An Indirect Approach to Improving Credit Scores: A Search for Demographic and Geographic Factors in U.S. Cities

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Abstract

Average credit scores differ from city to city. Thus people in some cities enjoy greater benefits from their credit scores than do people in other cities. Although credit scores are the direct result of credit histories, credit histories may be impacted by demographic and geographic factors, which thereby indirectly impact credit scores. If indirect factors that impact credit scores are identified, indirect ways to improve credit scores might be discovered. This study looks for demographic and geographic factors that explain city average credit scores. The methodology uses both statistical analyses and geographic information systems mapping. The analyses suggest that city average credit scores are explained by differences in the number of credit cards held, annual temperatures, travel time to work, debt level per capita, and the number of people in a household. The mapping reveals clusters of cities with similar credit scores.

Introduction

Credit scores are used in a variety of ways. Lenders use credit scores to decide if a loan will be made and the interest rate to charge as discussed in Perry (2008). Healthcare providers use credit scores to determine whether patients will receive free or discounted care as discussed in Bernerth, Taylor, Walker, and Whitman (2012). Insurance companies use credit scores to underwrite both automobile and homeowner's insurance as discussed in Kabler (2004). Credit scores are being used by employers in background checks for hiring decisions as discussed in Bernerth, Taylor, Walker, and Whitman (2012). Additional use of credit scores has been called for to help investors judge their risk exposure in asset-backed securities as discussed in Stachel

(2004), or in allocating accounts receivable in the healthcare industry to collection agencies as discussed in Jackson (2008). In all these uses, higher scores are associated with greater benefits, and lower scores are associated with greater costs. Therefore it is important to understand why average scores differ, and sometimes considerably, from one city to another. For example, according to Stachel (2004), a common benchmark for subprime lending is a credit score of 660, below which borrowing costs rise sharply. This suggests that the average person in Harlington, Texas where average credit scores are 686, is much closer to a subprime cutoff than the average person in Wausa, Wisconsin where average scores are 789. Therefore more people living in Harlington, Texas are likely to pay higher interest rates on loans than people in Wausa, Wisconsin. Many other cities also cluster around these average credit score extremes and suggest either costs or benefits to their typical residents.

Credit scores are directly impacted by bill and loan payment histories, as well as outstanding balances. However, there are likely to be indirect impacts to credit scores through factors that influence bill and loan payment histories and outstanding balances. Identifying those indirect factors should therefore identify the underlying factors that indirectly contribute to credit scores. Knowing the underlying factors that indirectly contribute to credit scores provides an opportunity for people and policymakers to manage those factors in order to help raise credit scores. Raising credit scores should increase the financial benefits to both individuals and the cities in which they live. Differences in average credit scores have already been explored among states in Newman and Newman (2013). The purpose of this study is to identify underlying demographic and geographic factors that indirectly explain why average credit scores differ among U.S. cities.

The study uses correlation, regression, and geographic information systems (GIS) mapping to test the influence of demographic factors previously found useful to explain credit scores, and and also some new influences to provide additional insight. Correlation and regression results provide evidence to suggest that some demographic factors found useful in previous studies to explain credit scores were also found useful in this study, but some were not corroborated. Factors found useful in past studies to explain credit scores and supported with evidence from this study are credit use, family members, and income level. This study finds that credit use, measured by the average number of credit cards held by a person in a city, is the strongest single variable associated with higher credit scores. However, also very important is climate, measured in by the average annual temperature in a city, where lower temperatures are associated with higher credit scores. Other important findings in this study are that average credit scores are higher in cities where: average debt per capita is lower; commute time to work is shorter; more people live alone; household income is higher; and more people own their homes. These significant variables are the most powerful measures of factors found to explain credit score differences. Measures of employment, race, health, education, and gender had no significant influence on credit score, even though previous studies found some of these factors to be significant explanatory variables. GIS mapping provides additional useful insight by showing that the cities with above average credit scores, and cities with below average credit scores, are clustered in regions of the United States. The primary contributions of this study are the findings associated with the measures of credit use and commute, the corroboration of earlier research findings and the questioning of some other findings, and the GIS mapping insights. These contributions are valuable for making private and public policy decisions that could lead to higher credit scores and subsequent benefits to people and the cities in which they live.

