven, driving record, and etc.) he would likely have found that nearly all the differences in average scores would have been explained. There would have been little or any difference remaining for him to ascribe to race and income.

In addition, missing variables usually affect the estimates for the other variables in the regression, and reduces the reliability of any inferences that can be made about those variables. In other words, if an important variable is missing from the analysis, it should raise doubts about the study's conclusions. In pages 25 through 30, the results of including income, average age, percentages of unemployed, renters, college education and the like are shown in the regression analysis. The information shown there raises doubts about the model specifications as to whether all important variables were included, and whether the structure of the variables was appropriate.

The importance of how variables are structured in a regression analysis, of multicollinearity, and of missing important variables can be illustrated using U.S. Census data for Missouri, at the zip code level. Our curiosity was piqued by the sign of the parameter estimate for "% Rent", as used in the multivariate analyses of average scores shown on Pages 25 through 30 in the Study. We doubted that renters have a higher insurance score than non-renters and were, therefore, surprised that the sign of the parameter was negative rather than positive. When we observed the opposite we became concerned that the analysis of independent variables may not have been thorough.

Since we do not have access to the Study's insurance score data, we could not attempt to duplicate and then review the results. To illustrate our concerns, we used Census data to estimate the percentage of households that rent in a zip code (% Renters) from other Census characteristics. Rather than using a percentile/ranking variable (as was done in the Study), we modeled the actual percentage, to allow the reader to more directly assess the model. Initially, we used only the zip percentage minority (% Minority) as the independent variable.

Independent Variable	% Renters (Dependent Variable)		
	Estimate	Std. Error	P-Value
Intercept	.2537	.00444	<.0001
% Minority	.3554	.01852	<.0001
Adj. R-Squared	.2659		

Note: The "P-value" reflects the likelihood that the observed relationship between the independent and dependent variables is due to chance. Small values suggest that the relationship is statistically significant.

Using the “% Renters” directly as the dependent variable indicates: that 25.4% of non-minority zip code households are renters, that there is a 35.5 point spread in the percentages, and that 60.9% of the minority zip code households are renters. This seems to be a plausible, reasonable result.

Next, we added age to the analysis, using two different approaches.

Variable	Median Age as Ind. Variable			Age Components as Ind. Variable		
	Estimate	Std. Error	P-Value	Estimate	Std. Error	P-Value
Intercept	.6760	.03456	<.0001	-.6237	.03102	<.0001
% Minority	.2760	.01844	<.0001	.2171	.01238	<.0001
Median age	-.0114	.00092	<.0001			
% Age 15-24				1.5713	.05589	<.0001
% Age 25-34				2.2508	.09130	<.0001
% Age 65-74				1.0433	.16844	<.0001
% Age 75+				1.7698	.10458	<.0001
Adj. R-Squared	.3608			.7083		

By adding median age, the spread between non-minority/100% minority areas was reduced to 27.6 points. Since additional age detail is readily available from the Census data, we chose to use more specific age variables, with the expectation that both the younger and older populations are more likely to be renters. Improving the structure of the age variable with the more refined age ranges impacted two statistics: the indicated spread was further reduced to 21.7 points, and the Adjusted R-Squared (.708) increased dramatically. This improvement does make the model a bit more difficult to statistically interpret, since one cannot as easily generalize what will happen to the expected % Renters value, as one can from a simple change in median age. This added refinement requires the analyst to also consider the other age variables. Although more difficult to interpret, the refinement makes intuitive sense that higher proportions of people in the younger and older age groups will increase the expected % Renters value.

We continued the analysis by adding population density and household income variables, followed by vehicle-ownership variables (i.e., the percentage of households that do not have a vehicle, and those with one vehicle).

Variable	Excluding Vehicle Ownership			Including Vehicle Ownership		
	Estimate	Std. Error	P-Value	Estimate	Std. Error	P-Value
Intercept	-.3585	.04754	<.0001	-.5728	.03702	<.0001
% Minority	.1428	.01443	<.0001	-.1025	.01404	<.0001
% Age 15-24	1.3628	.06597	<.0001	1.0598	.05311	<.0001
% Age 25-34	1.6514	.11077	<.0001	1.2254	.09241	<.0001
% Age 65-74	.4688	.19138	.0145	.5501	.14985	.0003
% Age 75+	1.4057	.10798	<.0001	.3734	.09110	<.0001
Pop. Density	1.67E-5	2.00 E-6	<.0001	-1.11 E-5	1.82 E-6	<.0001
Median Income	-1.44E-6	2.30 E-7	<.0001	1.73 E-6	2.07 E-7	<.0001
% No Vehicles				1.1899	.04790	<.0001
% One Vehicle				.7518	.04097	<.0001
Adj. R-Squared	.7306			.8483		

The estimates on the left side of the above table further reduced the minority/non-minority spread to 14.3 points, and the R-Squared (.731) increased slightly. The sign of the population density estimate is reasonable, since it suggests more renters in high density areas. The sign of the income measure also appears reasonable because the higher the income, the lower the percentage of renters.

