Report to the 79th Legislature

Use of Credit Information by Insurers in Texas

Texas Department of Insurance
December 30, 2004

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EXECUTIVE SUMMARY

Texas Insurance Code Article 21.49-2U, Section 15, requires the Texas Department of Insurance (Department) to present a report to the Governor, the Lieutenant Governor, the Speaker of the House of Representatives and the members of the 79th Legislature regarding the use of credit information by insurers in Texas. To prepare such a report, the Department obtained data from six leading insurer groups for approximately 2 million policies. Of these, approximately 1.2 million are for personal auto and 800,000 are for homeowners. The personal auto policies cover roughly 2.5 million vehicles. Six personal auto and three homeowners credit scoring models are represented in the data collection.

The Department obtained supplemental information from the Texas Department of Public Safety (DPS), including individual information on race. Additional information was obtained from the Texas Office of the Secretary of State (SOS), which the Department used to identify individuals of Hispanic ethnicity. The Department also obtained credit scores and the related input variables (e.g. number of credit cards, number of collections, etc.) to the credit models from credit vendors. Data regarding race/ethnicity, credit score, credit related variables, policy detail and claim history for each of the 2 million policies was entered into a database for each insurer group and line of business (personal auto or homeowners).

The Department used this data to analyze whether the use of credit scoring: (1) impacts certain classes of individuals more than others; and (2) predicts claims experience. In this regard, it is important to note that unlike previously published studies that relied on aggregate census or ZIP code data to approximate race and ethnicity, the Department's analysis is based on individual data for these characteristics. The Department also reviewed insurer rate filings regarding the use of credit scoring and consumer complaints as part of its analysis.

The Department makes the following initial findings based on a thorough analysis of the collected data, insurer rate filings, and consumer complaints:

- The individual policyholder data shows a consistent pattern of differences in credit scores among the different racial/ethnic groups. The average credit scores for Whites and Asians are better than those for Blacks and Hispanics. In addition, Blacks and Hispanics tend to be over-represented in the worse credit score categories and under-represented in the better credit score categories.

- There appears to be a strong relationship between credit scores and claims experience on an aggregate basis. However, credit scores, to some extent, may be reflective of other risk characteristics associated with claims. It is necessary to evaluate if, and to what extent, credit scoring enables an insurer to more accurately predict losses. Thoroughly analyzing this issue requires simultaneous analysis of the variables affecting likely claims experience. The Department is in the process of conducting a multivariate analysis using the individual policyholder data and will report the results by January 31, 2005.

- The individual policyholder data does not include information on individual income, as this data was not available. The Department performed some limited analysis of the relationship between credit score and median income using Census data by ZIP code. While the differences in average credit scores between income levels are not as large as they are for racial/ethnic groups, the data shows that the average credit scores for upper income level are better than those for lower and moderate income level populations. Additionally, the moderate income level populations tend to be over-represented in the worse than average credit score categories and under-represented in the better than average credit score categories.

- The individual policyholder data shows a consistent pattern of differences in credit scores depending on an individual's age, with younger people having worse credit scores than older people. The best average credit scores are for individuals older than 70.

- The number of credit related consumer complaints submitted to the Department increased substantially from 2000 to 2002 and leveled off at roughly half of their peak since 2002. For the year 2000, the Department received a total of only 40 credit related homeowners and personal auto complaints. By 2002, this number increased nearly 15 times to over 600 complaints. Since 2002, the number of credit related complaints has declined and is currently approximately 300 per year, or five to six per week. It should be noted that complaints related to credit may have also shown other complaint codes related to rating or underwriting.

- Based on a review of rate filings, insurers writing approximately 42% of the homeowners and 55% of the personal auto premiums use credit scoring to some degree in either determining rates or rating tiers. These numbers do not include those insurers whose use of credit information (with consideration of other applicable underwriting factors independent of credit information[1]) is to accept or reject applications for coverage.[2] If this use is included, these percentages increase to 54% and 82%, respectively.

- Based on the Department's review of rate filings, the relative impact of credit scores on rates (from either tiering or rating) varies significantly between insurers. For example, rates varied as little as 11% in one instance to 400% in another due to

[1] Texas Insurance Code Article 21.49-2U, Section 3, states that an insurer may not deny, cancel, or nonrenew a policy of personal insurance solely on the basis of credit information without consideration of any other applicable underwriting factor independent of credit information.

[2] Underwriting occurs when insurers apply a rule, standard, guideline, or practice, to decide whether to accept or reject an application for coverage or to determine how to classify those risks that are accepted for the purpose of determining a rate, based on individual characteristics. Tiering occurs when insurers apply a rule, standard, guideline, or practice, to decide, for an accepted policy, which particular rating level or tier an insured qualifies for based on individual characteristics. Rating occurs when insurers discount or surcharge a policy based on individual characteristics.

credit score as a measure of risk, with all other rating factors held constant. The variation in rates for any one insurer charging such extremes may have limited impact because there aren't many policyholders at the higher end of the risk/rate spectrum.

DISCUSSION

INTRODUCTION

Texas Insurance Code Article 21.49-2U, Section 15, requires the Texas Department of Insurance (Department) to present a report to the Governor, the Lieutenant Governor, the Speaker of the House of Representatives and the members of the 79th Legislature regarding the use of credit information by insurers in Texas. In summary, the report required under this statute must include:

- A summary statement ("Executive Summary") regarding the use of credit information, credit reports, and credit scores by insurers,

- A description of insurer practices and the effect of different credit models,

- The number of consumer complaints submitted to the department regarding the use of credit information,

- A description of favorable and unfavorable effects on consumers related to the use of credit scoring from information that may be provided by insurers, including the number of consumers receiving lower or higher premiums,

- Any disproportionate impact on any class of individuals, including classes based on income, race, or ethnicity, resulting from the use of credit,

- Recommendations from the department to the legislature regarding the use of credit information, and

- Any other information considered necessary by the commissioner.

The statute requires the Department to present information in a manner that protects the identity of individual insurers and consumers.

The Department established contractual relationships with the University of Texas and Texas A&M University to provide peer review and related assistance during the course of this study. The Office of Public Insurance Counsel (OPIC) also provided input and feedback throughout the course of the study.

The insurers who provided data for this study did not have the opportunity to review the details of this report prior to its release.

DESCRIPTION OF INSURER PRACTICES AND EFFECT OF DIFFERENT CREDIT MODELS

Credit scores are typically calculated using a model, which is essentially a mathematical formula. The inputs to the formula are various credit related statistics (e.g., number of credit cards, number of collections, etc.). The output is a single numerical value known as a credit score. The formula may be set up so that a high number indicates above average or better credit and a low number indicates below average or worse credit, or vice versa. For purposes of consistency, in this report all credit scores have been, when necessary, converted to where a higher score represents better credit. Additionally, models may be tailored to their intended use in that models used for homeowners may differ from those used for personal auto insurance, even within the same insurer. Similarly, credit models used for insurance applications may differ from those used for lending applications.

A credit scoring model is a common tool used by insurers for underwriting, tiering, and/or rating policies. Some companies do not use a model but do consider credit related information. For example, negative credit related information, such as prior bankruptcies, with consideration of other applicable underwriting factors independent of credit information, may make an individual ineligible for any coverage.

It is important to note that the credit models or scores are but one of many variables insurers may use to determine whether to extend coverage and at what cost to the insured. Insurers consider, for example, past claims experience, type of vehicle, age of driver and other characteristics together with their own particular underwriting and/or tiering rules. Given this mix, it is entirely possible that two insurers using identical credit scoring models, but different underwriting and/or tiering rules, could come to divergent underwriting decisions. For example, an insured with a credit score of 650 may be considered a good risk by one insurer but an average risk by another.

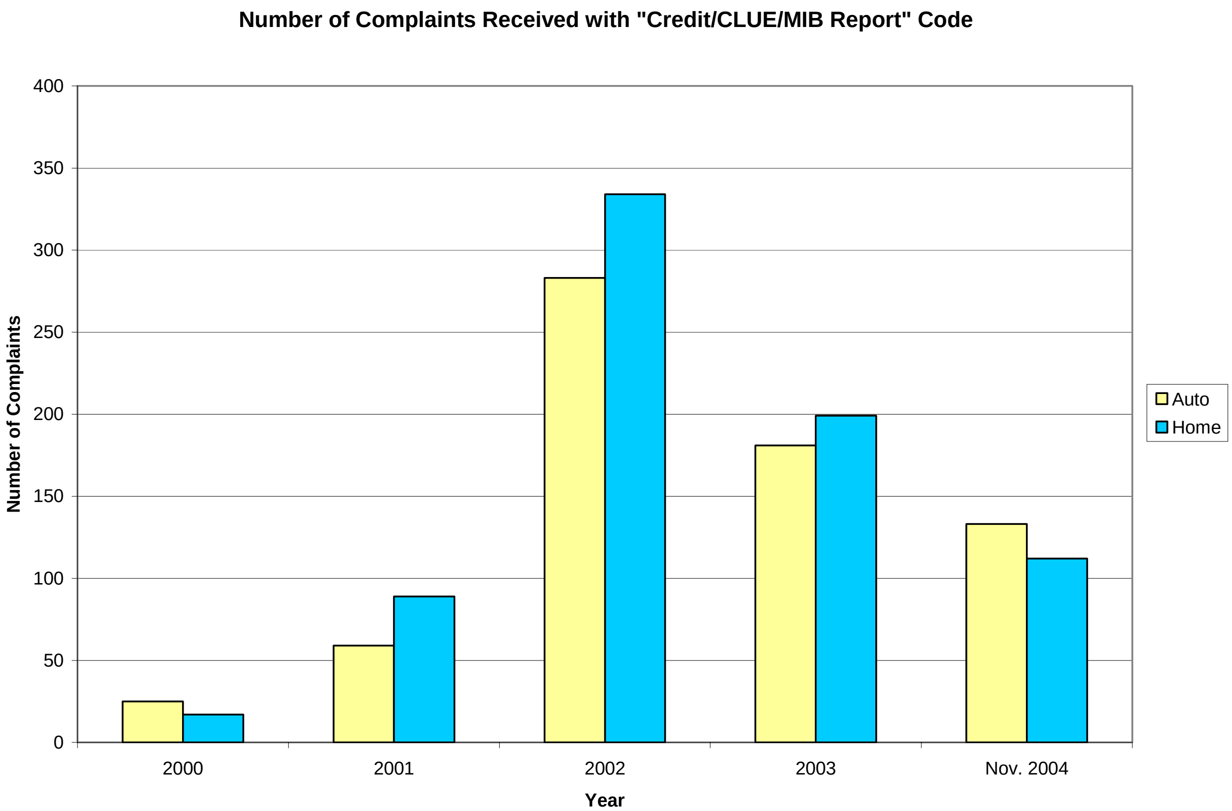
The effect of credit scores on rates varies significantly among insurers. In this regard, the Department reviewed individual insurer filings to determine the effect of credit scores on rates considering both tiering and rating procedures. For example, where the actual effect could be measured directly, rates varied as little as 11% in one instance to 400% in another due to credit score, as a measure of risk, with all other rating factors held constant. The variation in rates for any one insurer charging such extremes may be theoretical because there aren't many policyholders at the higher end of the risk/rate spectrum.

Insurer rate filings and underwriting guidelines show that, in general, a below average credit score will either be assigned to higher rated tiers or declined coverage. However, it can be difficult to isolate the impact of credit scoring from other variables used by insurers to make rating and underwriting decisions.

NUMBER OF CONSUMER COMPLAINTS

Chart 1 shows the number of credit related consumer complaints[3] for personal auto and homeowners insurance from year 2000 through November 2004.

Chart 1



The number of credit related consumer complaints submitted to the Department increased substantially from 2000 to 2002 and leveled off at roughly half of their peak. For the year 2000, the Department received a total of only 40 credit related homeowners and personal auto complaints. By 2002, this number increased nearly 15 times to over 600 complaints. Since 2002, the number of credit related complaints has declined and is currently approximately 300 per year, or five to six per week. It should be noted that complaints related to credit may also have shown other complaint codes related to rating or underwriting.

[3] Credit/CLUE/MIB is one of many different reason codes used by the Department for tracking consumer complaints. CLUE stands for Comprehensive Loss Underwriting Exchange and MIB stands for Medical Information Bureau. It is possible that some of the complaints may be due to concern over a consumer's CLUE report. It is much less likely that the complaints are coded this way for MIB since this report focuses on personal auto and homeowners insurance.

FAVORABLE AND UNFAVORABLE EFFECTS ON CONSUMERS

The use of credit scoring has produced rate outcomes favoring some individuals and groups, while adversely affecting others. From a rate perspective, the increased use of credit scores was accompanied by large rate swings. These swings resulted in reduced rates (or reduced rate increases) for some policyholders and increased rates for others. The Department estimated the range of rate impacts on individual policyholders based on a review of individual insurer rate filings. The range of rate impacts are summarized in Charts 2 and 3.

<u>Chart 2</u>

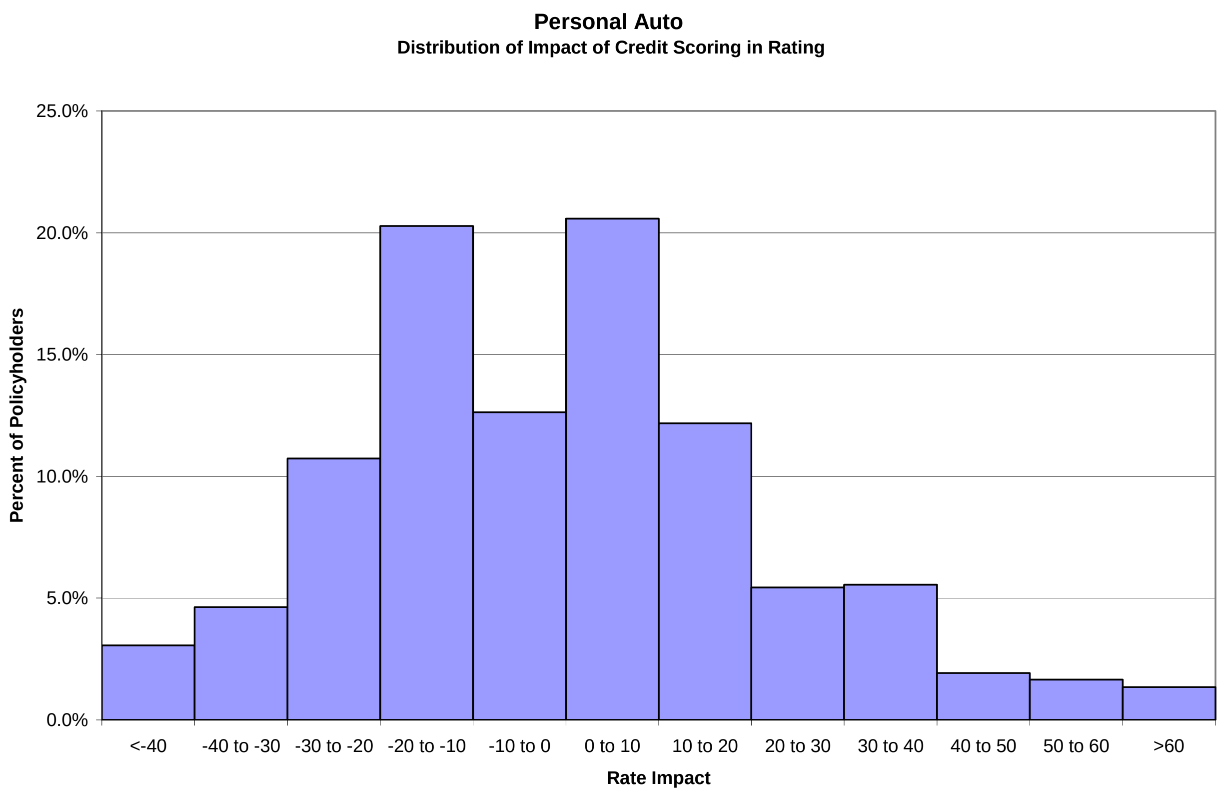
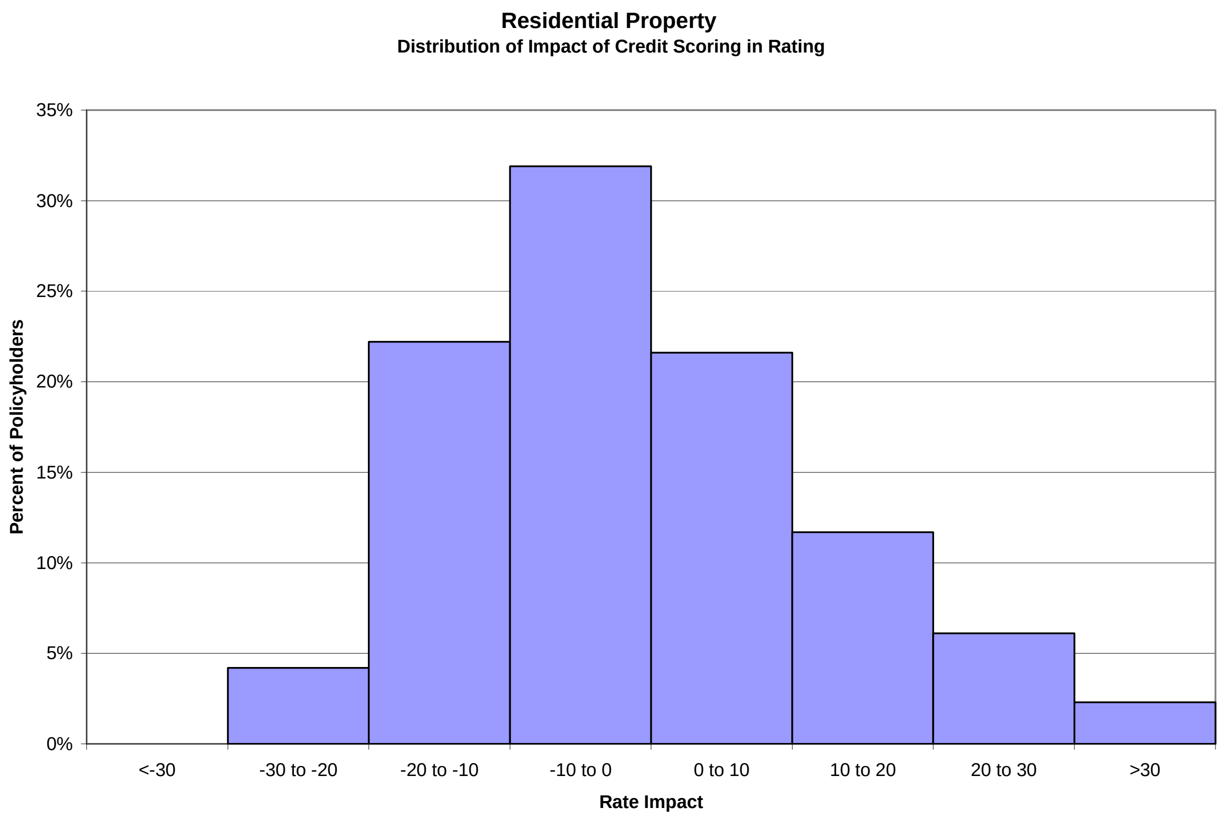


Chart 2 shows that as insurers started using or expanding their use of credit, the vast majority of policyholders (approximately 90%) experienced rate swings ranging from a 40% decrease to a 40% increase in the rates paid for personal auto insurance. Almost 10% of policyholders experienced more than a 40% increase or decrease.

For homeowners, the impact was not as dramatic: 90% of homeowners experienced rate increases or decreases of less than 30%.

Chart 3



From an availability perspective, insurance companies argue that the use of credit scores improves their ability to measure risk and therefore allows them to expand the spectrum of risks that they write. This benefits consumers because insurance may become more available, and may be particularly beneficial to more marginal applicants who might otherwise be declined coverage. On the other hand, the increased rates for policyholders with below average credit, or higher risk, may make insurance unaffordable and essentially unavailable for some consumers. Note that this outcome could occur with the use of other rating variables and is not limited to credit scoring.

Regarding consumer confidence in the insurance system, the increased use of credit information may have some unfavorable effects. In particular, some consumers may question the relevance of an individual's credit score to risk or probability of insurance claims. In contrast, the relationship for more traditional rating variables (e.g., age, driving record, etc.) to claims may be more widely accepted as reasonable.