The paper proceeds with a literature review identifying demographic factors previously found associated with credit scores, and why geographic factors might also impact credit scores. A methodology section specifies the hypotheses being tested, the data utilized, and the analytical techniques employed. A results section displays and discusses output from the analytical techniques. The paper ends with a conclusion section that highlights important findings of the study, emphasizes the limitations of the study, and proposes additional avenues for research.

Literature

Credit score research in the past focused on different concerns, but often used similar demographic factors to explain credit scores. Newman and Newman (2013) explained state average credit scores with demographic measures of education, family, income, and health. They found higher average credit scores in states where there is a greater percentage of high school graduates, lower percentage of single mothers, higher percentage of people living alone, higher average household income, and lower percentage of disabled people. Bernerth, Taylor, Walker, and Whitman (2012) focused on the use of credit scores as a screening tool in employment practices, but also found higher credit scores associated with more education. Perry (2008) used survey data to examine the effect of personality on credit scores, and also found higher scores related to increases in education, income, and age, but lower scores related to poor health, unemployment, and lower income. The study also describes a quiz administered to respondents that showed higher credit scores corresponding to more financial knowledge and feelings of control over life. Lyons, Rachlis, and Scherpf (2007) used surveys to understand the extent of knowledge people had regarding credit reports, and found less knowledge in people who were less educated, had lower income, were older, and identified themselves as Hispanic.

Several studies examined the extent to which low credit scores perpetuate themselves. Spader (2010) theorized that credit scores create a “feedback loop” because people are assigned credit products by their scores, and these products by their nature determine default risk. An example is a person with a low credit score being offered only subprime loans. However, Agarwal, Skiba, and Tobacman (2009) find evidence to suggest that people are not assigned credit products; instead, they choose them. Their study looks at payday loan borrowers who also had credit cards, and found that most borrowers could have used a credit card rather than a more expensive payday loan. In addition, after using the payday loan, borrowers were much more likely to default on their credit card. The authors conclude that poor choices, and not credit product assignment, cause lower credit scores. Those poor choices could be impacted by level of education.

An investigation of the effect of credit score on consumer payment choice was done by Hayashi and Stavins (2012). They provide evidence to suggest that people with lower credit scores tend to use debit cards more than credit cards, but also identify other significant variables. Their study shows higher credit scores exist for older people with more education and higher income, who are married or widowed, and Asian or white. Since their study used self-reported credit scores, the authors validated the relationships between reported credit scores and demographic variables by obtaining credit scores directly from a credit bureau and comparing credit score averages to census tract data. Their validation lends support to using aggregated demographic variables to explain state average credit scores and inferring useful lessons for individuals, and mitigates the aggregation inference concerns mentioned in Robinson (1950).

An attempt at explaining average credit scores with aggregate demographic variables is documented in Kabler (2004). That study used demographic data aggregated by ZIP code in Missouri to explain credit scores and found significant associations to income, education, divorce, age, population density, and race. Race dominated the associations with lower credit scores associated with racial minorities, and the race association could not be eliminated using other variables. These past studies provide useful categories of factors to explain average credit scores in cities throughout the United States using both a statistical analysis and a geographic information systems mapping as the methodology.

[Add discussion of Newman and Newman 2013 and other literature supporting why geographic factors could be an important indirect influence on city average credit scores.]

Methodology

The methodology used in this study starts with hypotheses about the relationship of credit scores to demographic factors, and then tests the hypotheses with empirical data using three different techniques.