When the vehicle ownership variables were added (right side of above table), the parameter estimate signs for the "% Minority", density and income variables changed and the expected impact of increasing income and density were reversed. Since we do not expect lower rental percentages in more urban areas, this suggests that some of these independent variables may be strongly correlated with one another.

We then chose to simplify the model drastically to illustrate our points about regression models.

Variable	% Minority and % No Vehicles			% No Vehicles Only		
	Estimate	Std. Error	P-Value	Estimate	Std. Error	P-Value
Intercept	.1767	.00495	<.0001	.1774	.00480	<.0001
% Minority	-.0123	.02211	.5790			
% No Vehicles	1.4732	.06480	<.0001	1.4469	.004417	<.0001
Adj. R-Squared	.5136			.5139		

When choosing only "% Minority" and "% No Vehicles" as independent variables, the "% Minority" variable is not statistically significant. By dropping that variable, we see that the "% No Vehicles" variable is strongly significant, and appears to be a "better" model than does using "% Minority" as the sole independent variable.

Summarizing, we have presented illustrations of how changes in regression variables can change the results. Our illustrations used some of the same variables analyzed in the Study:

1. Changing the form of an independent variable can improve results. Even relatively simple adjustments to one of the independent variables in the model had a substantial impact on the model. Little things could have a huge impact in Dr. Kabler's conclusions.

2. Multicollinearity can cause the estimates for a variable to flip-flop in sign and can often provide a warning flag about the poor selection of variables, as is the case in Dr. Kabler's study.

3. Omitting an important variable can make another variable appear inappropriately significant.

We know with certainty that important variables, readily available to Dr. Kabler, are missing from his analysis. For instance, the Study could have easily included consideration of differences in claim frequency, claim severity, and pure premiums by zip code using data gathered annually by the Missouri Department of Insurance.

Also, from our prior work with credit-based insurance scores, we know that scores have a great deal of variation at the individual level. If strong relationships exist between scores and other characteristics, averaging scores within a zip code should result in a much higher R-Squared value than observed in the Study. Based on the low R-Squared values, we suspect that the actual score distributions would not validate the regression results published by Dr. Kabler.

Individual Analysis

Dr. Kabler applied three analysis techniques to derive individual inferences from the aggregate data: Goodman's Regression, the Neighborhood Model, and the Ecological Inference Model. The Study's conclusions from these approaches are easy to find, and tend to the sensational. Although there are caveats and limitations, they tend to be general in nature. Some important issues are more difficult to find and are much less likely to be seen or understood by the lay reader.

For instance, unless readers look carefully they might miss that for some companies as few as 12%, and in the best case less than 50%, of Missouri zip codes were used to perform the analysis. They may also miss that these models are not well suited to "control for" additional variables.

On Page 32, the author mentions that making different assumptions about the underlying data can produce results that do not support the Study's conclusions. He supports his assumptions by describing ". . . the robustness of the correlation . . . even controlling for a fairly comprehensive set of area socioeconomic characteristics".

So, in effect, methodologies that are substantially affected by going-in assumptions are based on poor data, and questionable aggregate analysis results.

The author ends the report with: *"Ultimately, interpretation should be based on which set of assumptions readers believe are reasonable."* We have described the inherent flaws both in the data and in the aggregate analysis. Given those problems, it is difficult to now give credence to any of the assumptions, let alone to the individual-level results.

Recall that the operative word in the Study conclusions dealing with individual inferences is the word "inference". The inferences are not the result of a statistical study of individual data. Dr. Kabler doesn't really know whether there are differences in credit-based insurance scores by race or income within any ZIP code area. He has based his information on three statistical techniques with findings that he describes as "somewhat more speculative". Each of the three methods seems to suggest something different in terms of the magnitude of the differences in average scores by racial group. How can Dr. Kabler acknowledge that the results of his analysis are not proof of any individual-level disproportionate impact, and yet in the same sentence (page 13) declare "the evidence appears to be substantial, credible and compelling"? In our view, speculation and inferences always fall short of compelling proof.

Conclusion

In our judgment none of the major conclusions in the Study are supported by the data and data analysis described in the Study. There was a failure to control how the average scores were calculated by each participating insurer. There was a failure to call for data necessary to "normalize" the average scores for potential biases arising from non-geographic factors. There are apparent flaws in the regression analyses because of a failure to determine the extent of any non-linear relationships and to further investigate other important variables.

The issues addressed in the Study are important socially and politically, and deserve serious scientific study. This study does not further the research. Dr. Kabler delivered highly controversial conclusions and he described the results of some statistical analysis. Unfortunately, there is precious little, if any, connection between the conclusions and the data analysis.