IMPACT ON CLASSES OF INDIVIDUALS

The Legislature directed the Department to address whether the use of credit information has "any disproportionate impact on any class of individuals, including classes based on income, race or ethnicity." As described in detail below, the Department has determined that in the individual policyholder data, there are consistent patterns reflecting differences in credit scores, most notably, between different racial/ethnic classes. Other classes also present patterns, as discussed below.

Individual Policy Data Used in the Analysis

To study the impact of the use of credit information on certain classes of individuals, the Department compiled a database of information for a large number of policyholders.

Individual personal auto and homeowners policyholder information was compiled from a special data call directed to six leading groups of insurers. The insurers produced premium, claim, rating, and exposure data for approximately 2 million Texas policies. Of these, approximately 1.2 million are for personal auto and 800,000 are for homeowners. The personal auto policies cover roughly 2.5 million vehicles. While the time period varied somewhat by insurer, this data generally reflected experience for policies issued in 2001. Six personal auto and three homeowners credit scoring models are represented in the data collection.

The Department sent certain policyholder information collected from the insurers to the Texas Department of Public Safety (DPS) to obtain the race of the individual policyholder, as defined by DPS records. Individuals were classified as Asian, Black, White, Indian[4] or Other. This process involved matching the policyholder information previously collected by the Department for name, address, date of birth, driver's license, and social security number with the DPS database. The match rate between the information provided by the insurers and DPS was approximately 80% for personal auto and almost 60% for homeowners. The match rate is lower for homeowners because one of the insurers was unable to provide some of the information required by DPS to identify an individual.

The DPS does not separately identify Hispanics, which are generally classified as White in the DPS database. However, the Department determined there was a need to analyze this ethnic group for the study. To identify Hispanics, the Department used a list of Hispanic surnames obtained from the Texas Office of the Secretary of State (SOS). The SOS uses this list to distribute Spanish language materials as needed. This list was then compared to surnames in the collected data, and those that matched were then coded as Hispanic for study purposes. There were almost 459,000 individuals reclassified as Hispanic from the White class. Additionally, about 226,000 individuals were classified as Hispanic from the group of individuals which did not have a race code in the DPS data. The Department acknowledges that, in doing so, some Hispanics were likely miscoded as White, while some Whites were likely miscoded as Hispanic.

The Department sought to ensure that the credit score used during analysis reflected the model currently being used by a given insurer. Policyholder data was provided to

[4] For purposes of analysis, the Department included Native American with Other in the race classifications because of the low volume of data. DPS defines Native American as Indian.

each insurer's credit vendor (or internal credit scoring department). The vendor or scoring department used this policyholder data to identify individuals for the study, access their credit information, and compute a credit score using the appropriate model. It should be noted that each score was based on individual credit information from the approximate time period the policy was originally rated during 2001. For example, archived credit information from September 2001 may have been used to determine a credit score based on the insurer's current credit model.

For some individuals, the credit vendors were unable to match credit information with the individual. These individuals are classified as No Hit. Additionally, No Score represents individuals for which the credit vendors could match credit information, but the information was insufficient to generate a credit score.

The Department compiled all the information collected into a database for each insurer group and line of business within the group. In doing so, steps were taken to ensure compliance with the Fair Credit Reporting Act by all parties involved.

The Department was unable to obtain individual policyholder income data. In order to analyze the relationship between credit scores and income, the Department used 2000 Census median income data by ZIP code. This is the only instance where the Department relied on aggregate rather than individual data. The Department acknowledges that, while aggregate data may be useful for evaluating overall relationships, it is not an ideal source as it does not facilitate analysis of all the factors that impact an individual.

A formal audit of the collected data was not performed. However, the Department did perform cross checks between the data provided by the insurers pursuant to the data call and data routinely reported by the insurers under the Texas Statistical plans. In addition, the Department communicated frequently with insurer representatives who were responsible for providing the data to ensure that the Department understood the data and to ensure data integrity.

While the Department performed its analysis and presentation of the data at the individual insurer group level, it did so in a manner that preserved the anonymity of insurers and policyholders. The Department randomly assigned a letter to identify each data set collected. The nine data sets used in the study (six personal auto, three homeowners) are identified by the letters 'A' thru 'H'. Note that insurer groups providing both personal auto and homeowners data are not identified by the same letter; for example, one insurer's personal auto data set may be identified as Personal Automobile Group B, while the same insurer's homeowners data set may be identified as Homeowners Insurer Group I. Additionally, as some data sets were not sufficient and/or received in time to complete the analysis, not all insurer group letters A-I are presented within.

Impact of Underwriting on the Analysis

The Department's analysis is based on data restricted to insured persons. Individuals unable or unwilling to purchase insurance policies are not reflected in the data.

Credit Score and Race

Table 1 shows the total number of individuals for which data was available for an analysis of credit score and race/ethnicity for personal auto. The Unknown category represents those individuals for whom DPS could not match with race data.

Table 1: Total Number of Individuals by Race

	Personal Auto	
Race	**Number of Individuals**	**Percent of Total**
ASIAN	46,760	2.3%
BLACK	151,773	7.4%
HISPANIC	388,530	18.8%
OTHER	34,474	1.7%
WHITE	1,052,068	51.0%
UNKNOWN	390,439	18.9%
TOTAL	2,064,044	100.0%

For each data set, the Department compared the average and median credit scores by race and found a consistent pattern across all models. Whites and Asians, as a group, tend to have better credit scores than Blacks and Hispanics. In general, Blacks have an average credit score that is roughly 10% to 35% worse than the credit scores for Whites. Hispanics have an average credit score that is roughly 5% to 25% worse than those for Whites. Asians have average credit scores that are about the same or slightly worse than those for Whites.

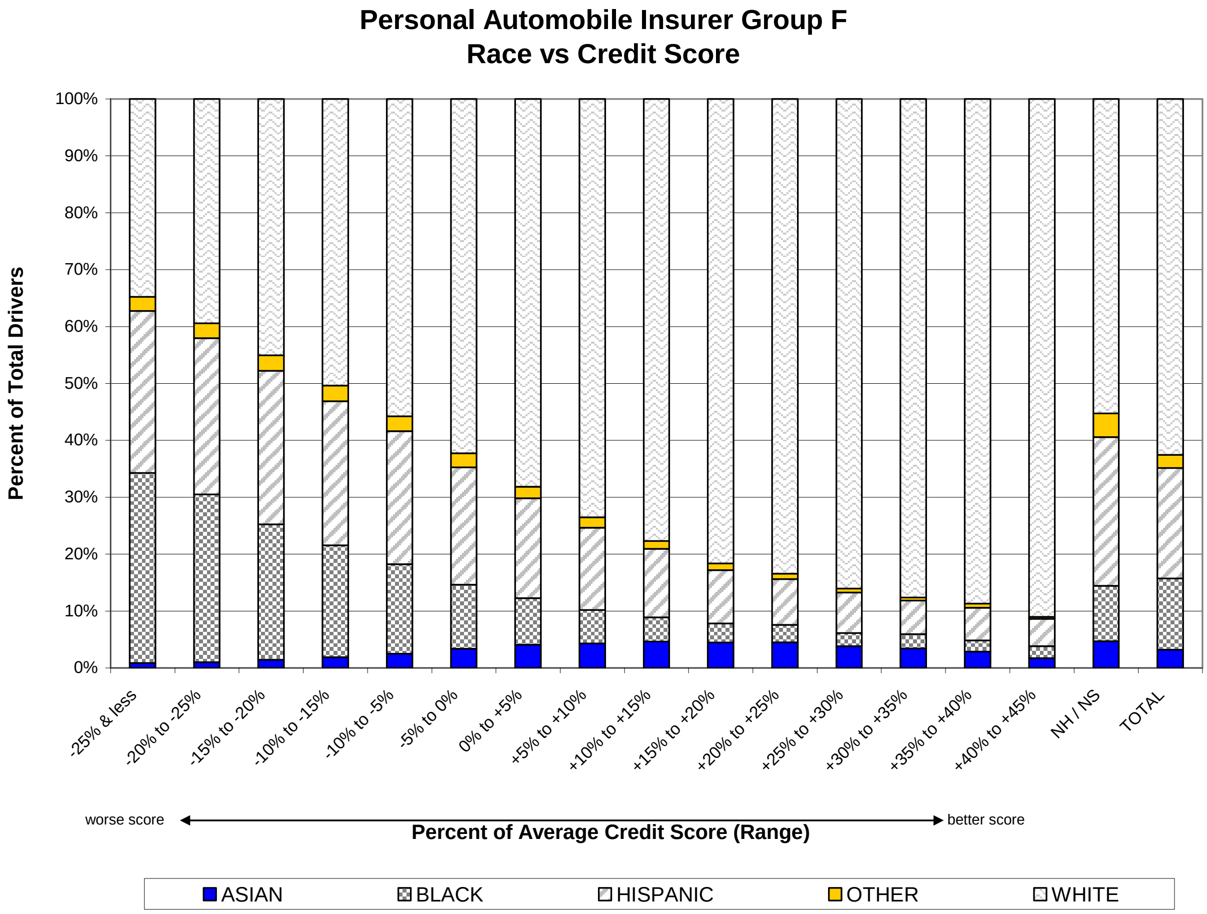
To further evaluate the difference in credit scores among racial/ethnic groups, the Department looked at the composition by race/ethnicity within different ranges of credit scores. Chart 4 is an example for personal auto. (Charts for all the available data sets can be found in the Appendix.) To ensure that the actual credit scores do not reveal a certain model or insurer, each range is depicted as a percent of the average credit score for the individuals in each respective insurer's database. For illustration purposes only, for an insurer with individuals who in total had an average credit score of 500, a range of scores from 550 to 600 would be shown as +10% to +20% of average credit score. For each data set, individuals were placed in the appropriate range determined by the degree to which their credit score was better or worse than the average credit score of the insurer group. Analysis was then performed to ascertain whether there was a consistent pattern of certain racial/ethnic groups being under- or over-represented in the various ranges.

Rather than showing the *number* of individuals or drivers by race/ethnicity in each range, the chart shows the *percent* of total individuals or drivers by race/ethnicity within each credit score range. This aids in comparing the distribution by race across the various credit score ranges. The last bar in the chart shows the race distribution for all the individuals in the particular data set with a known race code. For example, in Chart 4, Asians make up 3%, Blacks make up 13%, Hispanics make up 19%, Whites make up 63%, and Other makes up the remaining 2%. This bar can be compared to the other bars to determine if each race is represented in the same manner as it is for the entire data set.

While the percent of drivers in each bar relative to the total is not shown, note that it varies for each bar. In other words, the bars do not constitute an equal percentage of drivers. For example, the range for 0 to +5% of average credit score contains 10% of the individuals. The range for +20 to +25% of average credit score contains 3% of the individuals.

Chart 4 shows that Blacks and Hispanics make up an increasing percentage of the individuals in a given credit score range as the credit scores get worse while Whites make up an increasing percentage of the individuals in a given credit score range as the credit scores get better. For example, the bar with the best credit scores (+40 to +45%) shows that Whites make up about 90% of the drivers. In the far left bar with the worst credit scores (-25% and less), Whites make up about 35% of the drivers. On the other hand, Blacks make up about 2% of the policies in the best credit score range and about 33% in the worst credit score range. In a pattern similar to Blacks, Hispanics make up about 5% of the drivers in the best credit score range and 28% of the drivers in the worst credit score range.

Chart 4



Notes:
1. NH / NS = No Hit / No Score
2. OTHER includes OTHER and INDIAN from DPS data

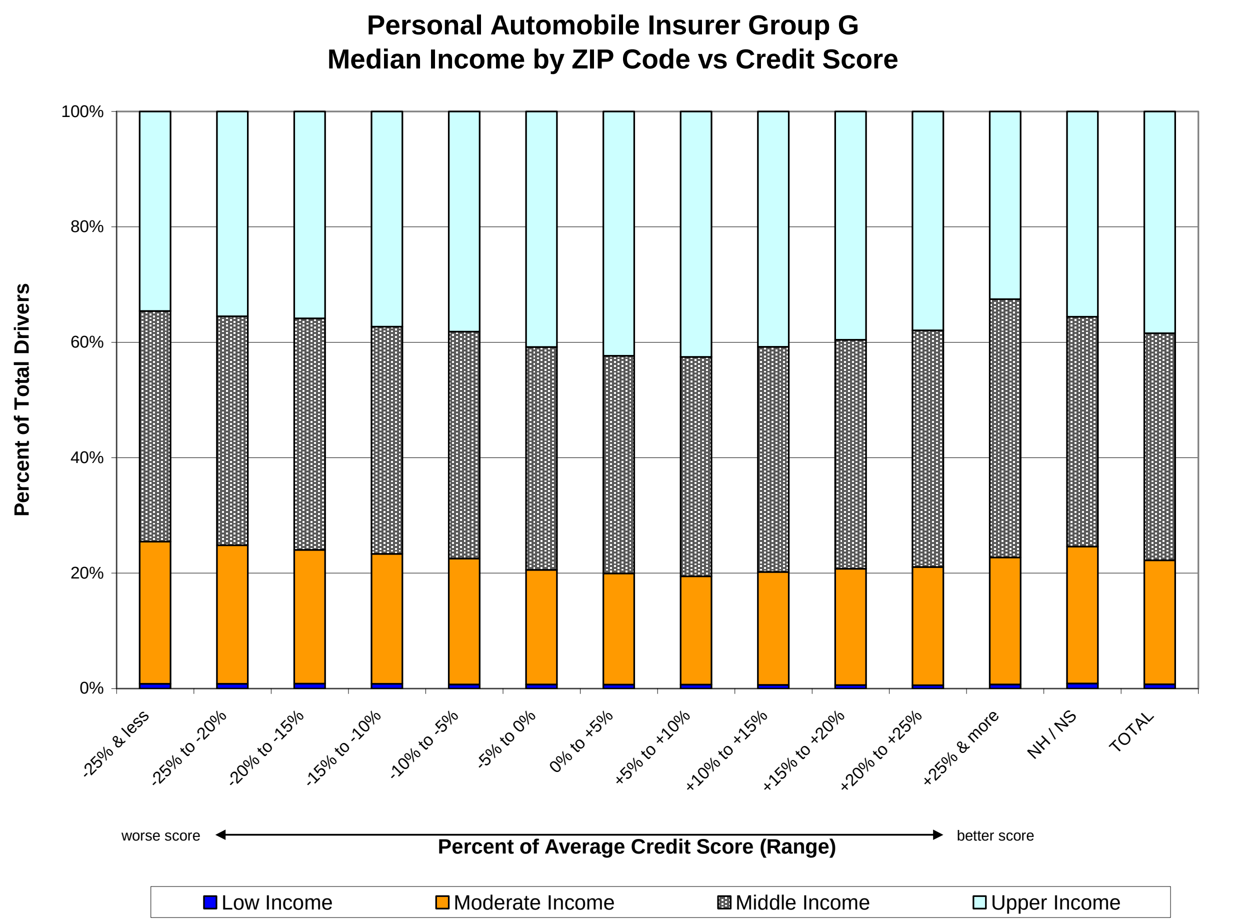
Credit Score and Median Income

As required by the Legislature, the Department performed an analysis of the relationship between credit score and income. Since insurers do not collect income data on their policyholders, the Department relied on median income data by ZIP code obtained from the 2000 Census. Median income was grouped into four classifications using the U.S. Census Bureau definitions. Low-income was defined as income below 50 percent of the median family income level; moderate-income was defined as 50 to 79 percent of the median family income level; middle-income was defined as income between 80 and 119 percent of the median family income level; and upper-income was defined as income equal to or greater than 120 percent of the median family income level. The 1999 Texas median family income of approximately $40,000 per the 2000 Census was used instead of a national income figure. The resulting break points for the income levels are approximately $20,000, $32,000, and $48,000. There was relatively little data in the low-income classification.

For each data set, the Department compared the average and median credit scores by median income by ZIP code and found that, in general, the average and median credit scores tend to get better as the income level rises.

The Department also analyzed the composition of median income levels for each credit score range. There were two apparent patterns among the data sets: about half the data sets show that the moderate income levels tend to be over-represented in the worse than average credit score categories and under-represented in the better credit score categories; conversely, upper income levels are over-represented in the better credit score categories and under-represented in the worse than average credit score categories. The other half of the data sets show very little variation in the distribution of income levels within each credit score range. An example of the latter is shown in Chart 5. (Charts for all the available data sets can be found in the Appendix.)

Chart 5

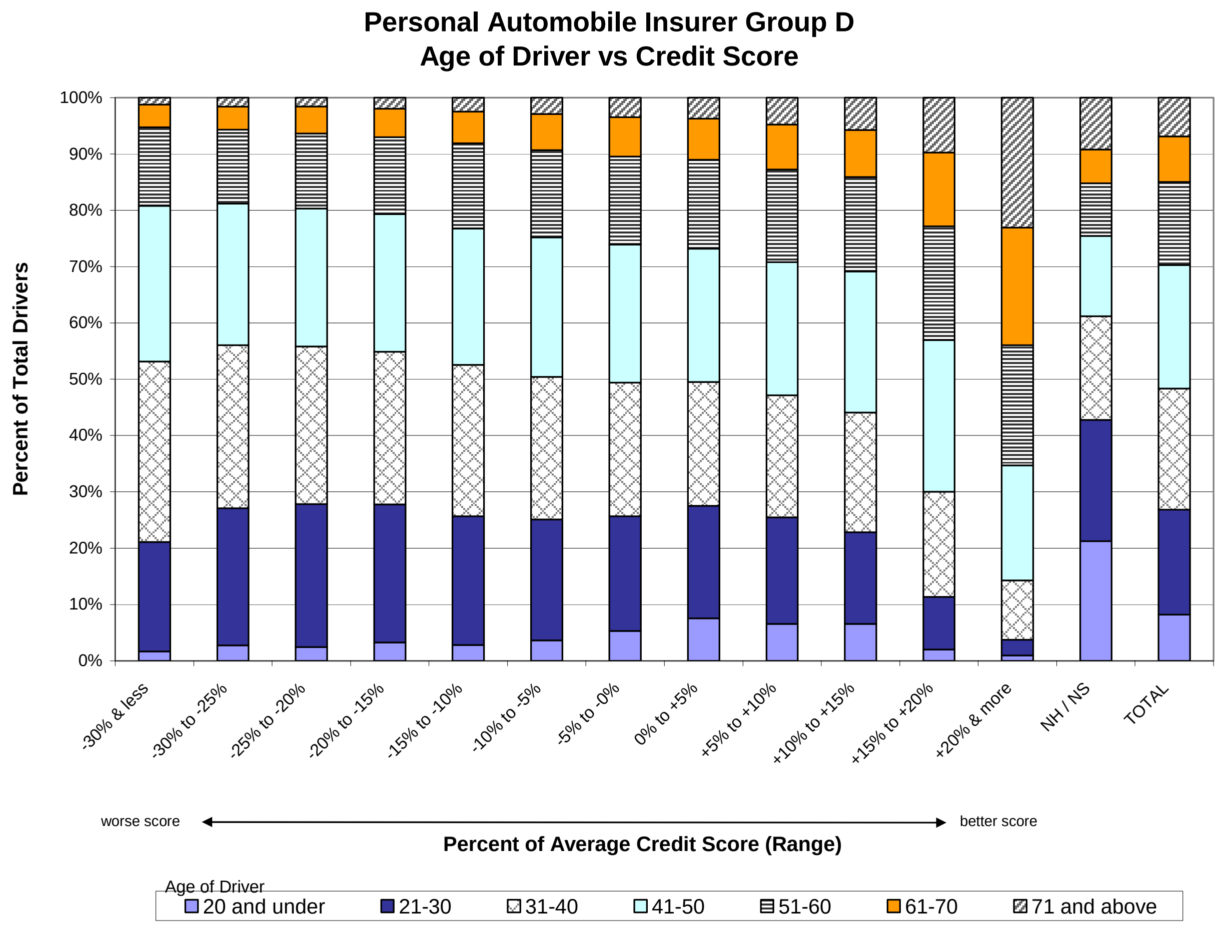


Notes:
1. NH / NS = No Hit / No Score
2. Income is derived from median income by ZIP code, based on 2000 Census data

Credit Score and Age of Driver/Individual

The Department analyzed the relationship between credit score and age. In undertaking this analysis, the Department examined policyholder data by looking at the average and median credit scores by age of driver for personal auto and age of individual for homeowners. Drivers/individuals were grouped by the following ages: 20 and under; 21-30; 31-40; 41-50; 51-60; 61-70; and 71 years and over. Drivers/individuals age 30 and younger have the worst average credit scores. The best average credit scores were for drivers/individuals older than 70 years of age. In general, individuals aged 71 and older were over-represented in the highest credit score range and under-represented in the worst credit score range. Individuals between the ages of 21-30 were over-represented in the worst credit score and under-represented in the best credit score range. Chart 6 is shown as an example. (Charts for all the available data sets can be found in the Appendix.)