Hypotheses

The hypotheses are concerned with the relationships of credit score to demographic factors. Therefore the null and alternative hypotheses are:

H_O = City average credit scores are not impacted by demographic factors.

H_A = City average credit scores are impacted by demographic factors.

Demographic factors found useful in past studies to explain credit scores include: education in Newman and Newman (2013), Perry (2008), Kabler (2004); Hayshi and Stavins (2012), and Bernerth, Taylor, Walker, and Whitman (2012); household in Newman and Newman (2013), Kabler (2004), and Hayashi and Stavins (2012); income in Newman and Newman (2013), Hayashi and Stavins (2012), Perry (2008), and Kabler (2004); health in Newman and Newman (2013) and Perry (2008); unemployment in Perry (2008) and Kabler (2004); age in Hayashi and Stavins (2012), Perry (2008), and Kabler (2004); and race in Hayashi and Stavins (2012) and Kabler (2004). Education, health, unemployment, age, and race measures were initially used to explain credit scores but were dropped from this study because their influence was apparently captured by measures from other factor categories.

Several new factor categories are introduced in this study to explain credit scores. First, the category of debt is introduced. Both available debt and actual debt measures are used and found to be significant explanatory variables for credit scores. Second, the category of climate is introduced to account for differences in expenses associated with different climates, as well as motivational aspects on the desire to work and save in different climates. Third, the category of commute is introduced to account for expenses and effort associated with the time it takes for a typical person in a particular city to go from home to work. Fourth and finally, the category of wealth is introduced to account for the incentive that wealth provides to build up and keep up a high credit score.

Therefore the general model for the final analyses used to test the null and alternative hypotheses is:

Score = f (Debt, Climate, Commute, Household, Income, Wealth)

The expected association between credit score and debt should be negative, since greater use of debt involves a greater risk for delinquent payments. The expected association between credit score and climate is debatable since milder climates should bring less expenses, but harsher climates may force people to save more to avoid hardships from having utilities turned off in the winter. The expected association between credit score and commute should be positive since people with longer commutes will likely have greater transportation expenses and will consume more human energy. The expected association between credit score and household is expected to be positive since couples are able to share expenses, and children may motivate greater attention to financial responsibilities that lead to higher credit scores. The expected relationship between credit score and income should be positive, since greater income should provide more discretionary income. The expected association between credit score and wealth should be positive since wealth provides reserves from which to draw to keep bills current. The relationships of credit score to the demographic factors are assumed to be monotonic so a linear functional form is utilized. The variables used in this study to measure credit score and the demographic factors are described next.

Data

Data for this study to explain credit scores in 134 cities across the United states are from various sources. The variable used to measure score is *Score,* which is the average city credit score reported by Experian for 2011. Two variables are used to measure debt. The first debt variable measure is *Cards,* which is the average number of open credit cards per capita for each city. The second debt variable measure is *Debt,* which is the average debt per capita by city reported for 2011 by Experian. The variable used to measure climate is *Temp,* which is the average annual temperature for each city from the Canty and Associates LLC Weatherbase data, which has averages using from 26 to 63 years of data and obtained in 2013. The variable used to measure commute is *Travel*, which is the average travel time to work for people in a city from the American Community Survey, 2009-2011, U.S. Census Bureau. The variable used to measure household is *Alone*, which is the percentage of households with the householder living alone from the U.S. Census Bureau, 2009-2011 American Community Survey. The variable used to measure income is *Income*, which is median household income by city from the U.S. Census Bureau, 2007-2011 American Community Survey. Two variables are used to measure wealth. The first wealth variable is *Own,* which is the percentage of households in a city who own their home from the U.S. Census Bureau, 2007-2011 American Community Survey. The second wealth variable is *Liquidity,* which is the ratio of average per capita income for a city divided by average per capita debt for the city. City per capita income data are from the U.S. Census Bureau's American Community Survey for 2007-2077, and city per capita debt data are from Experian for 2011. A list of other variables used to measure categorical influences not found to be significant predictors of credit scores is found in the Appendix.