Chart 6



Notes:
1. NH / NS = No Hit / No Score

RELATIONSHIP BETWEEN CREDIT SCORE AND CLAIMS (UNIVARIATE ANALYSIS)

The insurance industry and credit model vendors assert that an individual's credit score strongly correlates with the likelihood of filing future insurance claims. These groups argue that because credit score is predictive of future claims it enables insurers to better price their policies and to offer coverage to a broader spectrum of risks.

Similar to other published studies, there appears to be a strong relationship between credit score and insurance risk (or loss). Insurance risk was measured by either pure premiums[5] or loss ratios[6].

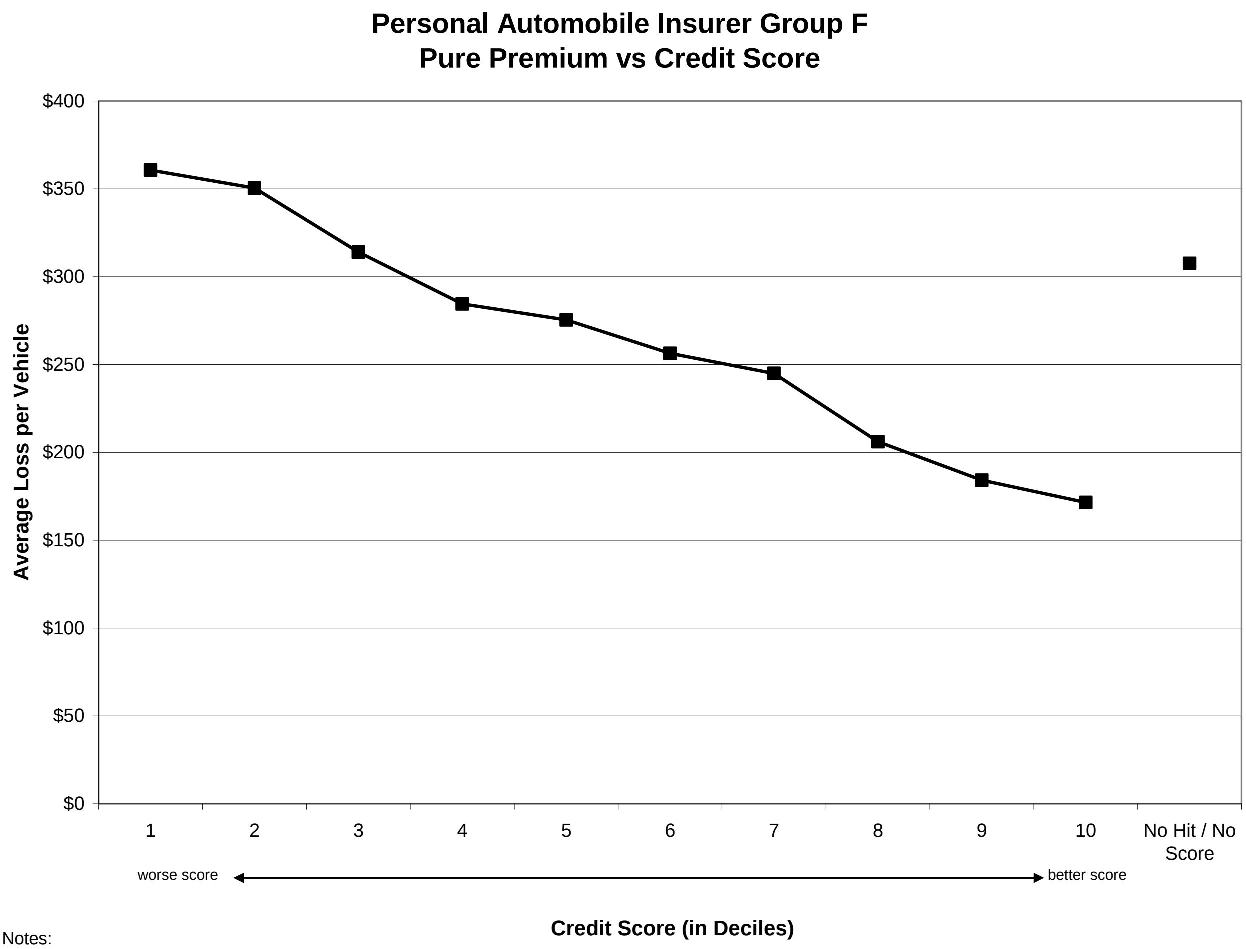
For personal auto insurance, the relationship between pure premium and credit score was examined. Chart 7 is characteristic of the data sets analyzed. It shows that as credit scores improve, the pure premium or average loss per vehicle decreases. Conversely, as the credit scores worsen, the average loss per vehicle increases.

For analysis in this section, the range of credit scores is shown in deciles. Each decile represents an equal or nearly equal group of policies. For example, Decile 1 represents the 10% of the policies with the worst credit score, and Decile 10 represents the 10% of the policies with the best credit score.

[5] Pure premium is defined as the dollar amount of basic limit ($20,000/$40,000/$15,000) losses per vehicle per year. For example, a pure premium of $200 means that, on average, insurance claims are $200 per vehicle per year.

[6] Loss ratio is the dollar amount of losses divided by the dollar amount of earned premium. For example, a loss ratio of 70% means that incurred losses amount to 70% of premium.

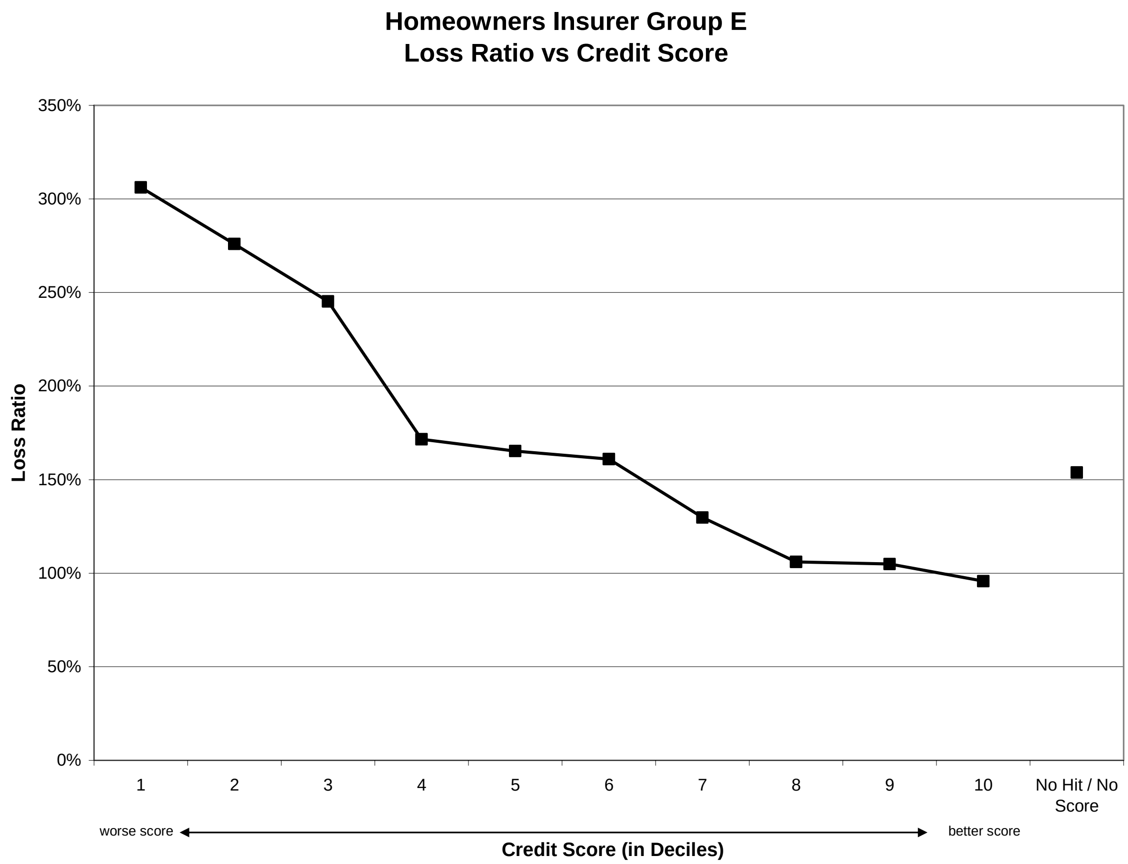
Chart 7



Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)

For homeowners insurance, the data did not readily lend itself to a pure premium approach given the wide range of differences in insured values. Therefore, the relationship between loss ratio and credit score was examined. In this analysis, the loss ratio was calculated using the premiums adjusted to the level they would have been prior to the use of credit scores. Chart 8 shows the average adjusted loss ratio for each decile of credit scores. (Charts for all available data sets can be found in the Appendix.) Like the personal auto data analysis, the homeowners data shows that as the credit scores improve the loss ratios improve.

Chart 8



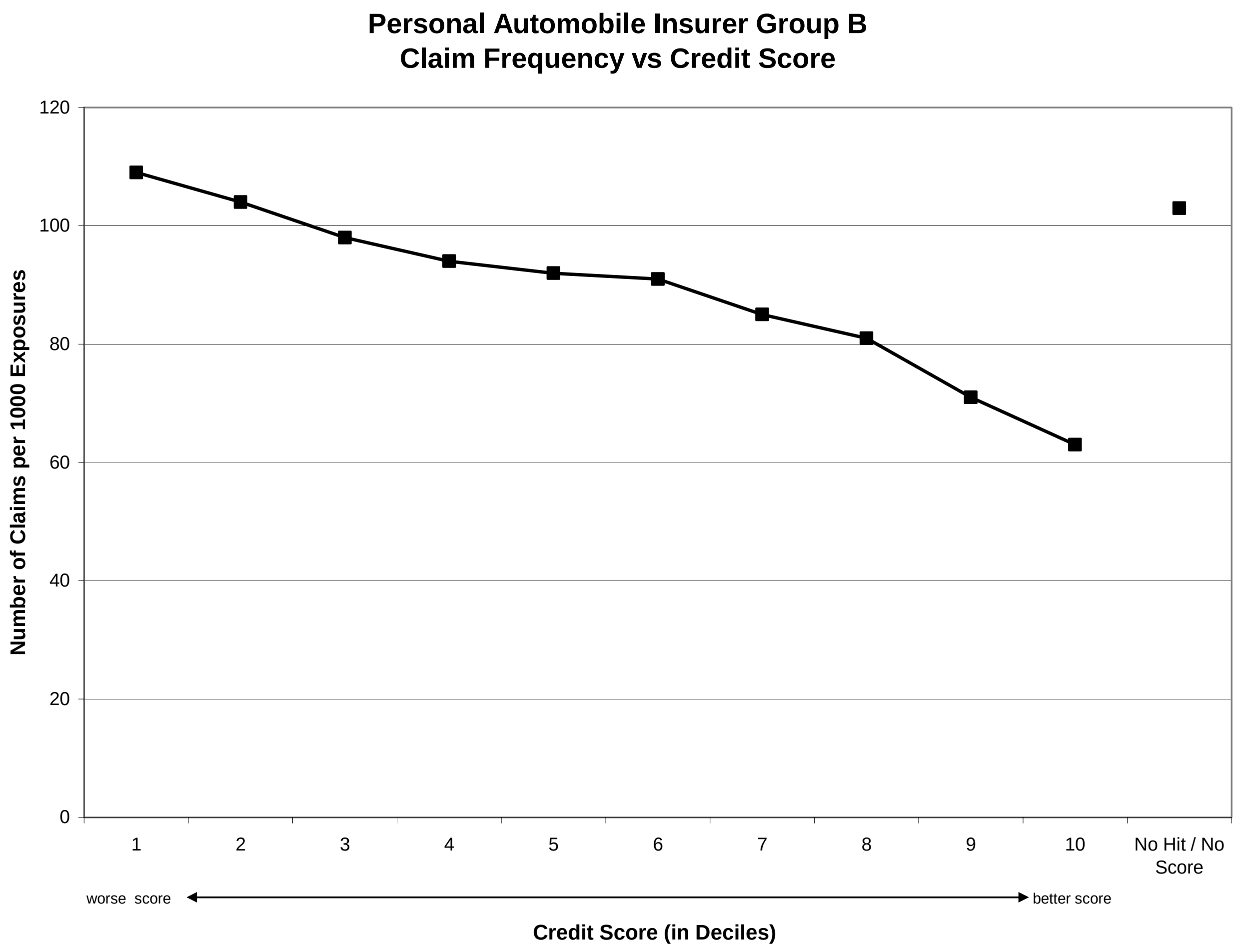
Notes:
1. Incorporates losses from all perils, including water damage, wind and hail

The Department also looked at claim frequency[7] and claim severity[8]. The data shows that credit score has a stronger relationship to frequency than severity. That is, as the credit scores improve, the frequency decreases, i.e. people have fewer accidents or claims. Severity may decrease as well, but not at the same rate as the frequency. For some data sets, severity is nearly flat.

Charts 9 and 10 show the frequency and severity for the same insurer group. (Charts for all available data sets can be found in the Appendix.)

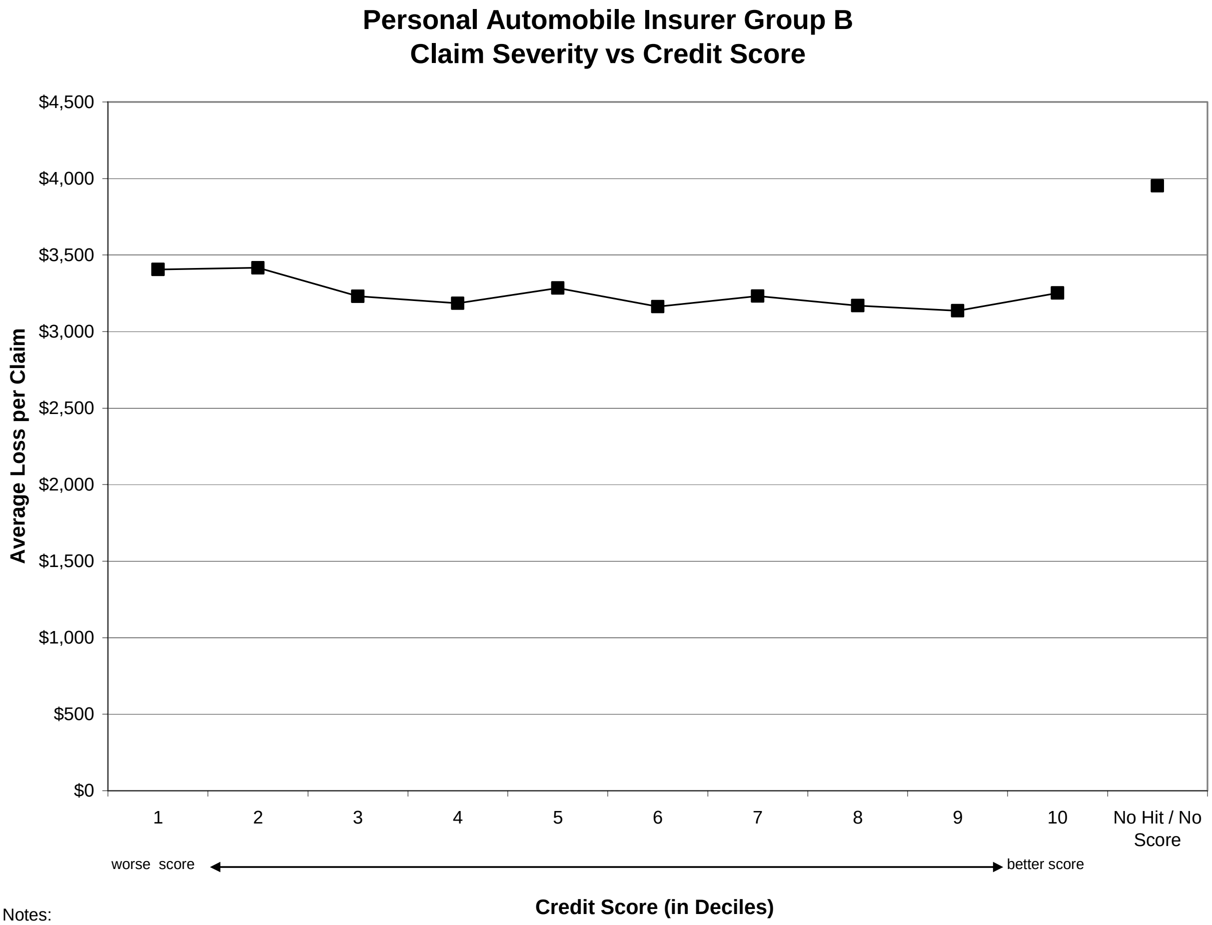
[7] Frequency is defined as number of claims divided by number of earned car years (or house years).
[8] Severity is defined as total losses divided by number of claims. Note that frequency times severity is pure premium.

Chart 9



Notes:
1. Includes BI (bodily injury) and PD (property damage)

Chart 10



Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)

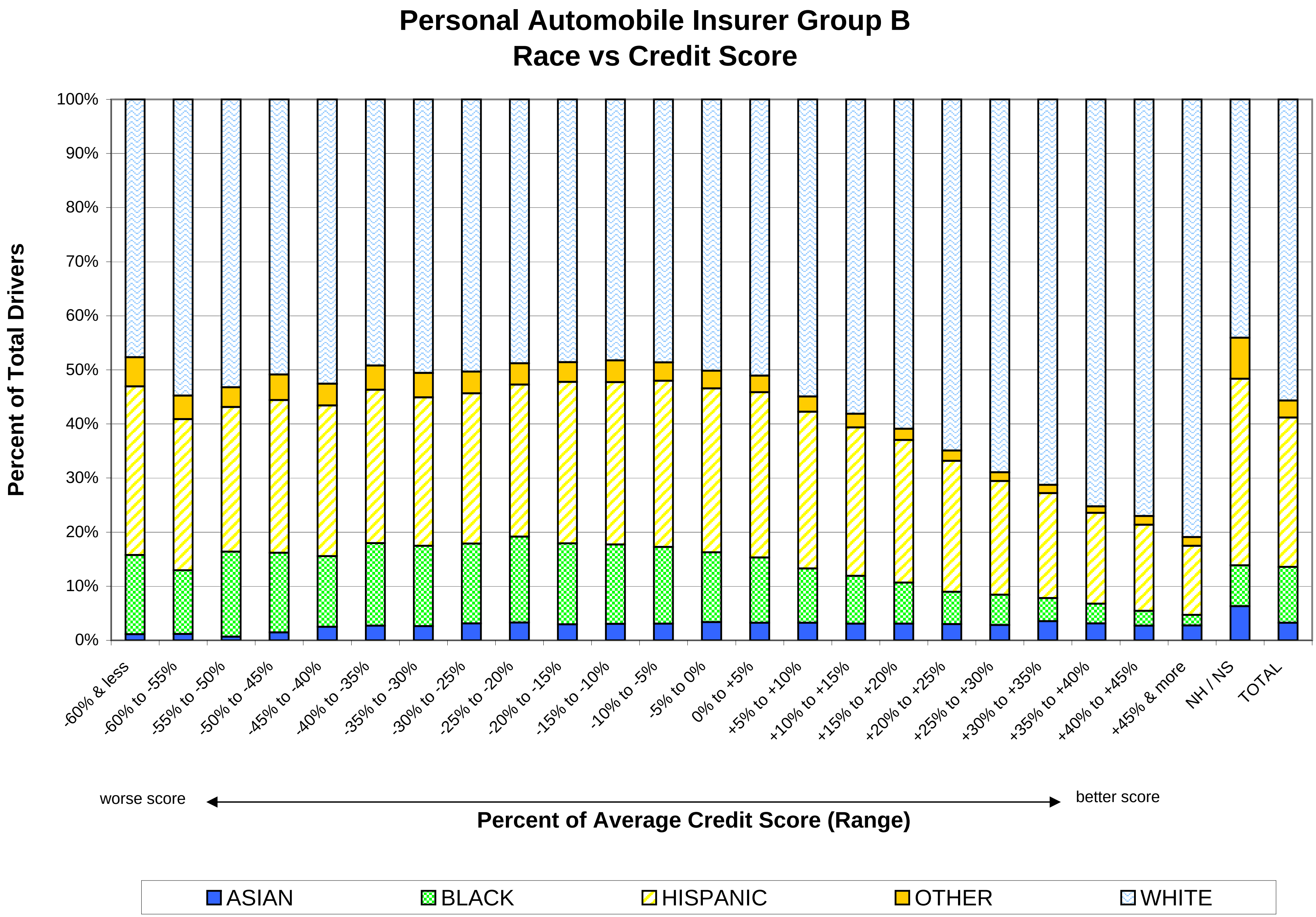
RELATIONSHIP BETWEEN CREDIT SCORE, CLAIMS, AND OTHER VARIABLES (MULTIVARIATE ANALYSIS)

Charts 7 through 10 are based on univariate analysis; they consider the relationship between claims experience and a *single* variable (credit score). In reality there are many other variables that impact claim costs, including type of vehicle, ZIP code and age of driver. Further, many of these variables are plausibly related to credit score directly (e.g., age of driver) or indirectly via another variable (e.g., high traffic congestion via territory). For example, high claims experience for younger drivers may reasonably be explained by fewer years of driving experience rather than their low credit scores. Similarly, as an example of an indirect relationship, high claims experience in certain areas of the state may reasonably be explained by factors such as high traffic congestion and crime rates rather than low credit scores. Thus, the issue is not whether credit scoring is related to claims experience, but rather, whether credit scoring provides additional information, over and above traditional or existing rating variables, which can enable an insurer to more accurately predict losses. Additionally, it should be ascertained whether the impact of credit scoring (both positive and negative) is lessened due to other explanatory variables.

To answer these questions, it is necessary to augment the univariate analysis discussed above by incorporating a multitude of other variables known to impact claims. The Department is in the process of conducting such a multivariate analysis using the individual policyholder data and will report its results by January 31, 2005.

APPENDIX

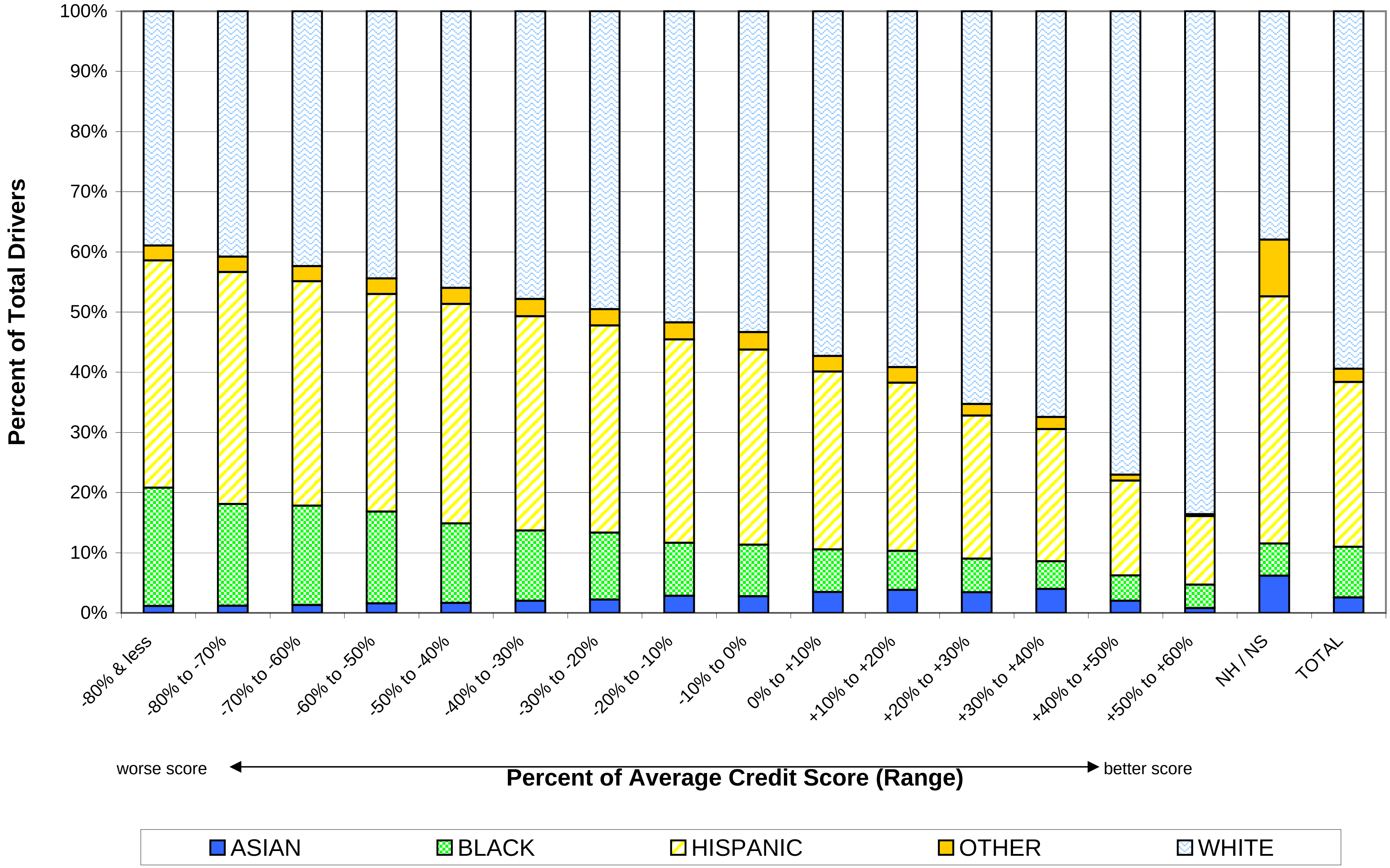
The following charts examine the relationship between
RACE and **CREDIT SCORE**.



Notes:

1. NH / NS = No Hit / No Score
2. OTHER includes OTHER and INDIAN from DPS data

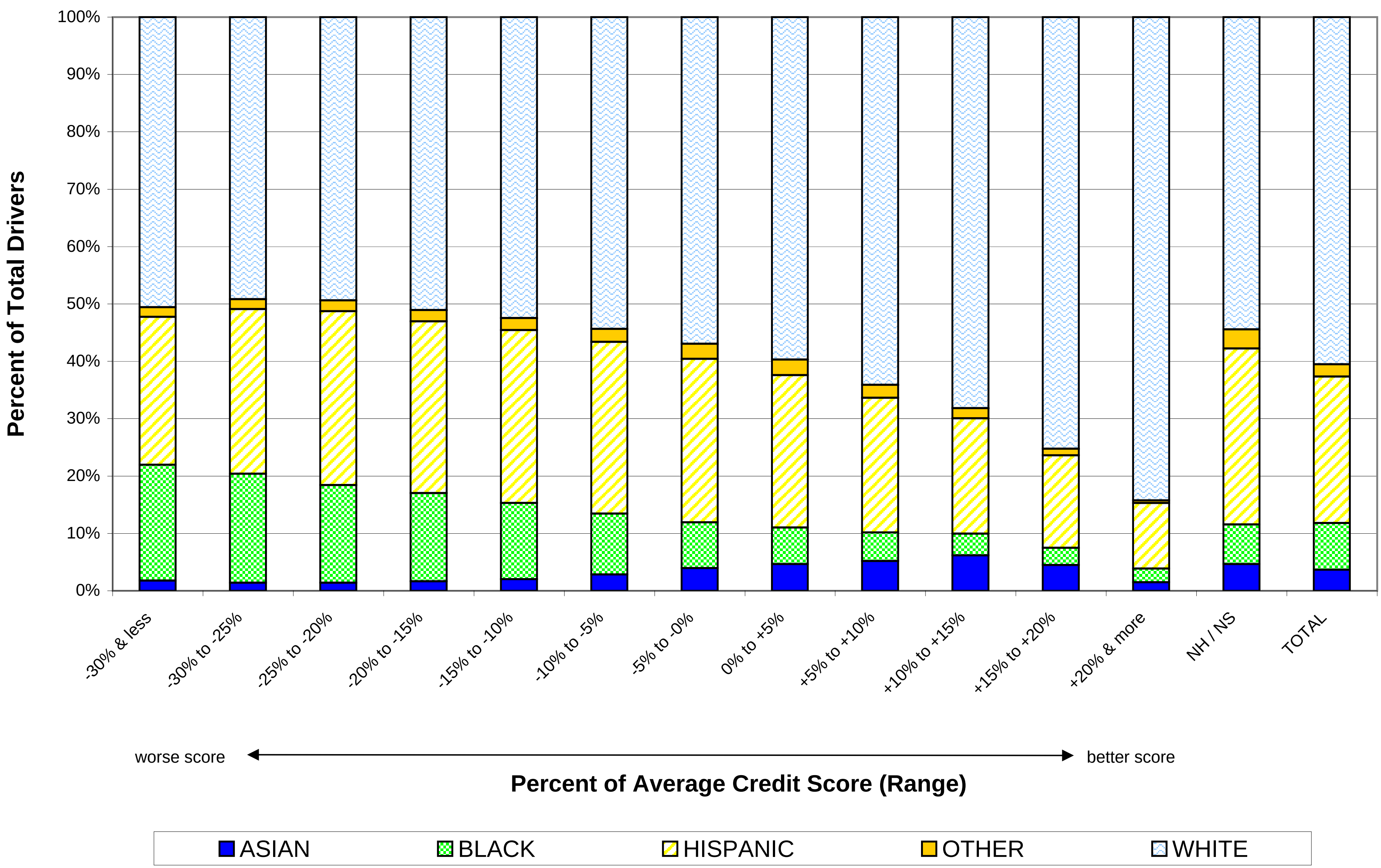
Personal Automobile Insurer Group C
Race vs Credit Score



Notes:

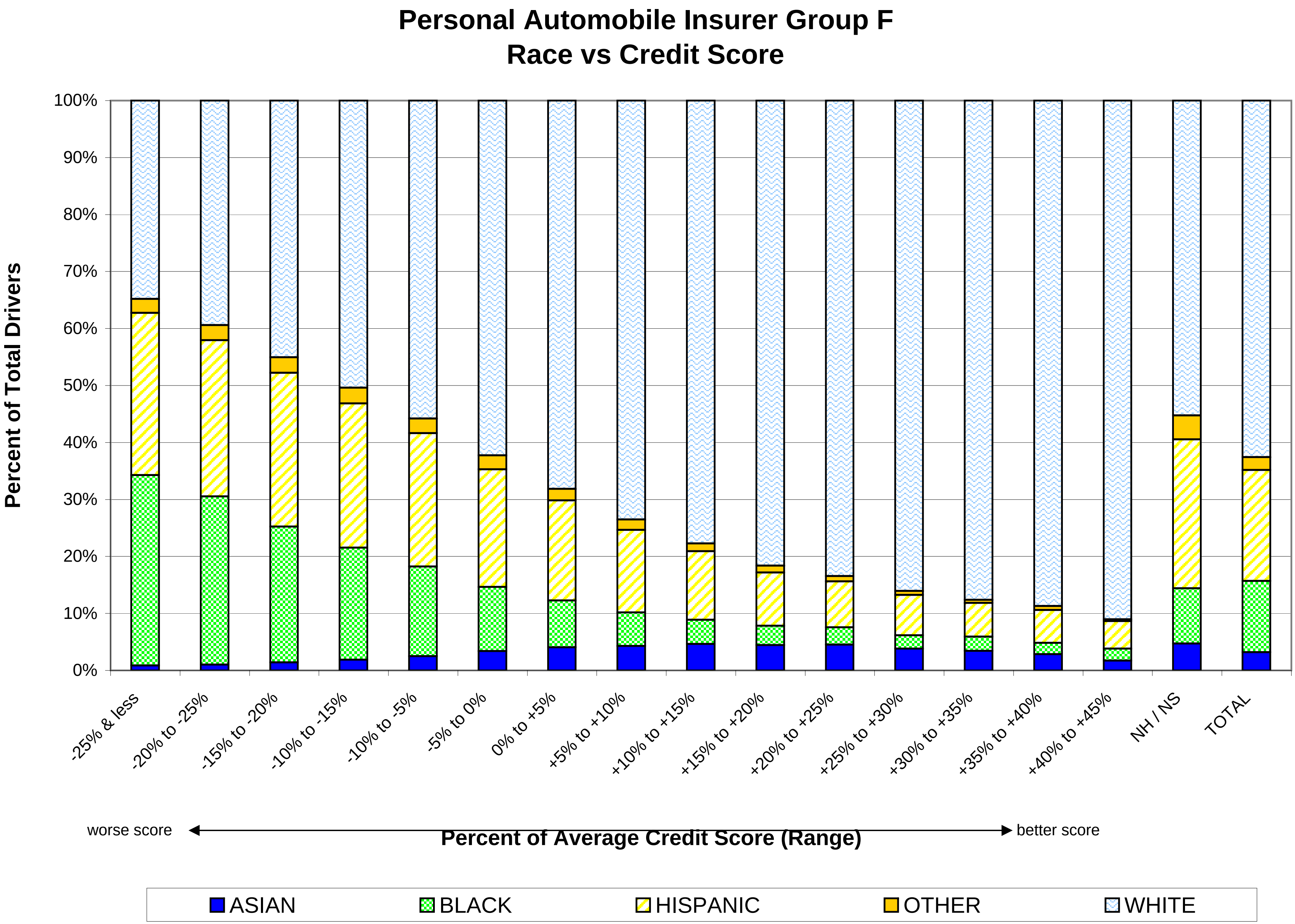
1. NH / NS = No Hit / No Score
2. OTHER includes OTHER and INDIAN from DPS data

Personal Automobile Insurer Group D
Race vs Credit Score



Notes:
1. NH / NS = No Hit / No Score
2. OTHER includes OTHER and INDIAN from DPS data

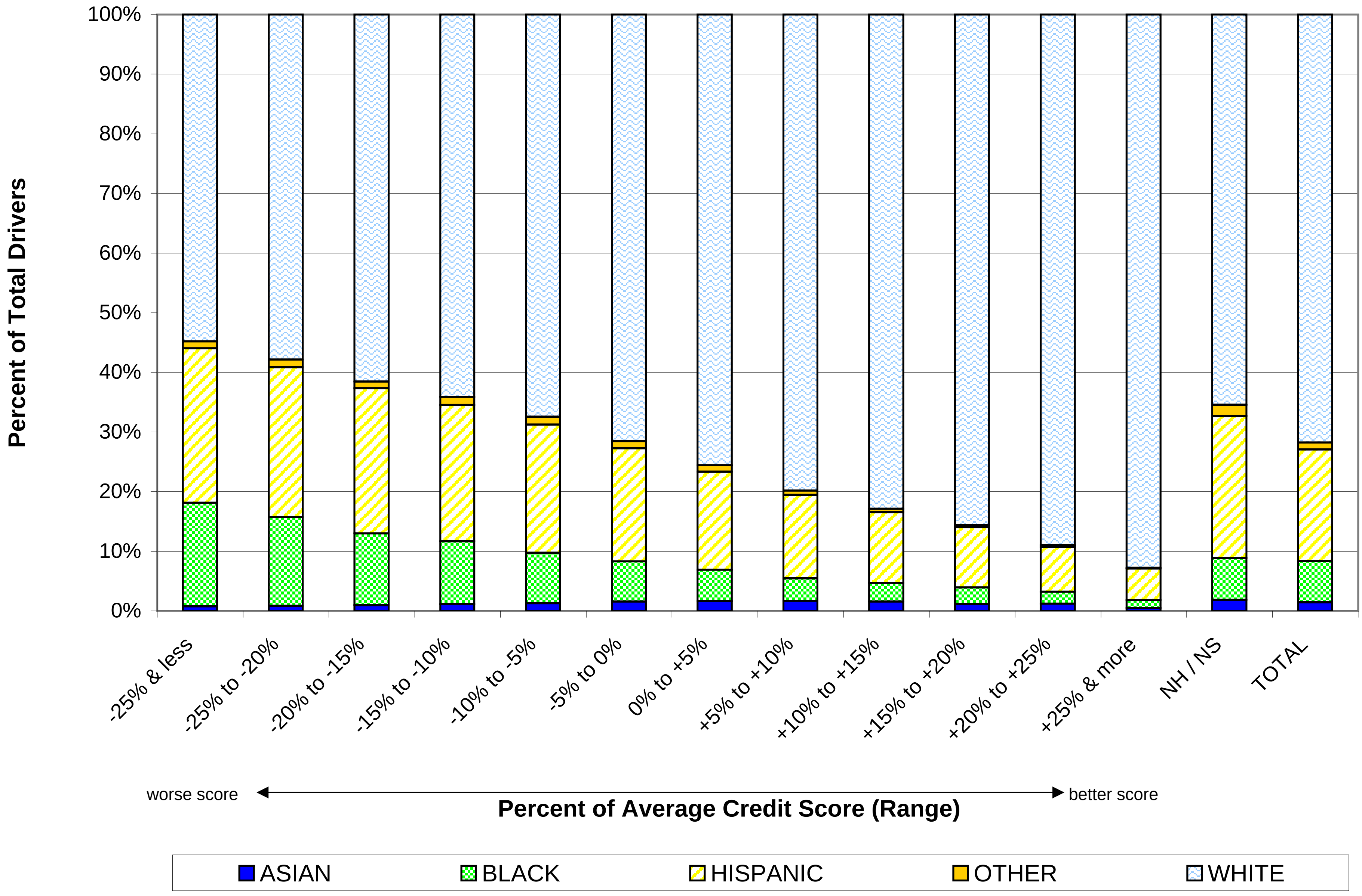
Use of Credit Information by Insurers in Texas
Texas Department of Insurance, December 30, 2004



Notes:

1. NH / NS = No Hit / No Score
2. OTHER includes OTHER and INDIAN from DPS data

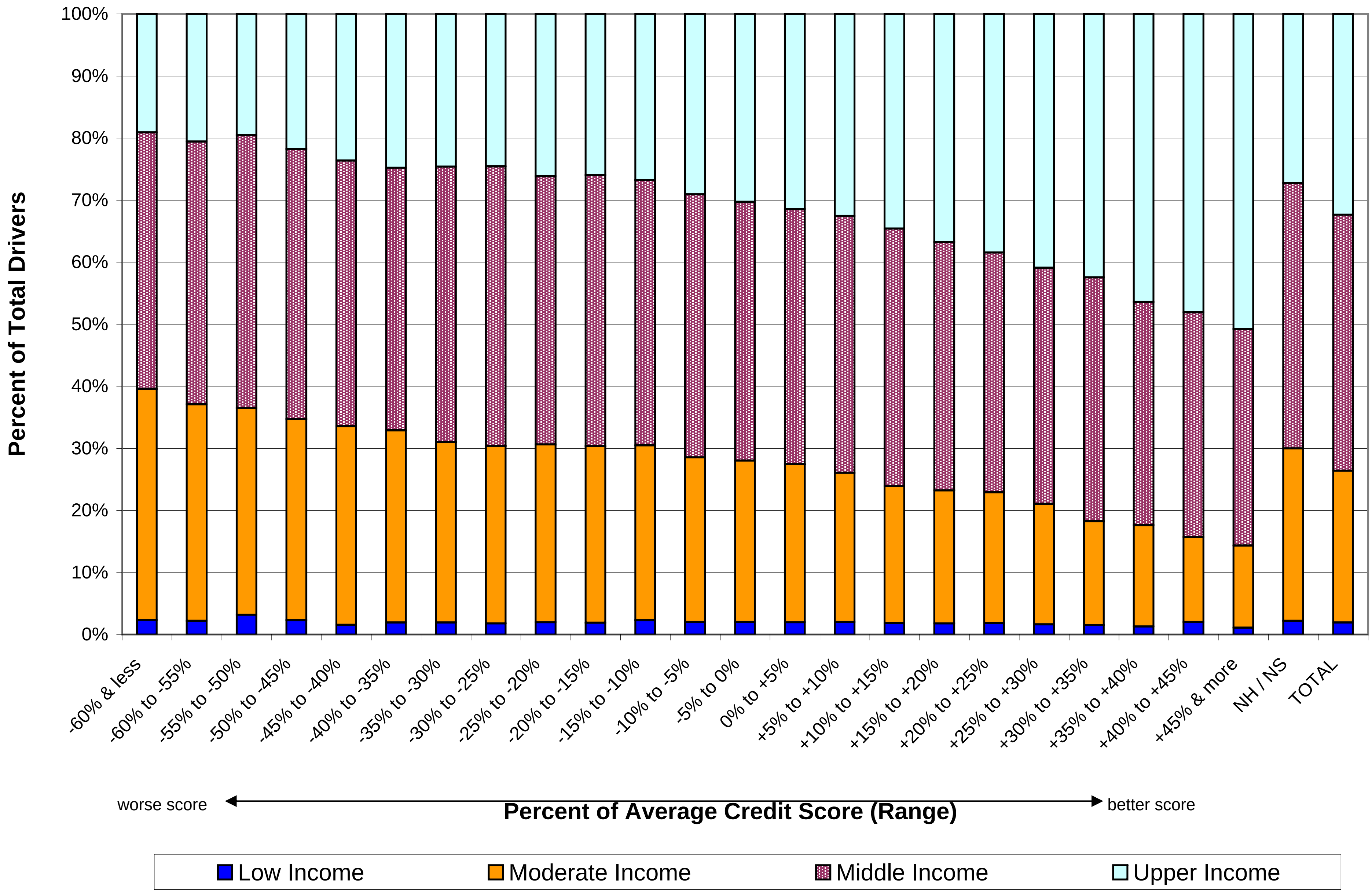
Personal Automobile Insurer Group G
Race vs Credit Score



Notes:
1. NH / NS = No Hit / No Score
2. OTHER includes OTHER and INDIAN from DPS data

The following charts examine the relationship between
MEDIAN INCOME and **CREDIT SCORE**.