Summary statistics are provided in Table 1 for each variable used in the final analyses. Table 1 has mean, standard deviation, minimum, median, maximum, skewness, and kurtosis values for each variable. A cursory examination of the data comparing means to medians shows slight differences between the two statistics, which supports the view that symmetry exists in the variable distributions. In addition, skewness measures that might suggest outliers and kurtosis measures of the distribution peaks generally support normal distributions. However, the *Travel* variable has a somewhat higher positive skewness and a higher positive kurtosis than the other variables, suggesting a possible right tail outlier and a leptokurtic distribution with more mass in its tails. Therefore a more thorough test for influential observations, the Cook's Distance score, is reported for each regression output.

Table 1: Descriptive Statistics for Variables

	Mean	Standard Deviation	Minimum	Median	Maximum	Skewness	Kurtosis
Score	746	22	686	750	789	-0.29	-0.66
Climate	57.5	8.4	40.3	57.0	76.0	0.23	-0.90
Housing	179,054	126,759	49,900	146,500	926,100	3.32	13.94
Poverty	21.8	5.8	9.5	21.4	38.2	0.53	-0.11
Marriage	34.9	6.9	18.4	35.5	50.1	-0.16	-0.62
Race	61.3	17.7	10.6	62.0	93.8	-0.32	-0.43
Commute	20.4	3.9	14.5	19.7	39.2	1.53	3.96

Descriptive statistics are from data for 134 U.S. cities. *Score* is the average city credit score reported by Experian for 2011. *Climate* is the average annual temperature for a city from the Canty and Associates LLC Weatherbase data, which has averages using from 26 to 63 years of data and obtained in 2013. *Housing* is the median value of owner-occupied housing units for 2007-2011 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce. *Poverty* is the percent of the population living below the poverty level in 2007-2011 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce. *Marriage* is the percentage of households with a married couple family from the U.S. Census Bureau, 2009-2011 American Community Survey. *Race* is the percentage of the population reporting to be only white in 2010 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce. *Commute* is the mean travel time to work in minutes for workers age 16 and greater for 2007 to 2011 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce.

Techniques

The techniques used to look for relationships between city average credit scores and city demographic variables include correlation, regression, and mapping. The Pearson product moment correlation is calculated for each pair of variables to measure their linear relationships and to test for significance. Regressions investigate the relationship between the dependent variable, *Score*, and the other demographic independent variable predictors. Since the dependent variable is continuous, least squares regression is employed. Mapping is done using geographic information systems software to see regional similarities and differences on a map of the contiguous United States. Cities are coded corresponding to their level of credit score either below or above the average for all cities in this study.

Results

Results were obtained by calculating Pearson correlations and ordinary least square regressions, and doing geographic information systems mapping.

Correlations

The correlations for variables used in the final analyses are in Table 2. P-values are in parentheses directly below the correlations and indicate significance. Correlations between the city average credit scores (*Score*) and the independent variables used to explain those scores are in the first column labeled *Score*. The average number of open credit cards per person in a city variable (*Cards*) has the highest correlation to city average credit scores. Average credit scores tend to be high in cities with a high average number of open credit cards per capita. The average annual temperature for a city variable (*Temp*) also has a high correlation to city average credit scores, but the correlation is negative. Average credit scores tend to be high in cities with low average annual temperatures. The ratio of average per capita income for a city divided by average per capital debt for a city variable (*Liquidity*), the percentage of households with the householder living alone variable (*Alone*), and the median household income by city variable (*Income*), all have small yet significant positive correlations to city average credit scores.

Average credit scores tend to be high in cities where per capita income relative to per capita debt is high, where there are more householders living alone, and where median household income is high. The average debt per capita by city variable (*Debt*) has small yet significant negative correlations to city average credit scores. Average credit scores tend to be high in cities where average debt per capita is low, and where there are fewer people who own their home. The average travel time to work by city variable (*Travel*) and the percentage of households in a city who own a variable (*Own*) both have insignificant correlations to city average credit scores. The p-values indicate that all significant correlations in the *Score* column are significant at the two percent level.