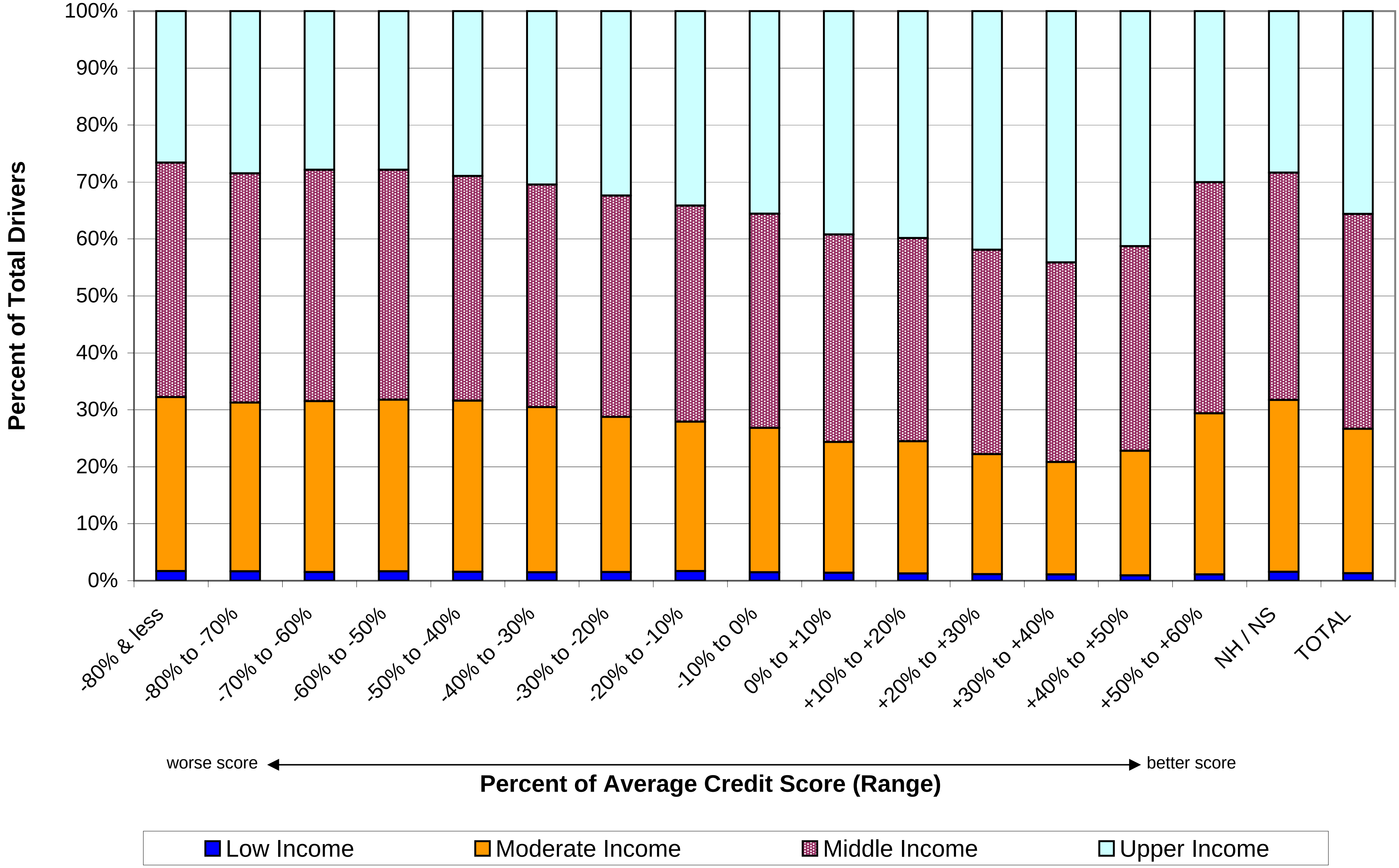
Personal Automobile Insurer Group B
Median Income by ZIP Code vs Credit Score



Notes:

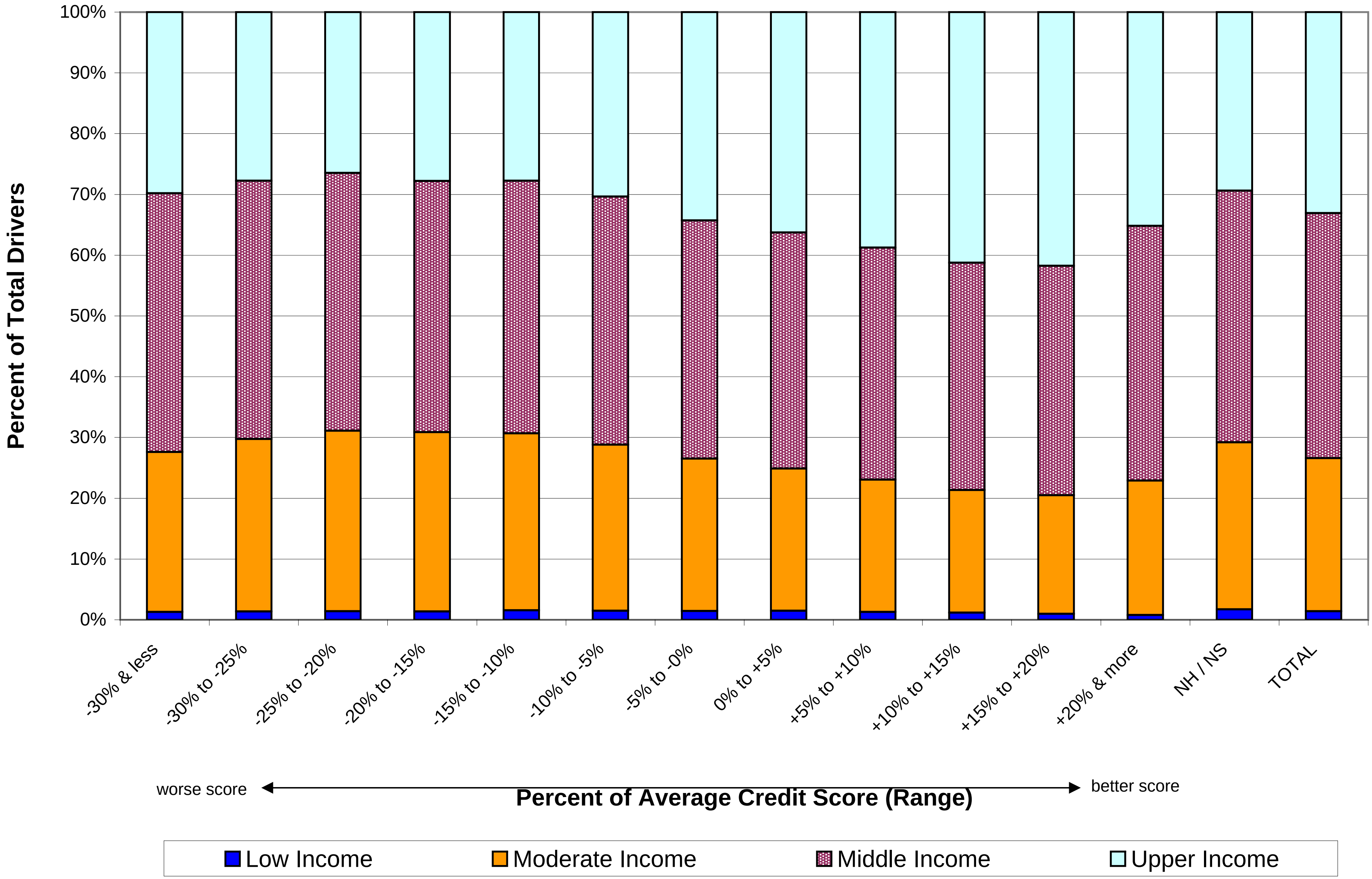
1. NH / NS = No Hit / No Score
2. Income is derived from median income by ZIP code, based on 2000 Census data

Personal Automobile Insurer Group C
Median Income by ZIP Code vs Credit Score



Notes:
1. NH / NS = No Hit / No Score
2. Income is derived from median income by ZIP code, based on 2000 Census data

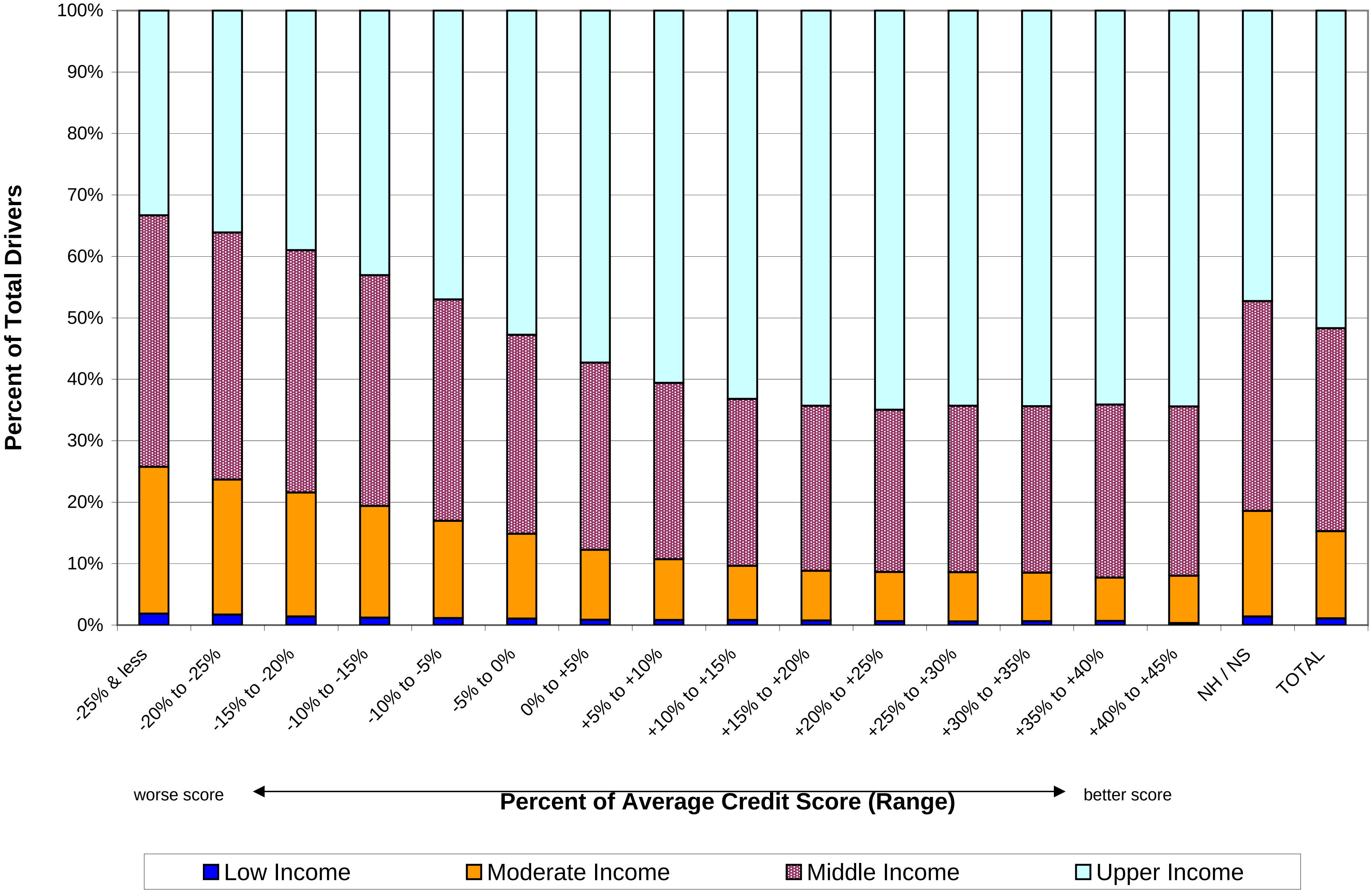
Personal Automobile Insurer Group D
Median Income by ZIP Code vs Credit Score



Notes:

1. NH / NS = No Hit / No Score
2. Income is derived from median income by ZIP code, based on 2000 Census data

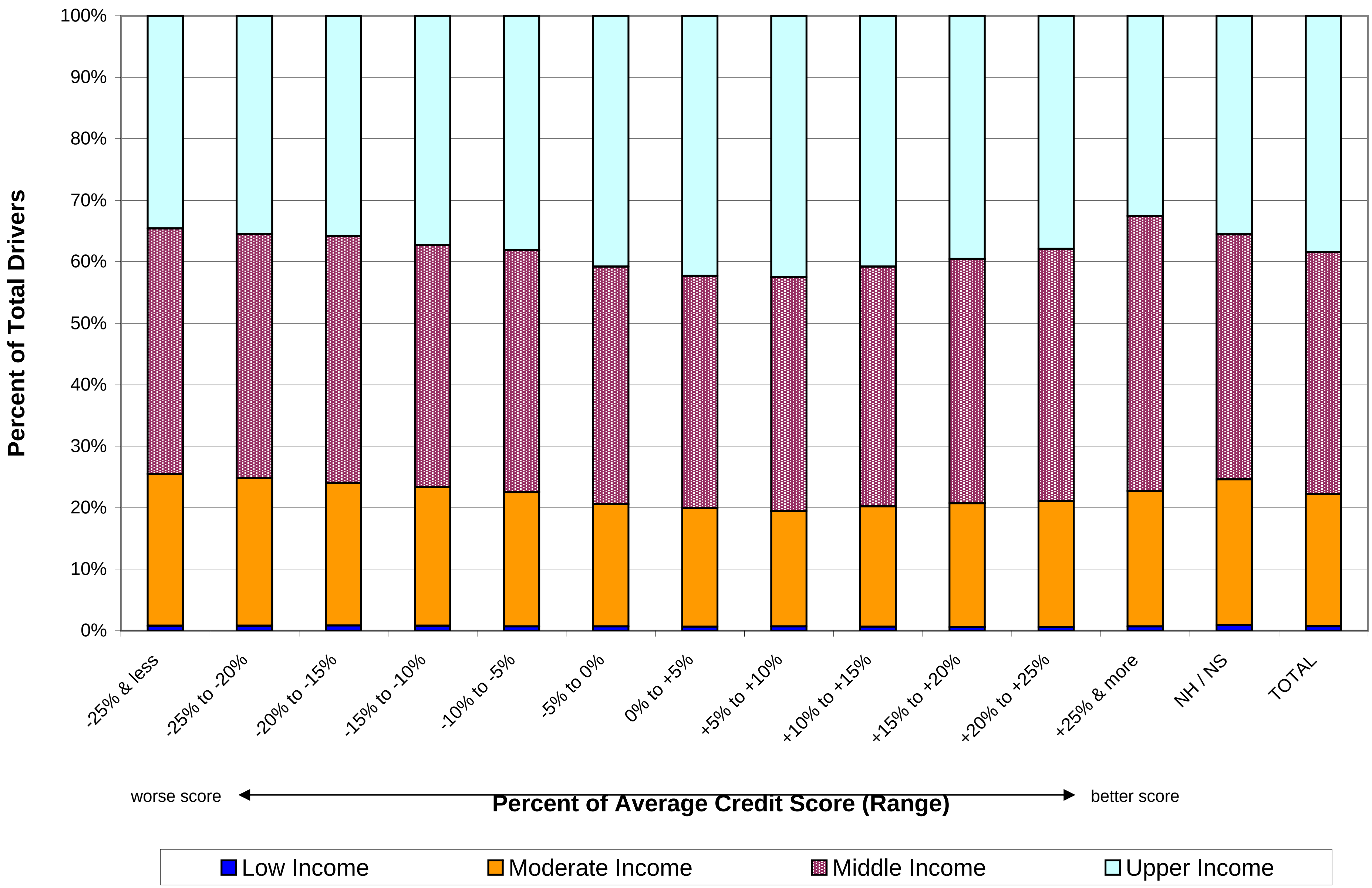
Personal Automobile Insurer Group F
Median Income by ZIP Code vs Credit Score



Notes:

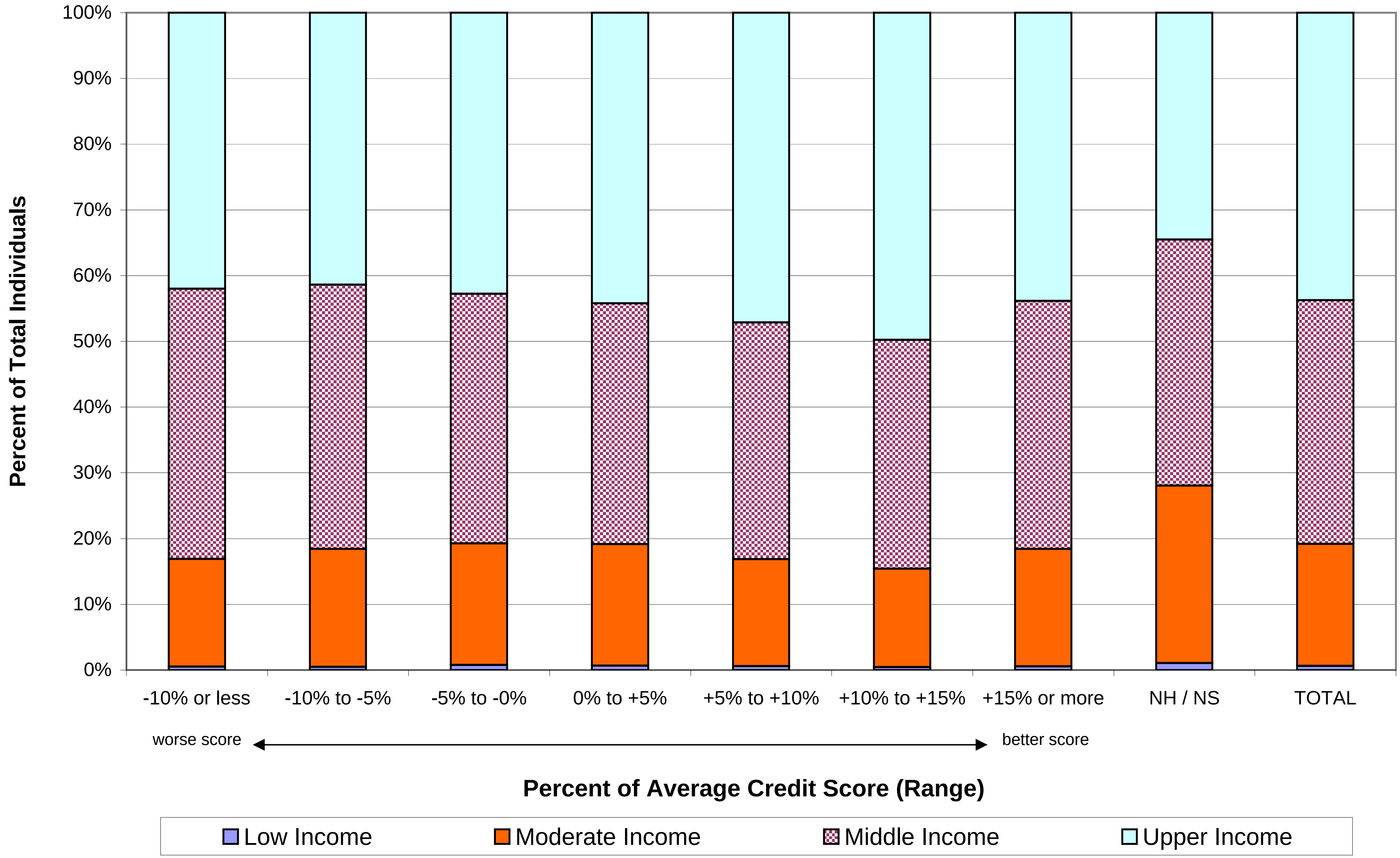
1. NH / NS = No Hit / No Score
2. Income is derived from median income by ZIP code, based on 2000 Census data

Personal Automobile Insurer Group G
Median Income by ZIP Code vs Credit Score



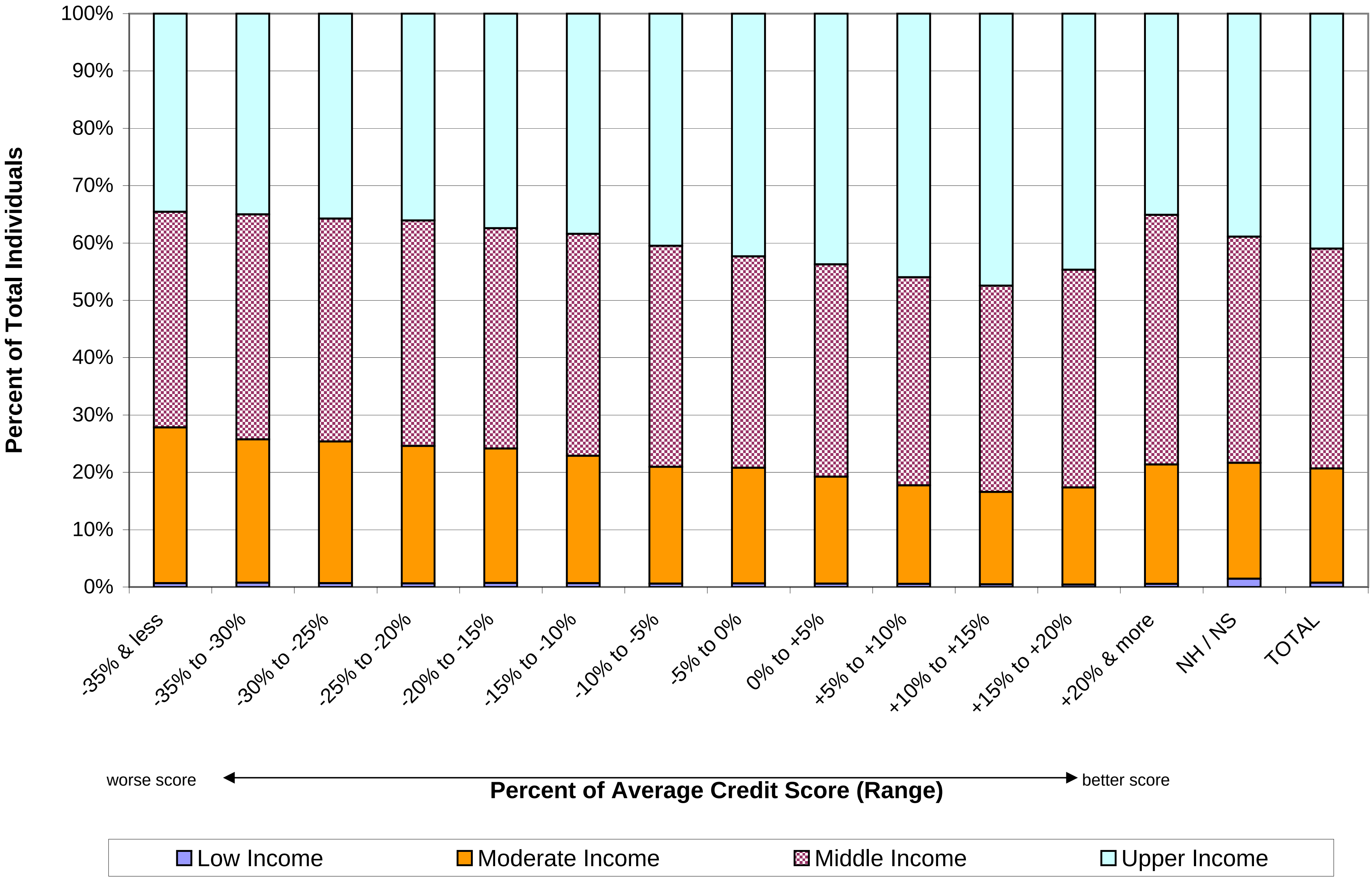
Notes:
1. NH / NS = No Hit / No Score
2. Income is derived from median income by ZIP code, based on 2000 Census data

Homeowners Insurer Group A
Median Income by ZIP Code vs Credit Score



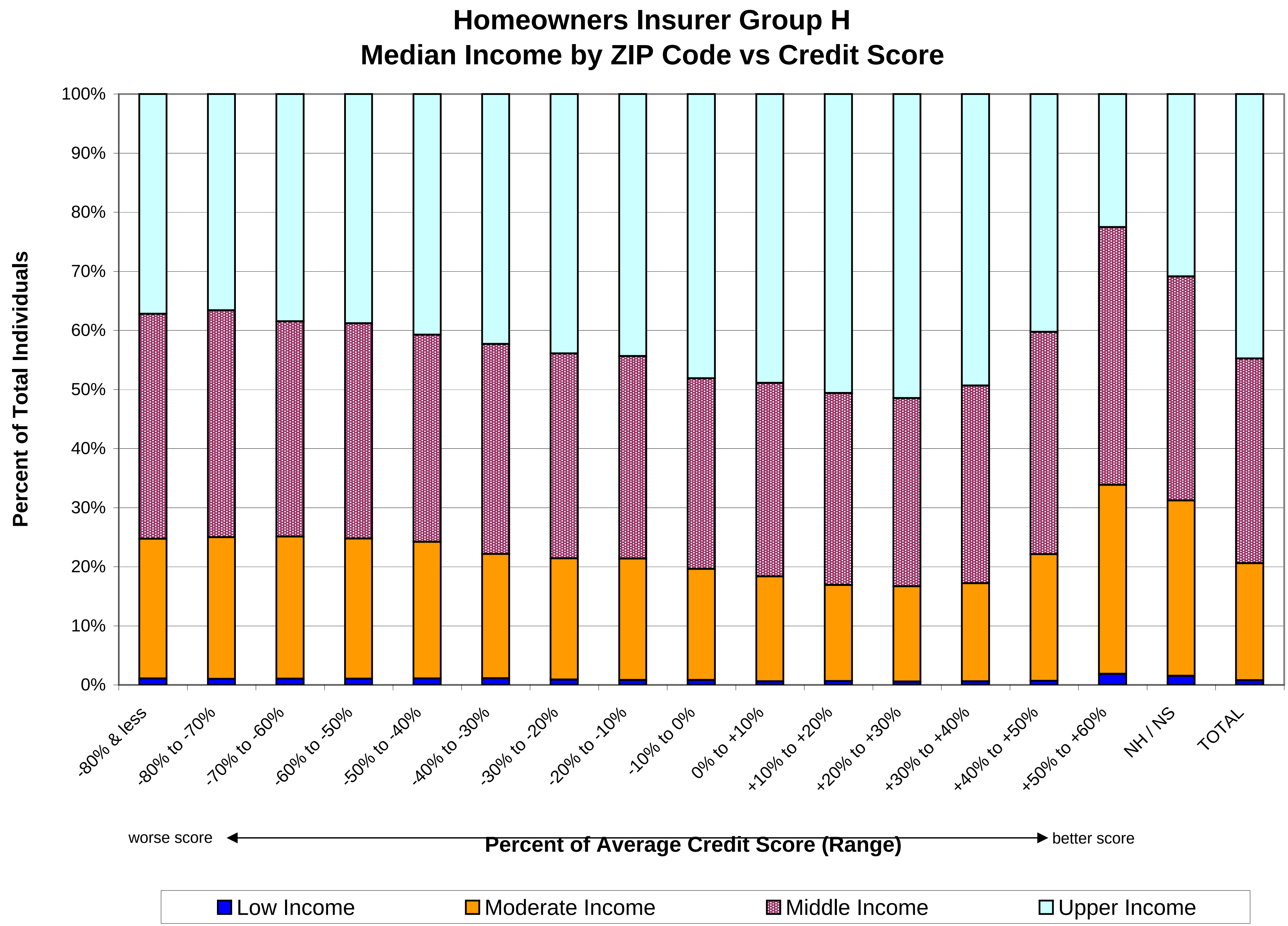
Notes:
1. NH / NS = No Hit / No Score
2. Income is derived from median income by ZIP code, based on 2000 Census data

Homeowners Insurer Group E
Median Income by ZIP Code vs Credit Score



Notes:

1. NH / NS = No Hit / No Score
2. Income is derived from median income by ZIP code, based on 2000 Census data

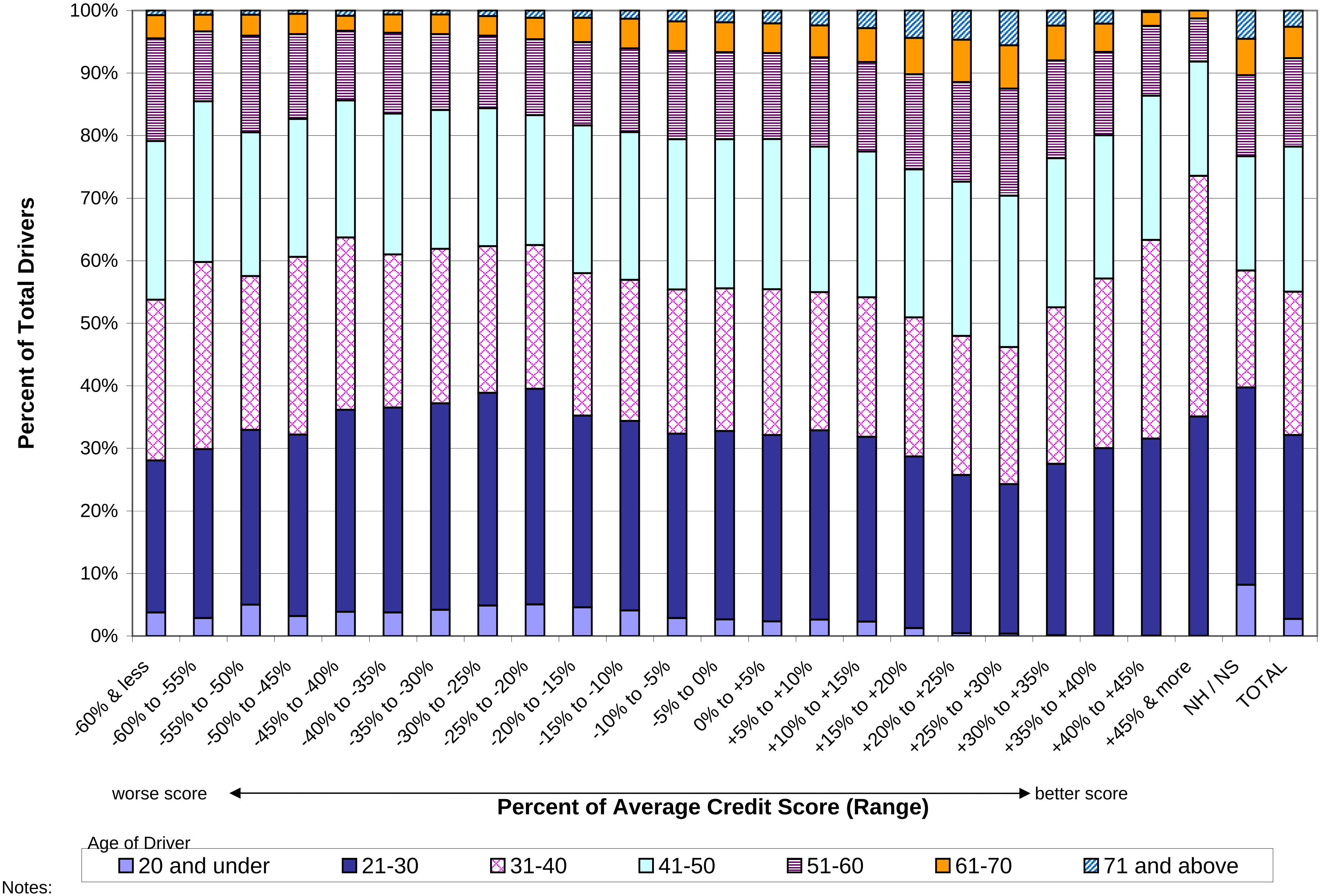


Notes:

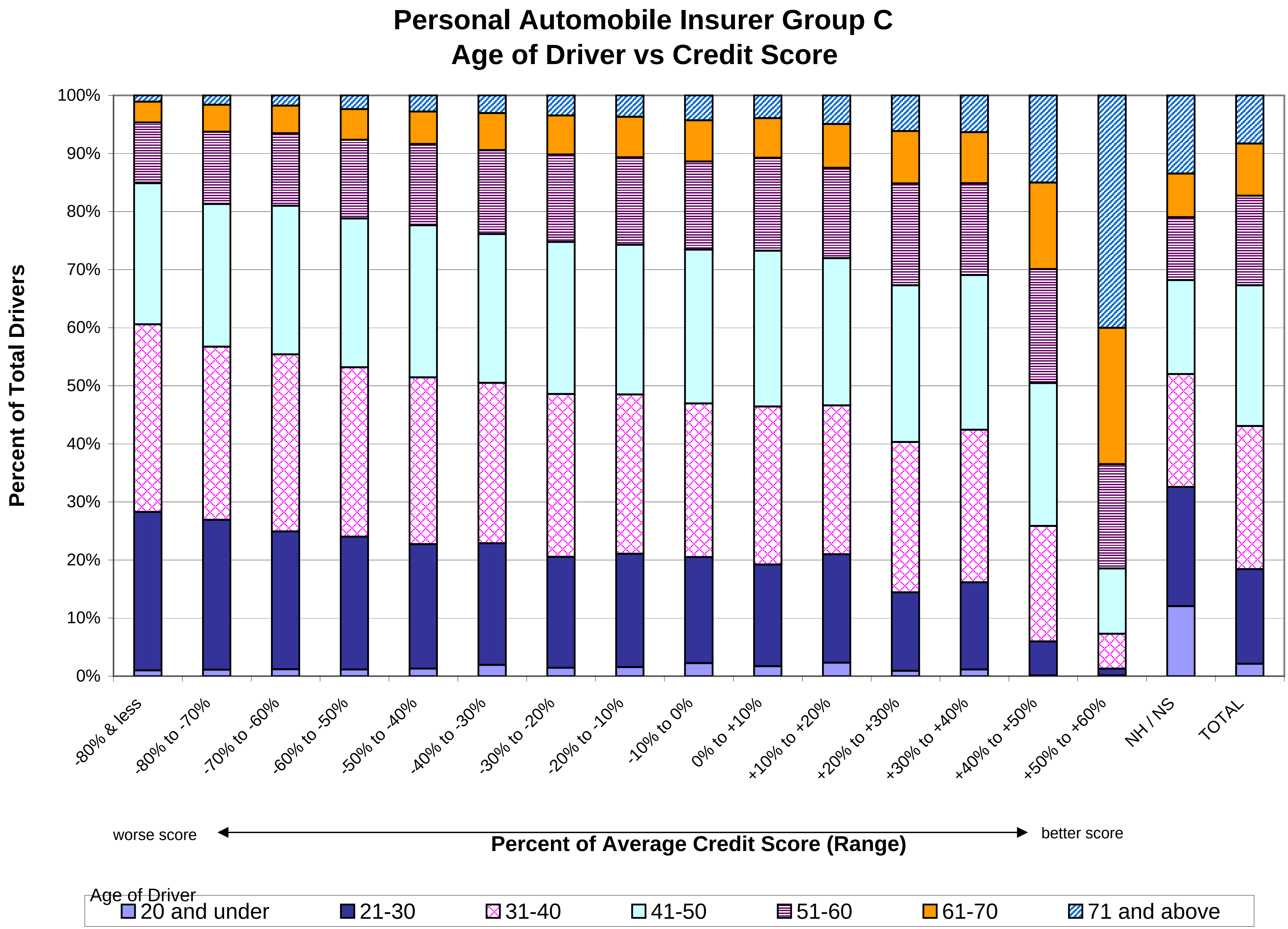
1. NH / NS = No Hit / No Score
2. Income is derived from median income by ZIP code, based on 2000 Census data

The following charts examine the relationship between
AGE and **CREDIT SCORE**.