Table 2: Correlations Between Variables

	Score	*Climate*	*Housing*	*Poverty*	*Marriage*	*Race*
Climate	-0.76					
	(0.00)					
Housing	-0.23	0.08				
	(0.01)	(0.38)				
Poverty	-0.21	-0.01	-0.42			
	(0.02)	(0.90)	(0.00)			
Marriage	-0.15	0.13	0.09	-0.66		
	(0.08)	(0.14)	(0.32)	(0.00)		
Race	0.31	-0.26	0.10	-0.55	0.62	
	(0.00)	(0.00)	(0.26)	(0.00)	(0.00)	
Commute	0.02	0.19	0.31	0.01	-0.22	-0.44
	(0.83)	(0.03)	(0.00)	(0.89)	(0.01)	(0.00)

Correlations are from data for 134 U.S. cities. P-values are shown below each correlation in parentheses. *Score* is the average city credit score reported by Experian for 2011. *Climate* is the average annual temperature for a city from the Canty and Associates LLC Weatherbase data, which has averages using from 26 to 63 years of data and obtained in 2013. *Housing* is the median value of owner-occupied housing units for 2007-2011 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce. *Poverty* is the percent of the population living below the poverty level in 2007-2011 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce. *Marriage* is the percentage of households with a married couple family from the U.S. Census Bureau, 2009-2011 American Community Survey. *Race* is the percentage of the population reporting to be only white in 2010 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce. *Commute* is the mean travel time to work in minutes for workers age 16 and greater for 2007 to 2011 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce.

Correlations between pairs of independent variables are in the columns of Table 2 labeled *Cards, Temp, Liquidity, Travel, Debt, Alone,* and *Income*. Only two correlations in those columns are greater than 0.50. The average number open credit cards per capita variable (Cards) has a high negative correlation with the average annual temperature for a city variable (Temp). There tends to be more credit cards per capita in cities where average annual temperatures are lower. In addition, the ratio of average per capita income for a city divided by average per capita debt for a city has a very high positive correlation with the median household income variable (Income). There tends to be more income per debt in cities with higher median household incomes. Both of these correlations are significant at the zero percent level. There are numerous other significant but not high correlations between independent variables, and there are numerous correlations that are not significant. The high significant correlations between some of the independent variables justify using a stepwise regression procedure in addition to a full model regression to see the extent to which regression coefficients are impacted by the inclusion of other independent variables.

Regressions

Regression output using *Score* as the dependent variable for a full model and a stepwise procedure using data from 134 U.S. cities is in the columns of Table 3. Output from the full model is in the column labeled Full Model and shows that all independent variables are significant except *Liquidity* at the one percent level or lower. All of the independent variables have signs on their estimated coefficients consistent with their correlations except *Travel* and *Own*. For the independent variables with estimated coefficients with signs consistent to their correlations to *Score*, more credit cards, lower temperatures, less debt, more people living alone, and higher household incomes predict higher city average credit scores. For the variables in the full model with signs inconsistent to their correlations to *Score*, *Travel* now shows the expected negative sign, and *Own* now has the expected positive sign. More time commuting predicts lower city average credit scores, and a higher percentage of home ownership predicts higher city average credit scores in the full regression model. The F-statistic for the full model shows significance at the one percent level. The adjusted r-square for the full model shows that the independent variables explain 84.6 percent of the variation in city average credit scores. Outliers do not appear to significantly influence coefficients since the highest Cook's distance measure is 0.09, well below the 0.80 threshold.

Table 3: Regressions to Explain *Score*

Independent Variables	Stepwise Procedure						
	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7
Climate							
Housing							
Poverty							
Marriage							
Race							
Commute							
F-Statistic							
Adjusted R^2							
Cook's High							

Regressions use data for 134 U.S. cities to explain city average credit scores. The dependent variable, *Score* is the average city credit score reported by Experian for 2011. *Climate* is the average annual temperature for a city from the Canty and Associates LLC Weatherbase data, which has averages using from 26 to 63 years of data and obtained in 2013. *Housing* is the median value of owner-occupied housing units for 2007-2011 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce. *Poverty* is the percent of the population living below the poverty level in 2007-2011 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce. *Marriage* is the percentage of households with a married couple family from the U.S. Census Bureau, 2009-2011 American Community Survey. *Race* is the percentage of the population reporting to be only white in 2010 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce. *Commute* is the mean travel time to work in minutes for workers age 16 and greater for 2007-2011 from the State and County Quickfacts of the United States Census Bureau, U.S. Department of Commerce. The variable coefficients and F-statistics have their p-values below them in parentheses. Cook's High is the highest Cook's distance measure for any observation in each regression and should be above 0.80 to indicate an outlier.

Regression output from the stepwise procedure is in the nine columns beneath the Stepwise Procedure heading in Table 3. The first independent variable to enter the procedure is *Cards*, and although its coefficient falls in subsequent regressions, it remains significant in the last regression, Step 9. The second variable to enter the procedure is *Temp,* and its coefficient also falls in subsequent regressions yet remains significant. The third variable to enter is *Liquidity*, and although its coefficient remains significant through Step 6, it becomes insignificant when *Income* is entered in Step 7 and does not return. The fourth variable to enter is Travel, and it remains significant through Step 9. The fifth variable to enter the stepwise procedure is Debt, the sixth is Alone, the seventh is Income, and the eighth is Own, all of which remain significant through the last step. All coefficients that remain in the stepwise regression through Step 9 are significant at one percent or lower. The F-statistics indicate that all stepwise procedure regressions are significant at the one percent level. The adjusted r-squares of the stepwise regressions rise monotonically in every step where variables are added and all variables are significant. The Cook's distance measures for the stepwise regressions are all well below the 0.80 threshold and provide evidence that outliers are not distorting any stepwise regression coefficients.

Mapping

A geographic information systems (GIS) mapping with two attribute queries created from one existing variable appears in Figure 1. The two attribute quarries are made by isolating the credit score variable, then using a formula within GIS software called GeoMedia Professionals, to write a code which isolates credit scores above the average for all cities in the study to obtain one quarry. Another code is written to isolate credit scores below the average for all cities in the study. This creates two quarries. The GIS map in Figure 1 is the result of using the two attribute quarries created to see the location of cites where average credit scores are above average, and also see where average credit scores are below average. Out of the one hundred and thirty-four cities used in this study, hollow circles on the map depict cities where average credit scores are above the average for all cities, and solid dots depict cites where average credit scores are below the average for all cities. The map does not show the states of Alaska and Hawaii because there are no cities in the sample from those states. The two attribute queries on this map work to provide a visual distribution of regions of the United States with cities that have above average credit scores, and regions with cities that have below average credit scores. Overall, northerly regions contain cities with above average credit scores, and southerly regions contain cities with below average credit scores. Thus the upper portion of the map has most of the hollow circles, and the lower portion of the map in Figure 1 has most of the solid dots.

Figure 1: Above and below average credit scores by city

Note: Above average credit scores by city depicted with a hollow circle. Below average credit scores by city are shown in a solid black circle.

Conclusion

Demographic and geographic factors appear to indirectly influence credit scores in U.S. cities. Most of the variation in city average credit scores is explained by four demographic factors, and two geographic factors. Demographic factors found to explain average credit scores in cities include debt level, household makeup, household income, and household wealth. Geographic factors found to explain average credit scores in cities include average climate and necessary commute. Variables used to measure these factors were found to significantly influence credit scores. Individuals and policy makers should be able to take steps to increase city average credit scores if they can improve any of these demographic or geographic factors. For example, average credit scores might increase if people found a way or were encouraged to use a few more credit cards in a responsible manner, while at the same time reducing their level of debt. Another way average credit scores might increase is if a individuals or a city found a way to increase household incomes. Credit scores might also increase if a city would promote a transportation system that lowered the commute time to work. Finally, average credit scores might also increase if cities used zoning laws and building codes to provide more affordable housing that people could own. To the extent that these factors improve in a city, average credit scores might also improve. When city average credit scores improve, those cities should enjoy the benefits of a population that has access to more credit at a lower cost, pays lower auto and homeowner insurance premiums, and has greater employment opportunities. In addition, people with better credit scores should need less free health care or discounted services, putting less financial pressure on healthcare providers. Finally, investors who see better average credit scores in mortgage-backed securities will provide funds at lower interest rates, thereby providing mortgage funds at a lower cost to borrowers.

[(Rewrite after seeing GIS map) Regional credit score differences are evident. States in the southern part of the contiguous 48 states have credit scores lower than national averages. States in northern sections of the contiguous 48 states have credit scores higher than national averages. A major factor associated with the regional differences is the percentage of adults in them who have high school diplomas. It appears reasonable to suggest that if a state raises its percentage of adults with high school diplomas, it should indirectly be contributing to higher state average credit scores. Higher state average credit scores should be especially helpful to states located in the southern part of the contiguous 48 states.]

More research is needed. For example, more and varied measure of demographic and geographic factors could be used in an attempt to indirectly explain credit scores. As another example, studies could be done for metropolitan areas or counties. In addition, the ideal research project would use individual credit scores along with their associated demographic and geographic data.

This study is limited by the use of variables associated with cities and the limited number of cities examined. The ecological paradox may apply to this analysis, so caution should be used in using city average relationships to explain the credit scores of individuals. However, previous research by Kabler (2004) did show a high correlation in credit score relationships using both averages and individual data. Therefore the results from this study should not be entirely dismissed. This study provides some evidence that demographic and geographic factors do impact credit scores, based on results from statistical methods and a visual inspection from geographic information systems mapping.

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Appendix

Table 4: Variables unable to explain credit score

Category	Variable	Definition
Education	*College*	Percentage of population in a city age 25 and older with a bachelor's degree from the 2007-2011 American Community Survey, U.S. Bureau of the Census.
Gender	*Female*	Percentage of population in the city that is female in 2010 from the U.S. Bureau of the Census.
Health	*Disabled*	Percentage of the civilian non-institutionalized population in a city aged 18 to 64 years from the 2009-2011 American Community Survey, U.S. bureau of the Census.
Household	*Married*	Percentage of households in a city with a married couple living as a family from the 2009-2011 American Community Survey, U.S. Bureau of the Census.
Household	*Mother*	Percentage of households in a city headed by a female without a husband and children under age 18 from the 2009-2011 American Community Survey, U.S. Bureau of the Census.
Housing	*House*	Median value of owner-occupied housing in a city from the 2007-2011 American Community Survey, U.S. Bureau of the Census.
Income	*Poverty*	Percentage of households living below the poverty level in a city from the 2007-2011 American Community Survey, U.S. Bureau of the Census.
Income	*Salary*	Per capital income for people living in a city from the 2007-2011 American Community Survey, U.S. Bureau of the Census.
Income	*Jobless*	Percentage of workers unemployed in a city from the 2009-2011 American Community Survey, U.S. Bureau of the Census.
Race	*White*	Percentage of the population in a city reporting to be white only in 2010 from the U.S. Bureau of the Census.

Note: Three other variables, formed from variables in this table and some of those that remained in the analysis were also put into a stepwise regression and found to be insignificant. The ratios of Salary to Debt, Salary to House, and Income to House were all found to be insignificant predictors of Score.