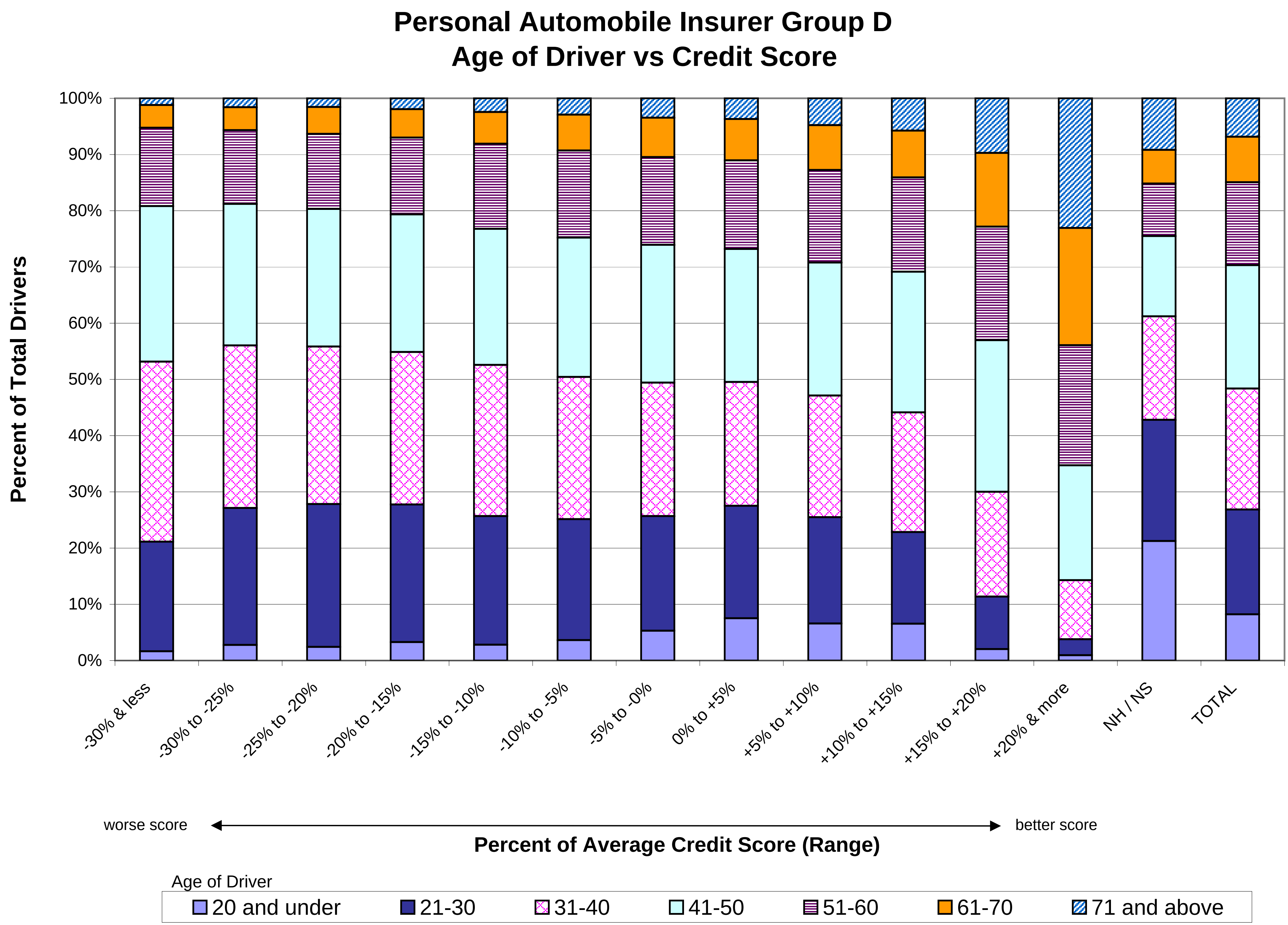
Personal Automobile Insurer Group B
Age of Driver vs Credit Score



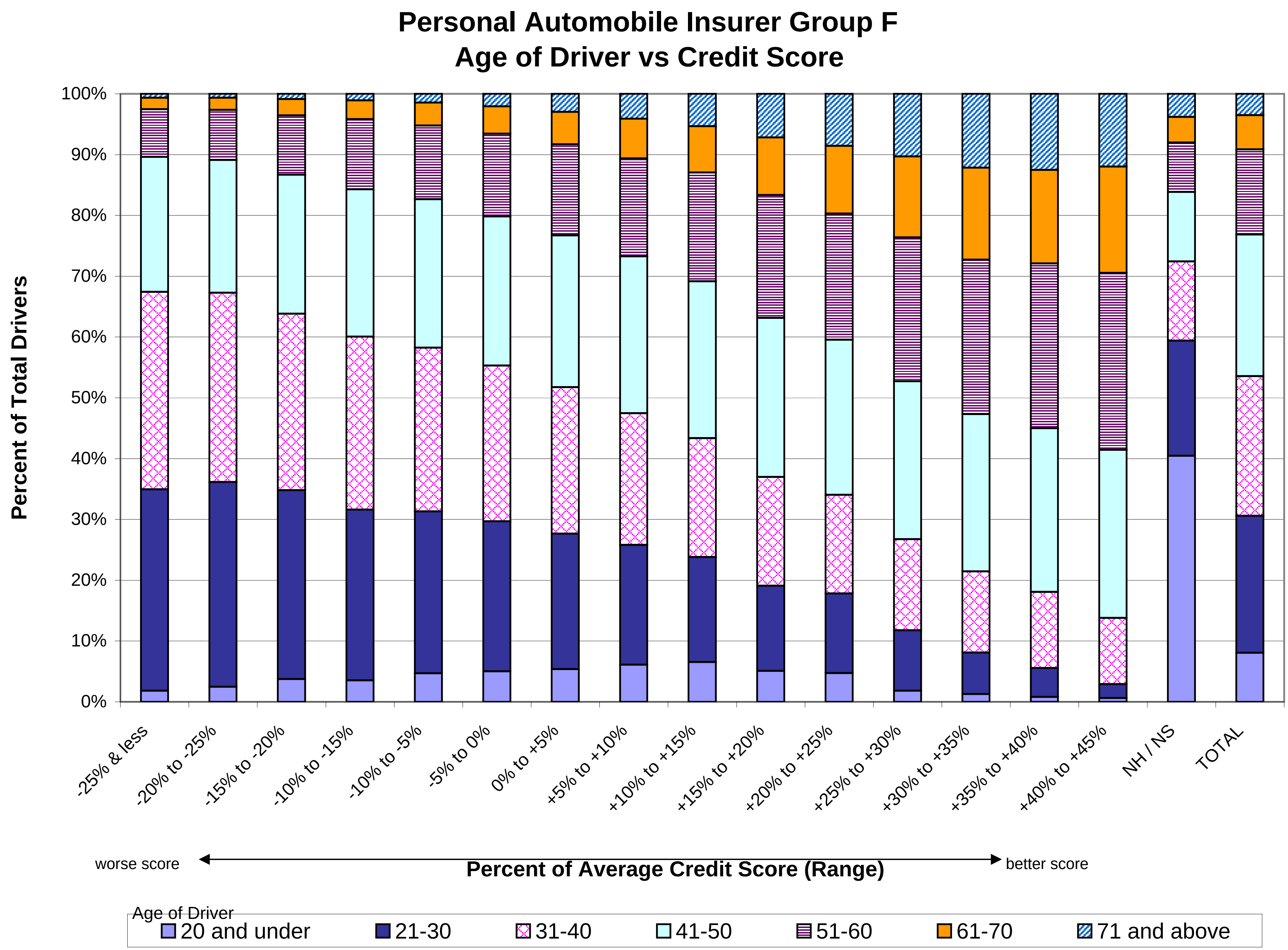
Notes:
1. NH / NS = No Hit / No Score



Notes:
1. NH / NS = No Hit / No Score

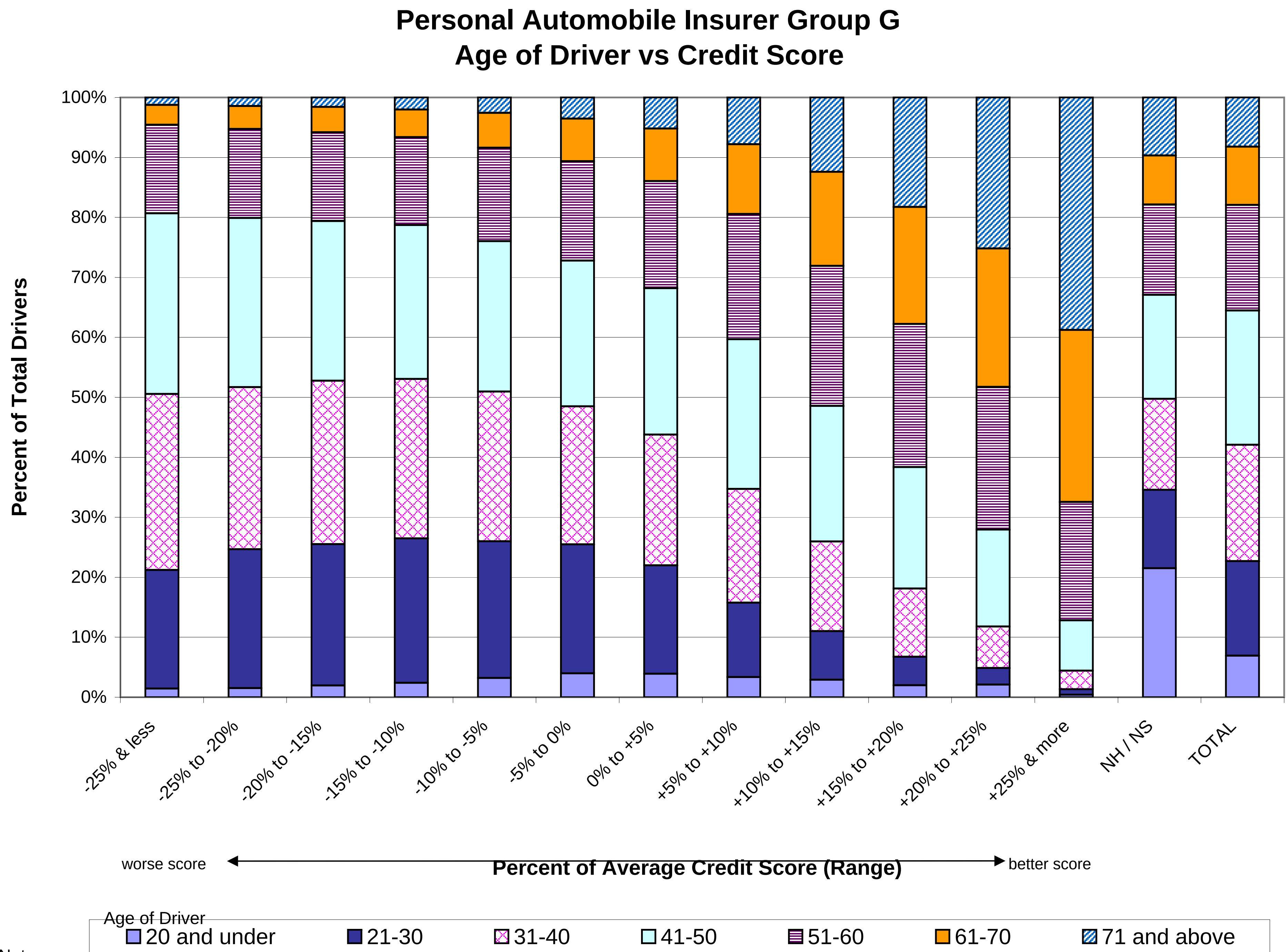


Notes:
1. NH / NS = No Hit / No Score



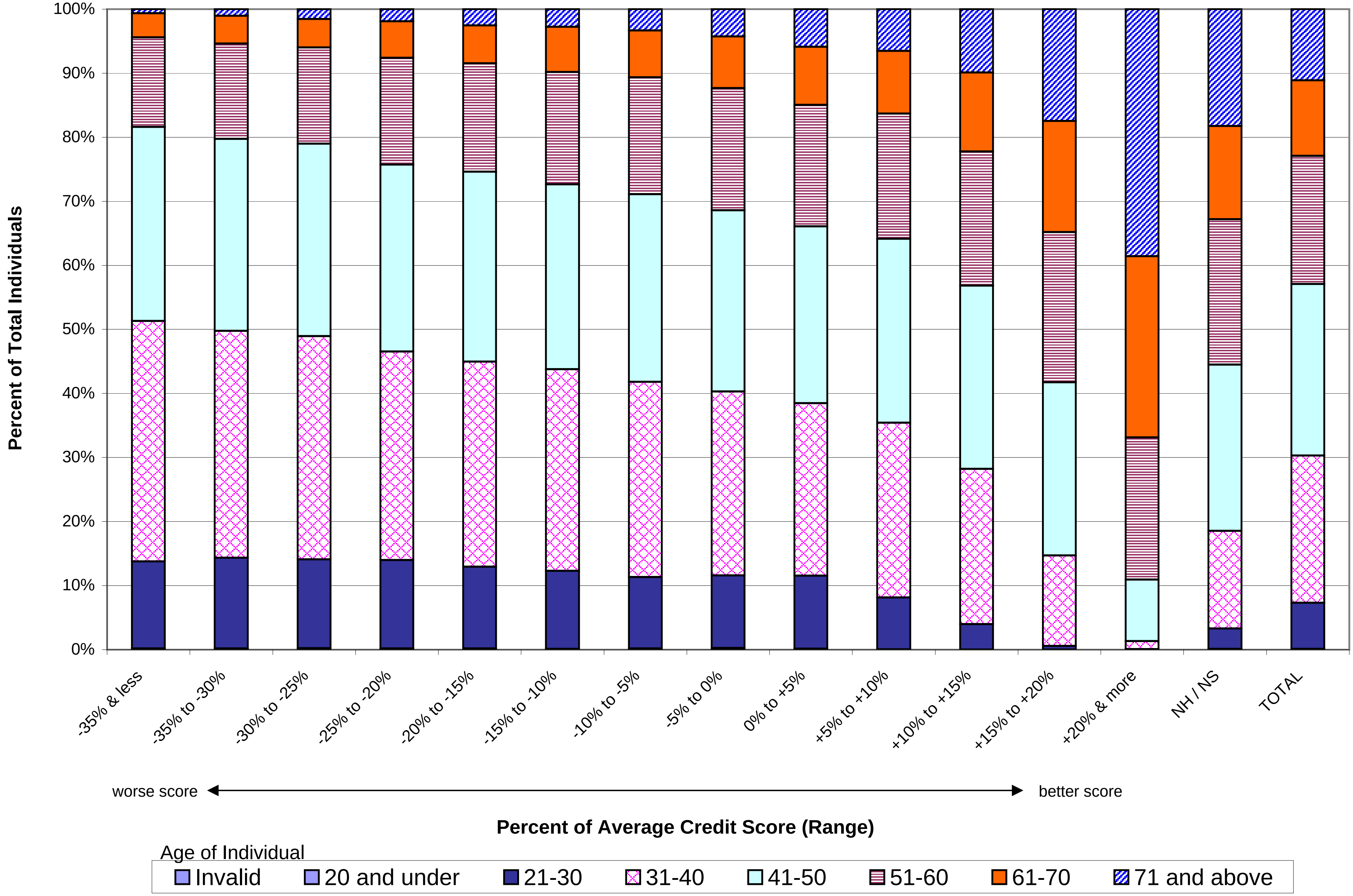
Notes:

1. NH / NS = No Hit / No Score

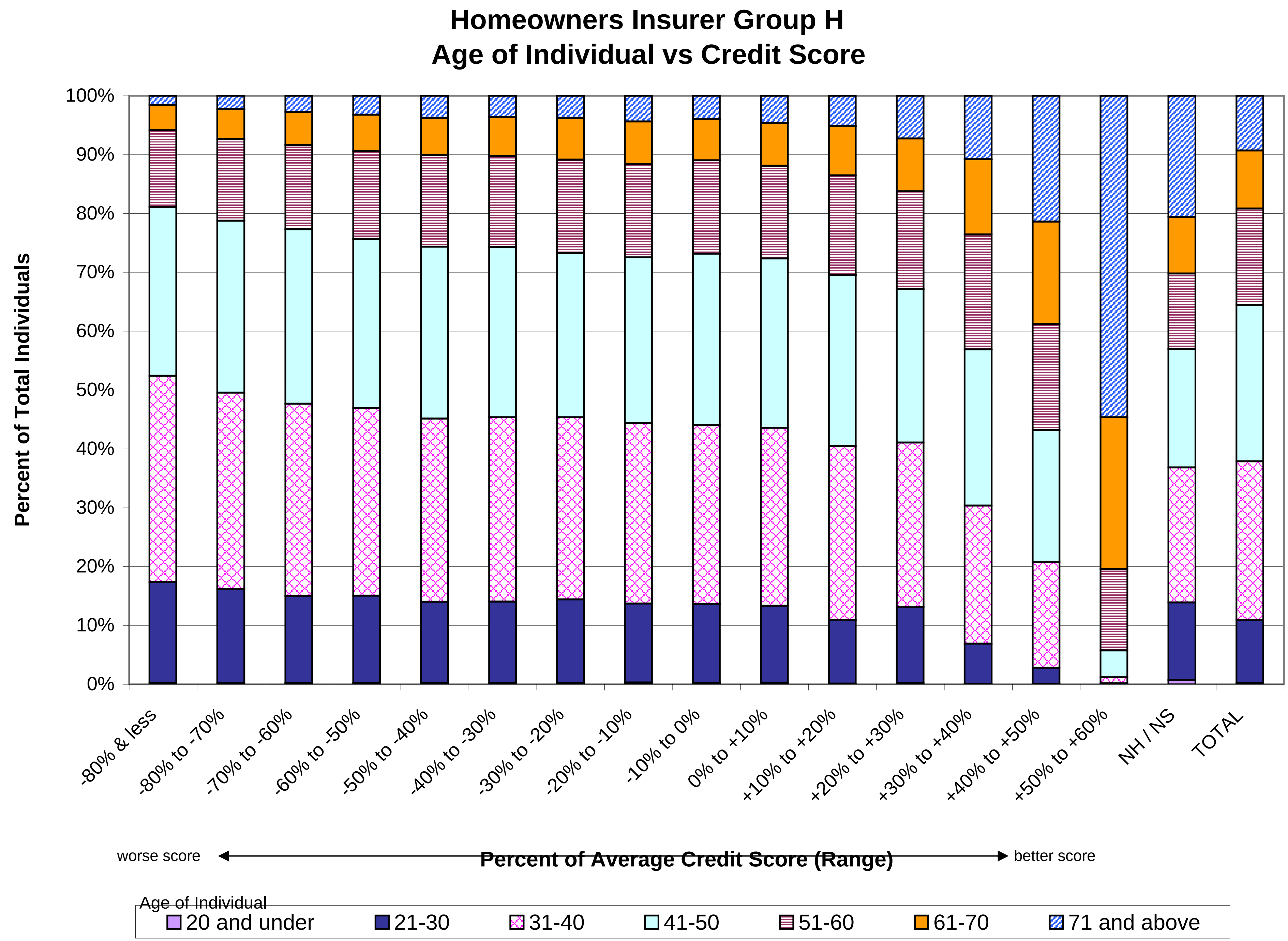


Notes:
1. NH / NS = No Hit / No Score

Homeowners Insurer Group E
Age of Individual vs Credit Score



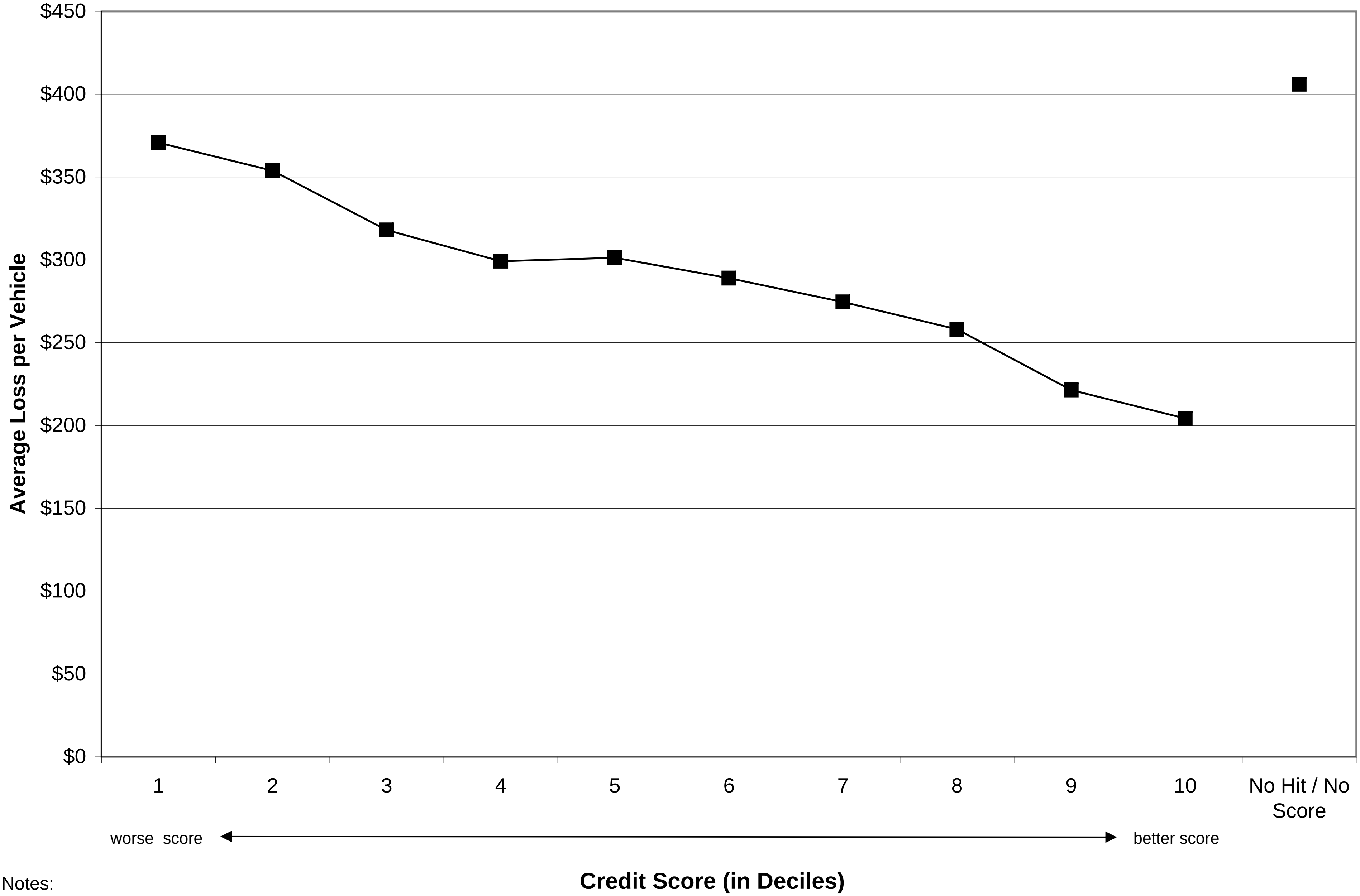
Notes:
1. NH / NS = No Hit / No Score



Notes:
1. NH / NS = No Hit / No Score

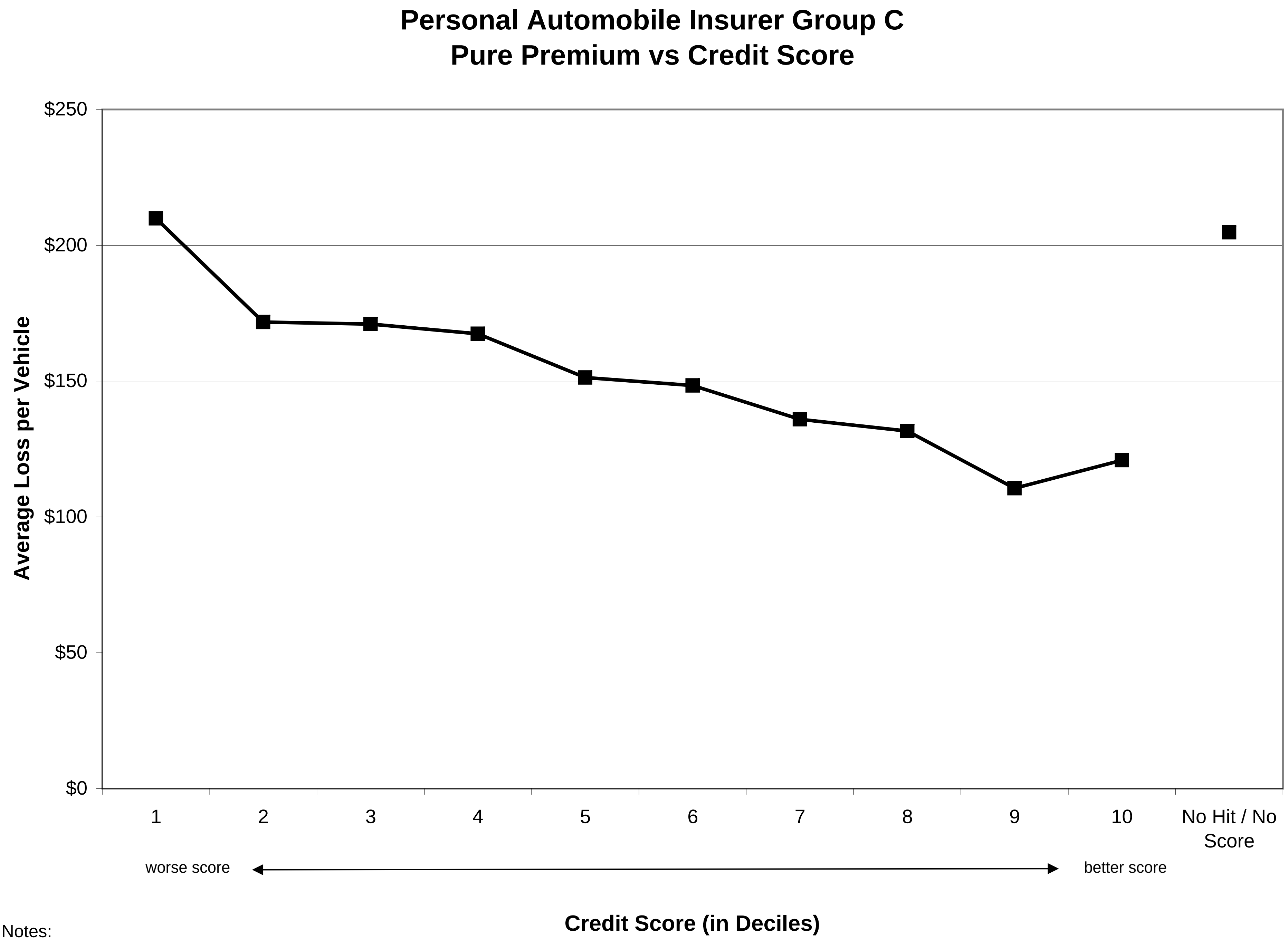
The following charts examine the relationship between
PURE PREMIUM (for PA), LOSS RATIO (for HO) and **CREDIT SCORE**.

Personal Automobile Insurer Group B
Pure Premium vs Credit Score



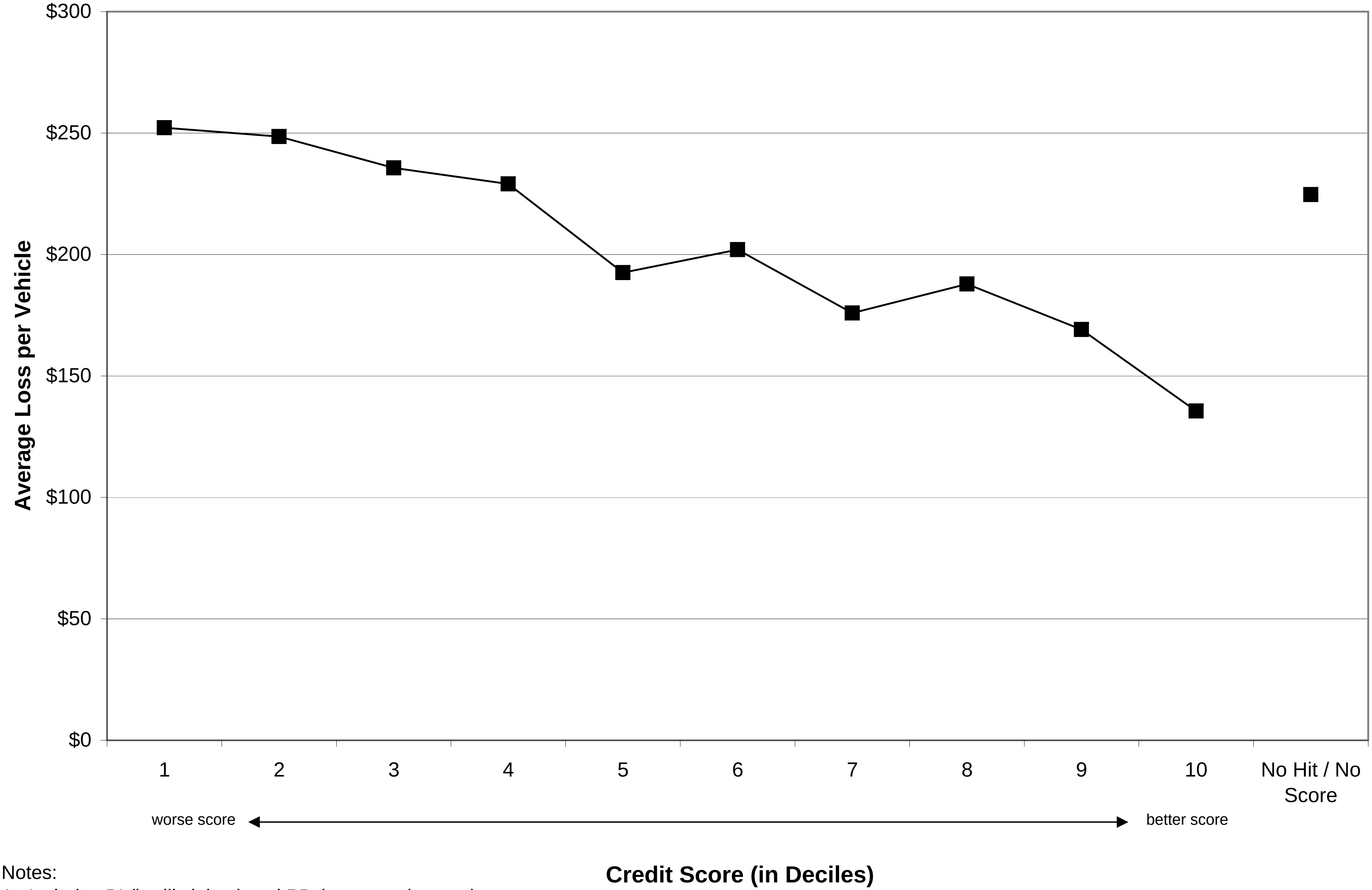
Notes:

1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)



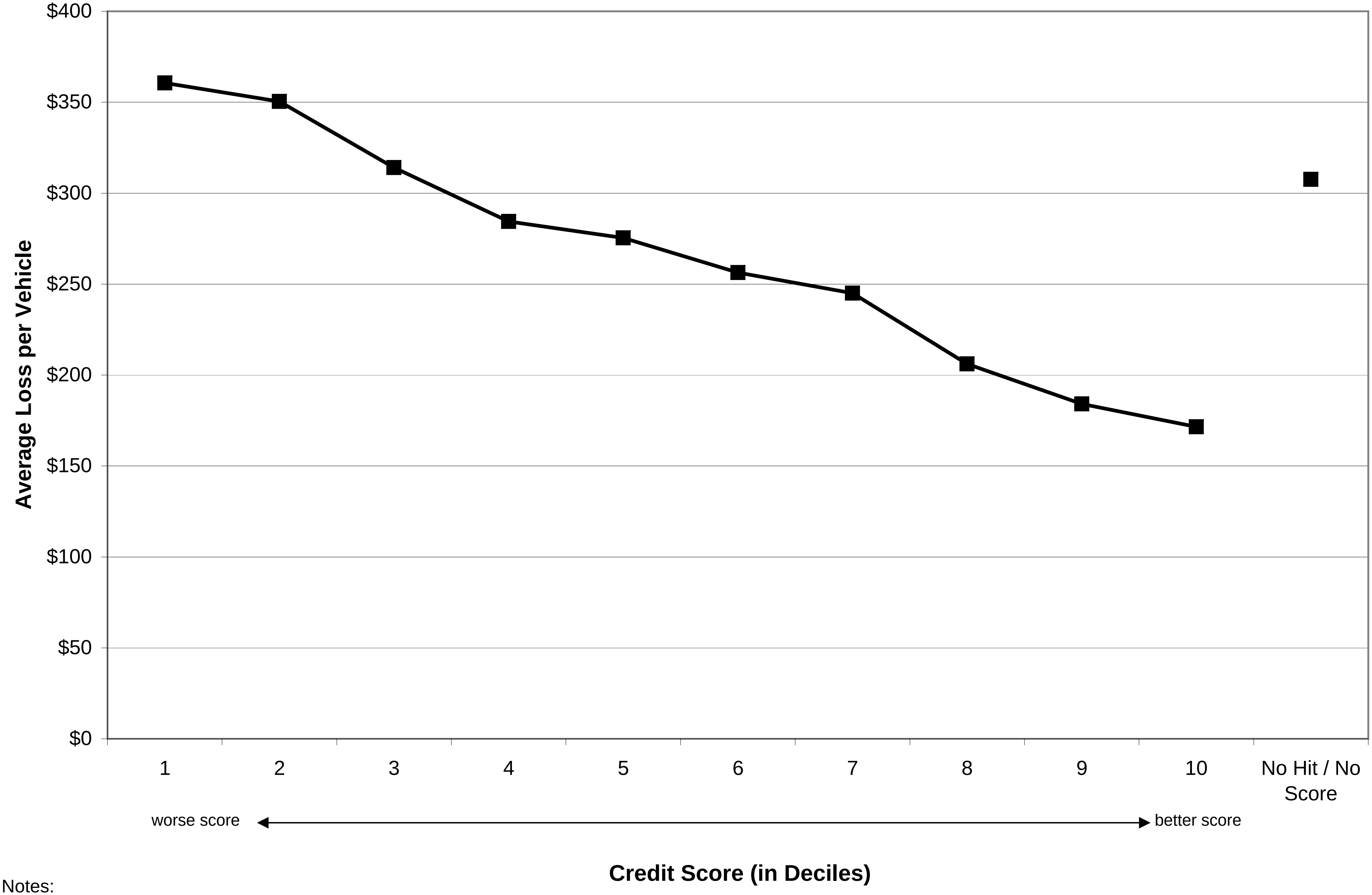
Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)

Personal Automobile Insurer Group D
Pure Premium vs Credit Score



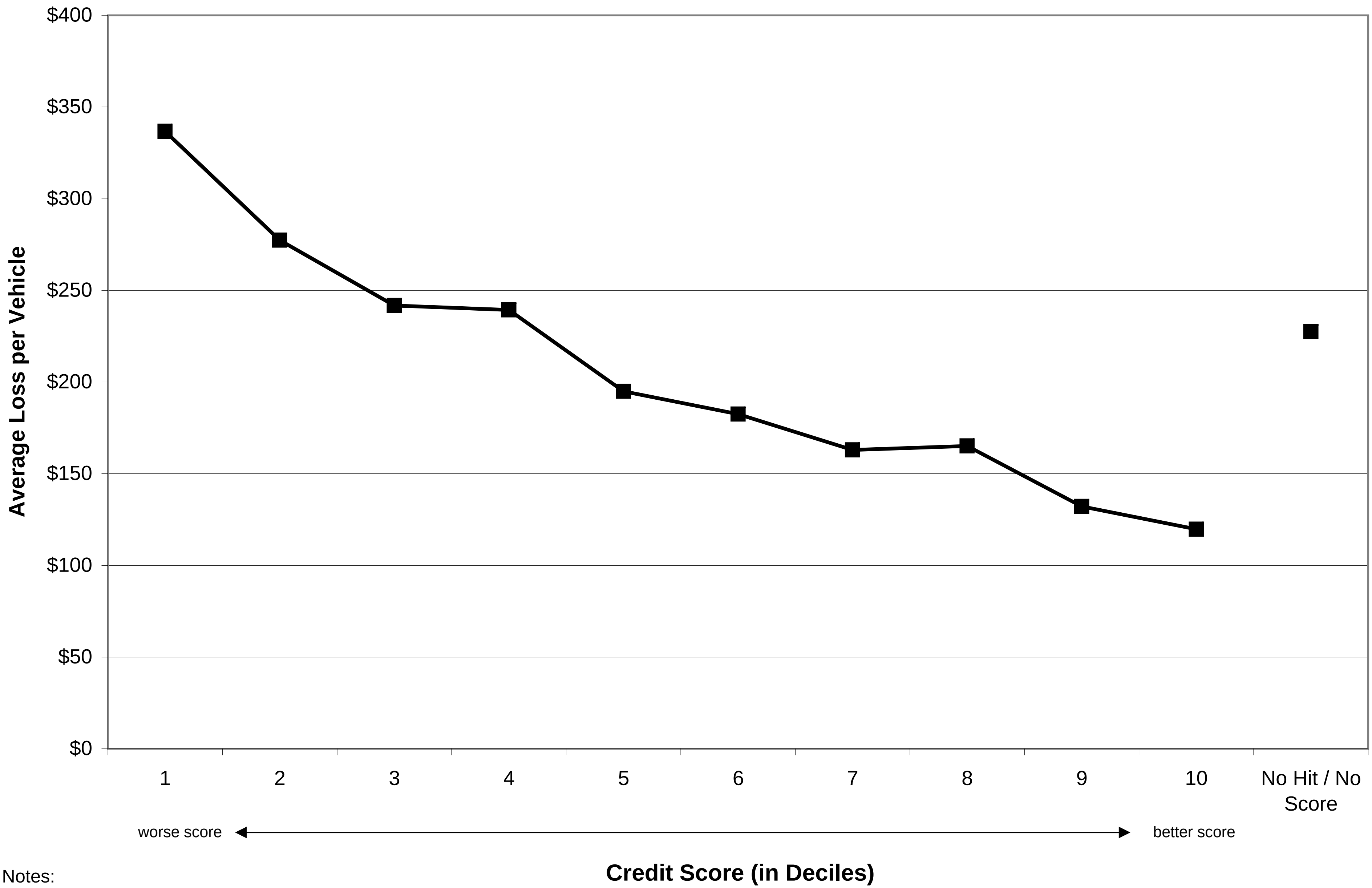
Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)

Personal Automobile Insurer Group F
Pure Premium vs Credit Score



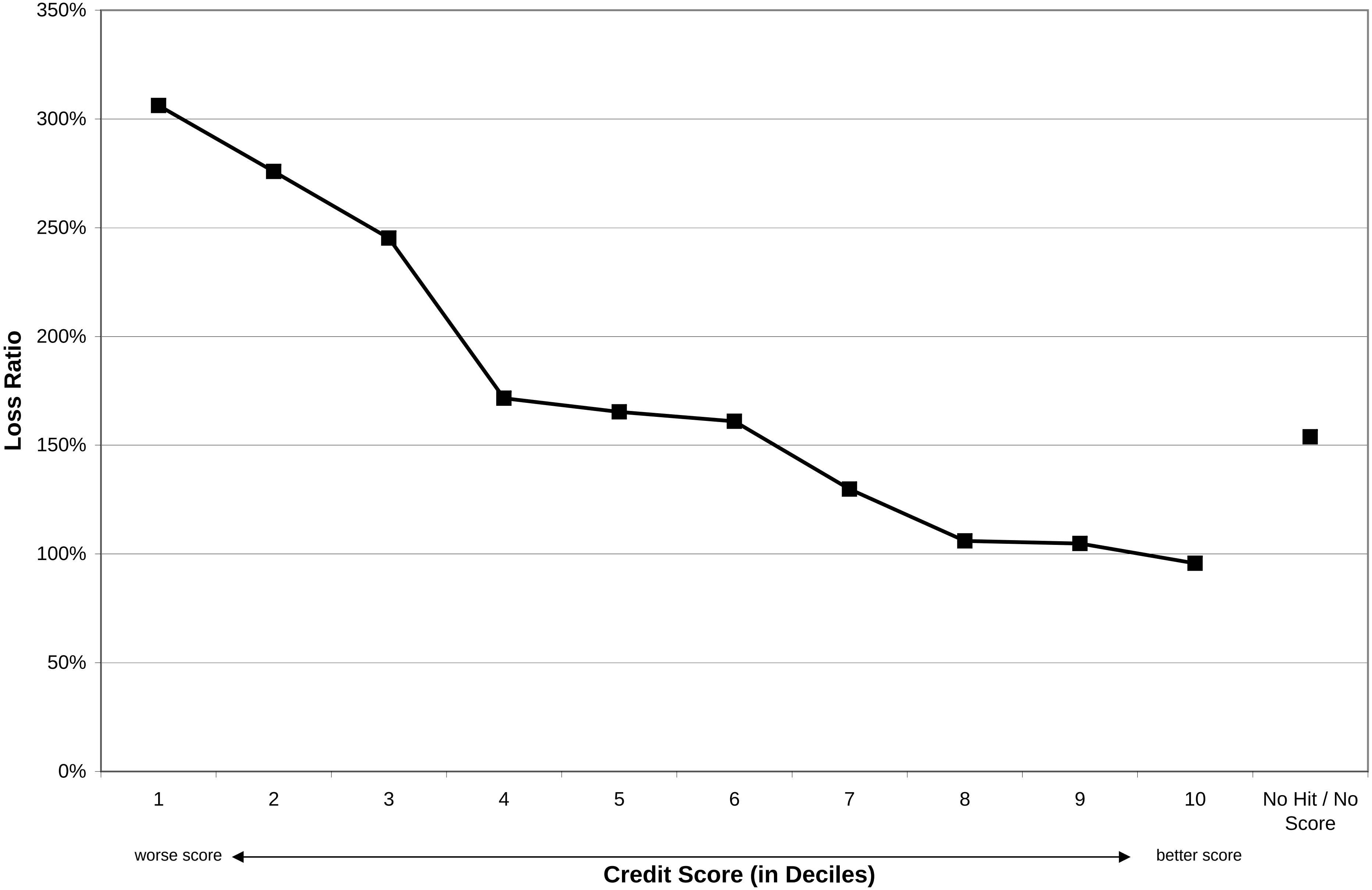
Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)

Personal Automobile Insurer Group G
Pure Premium vs Credit Score



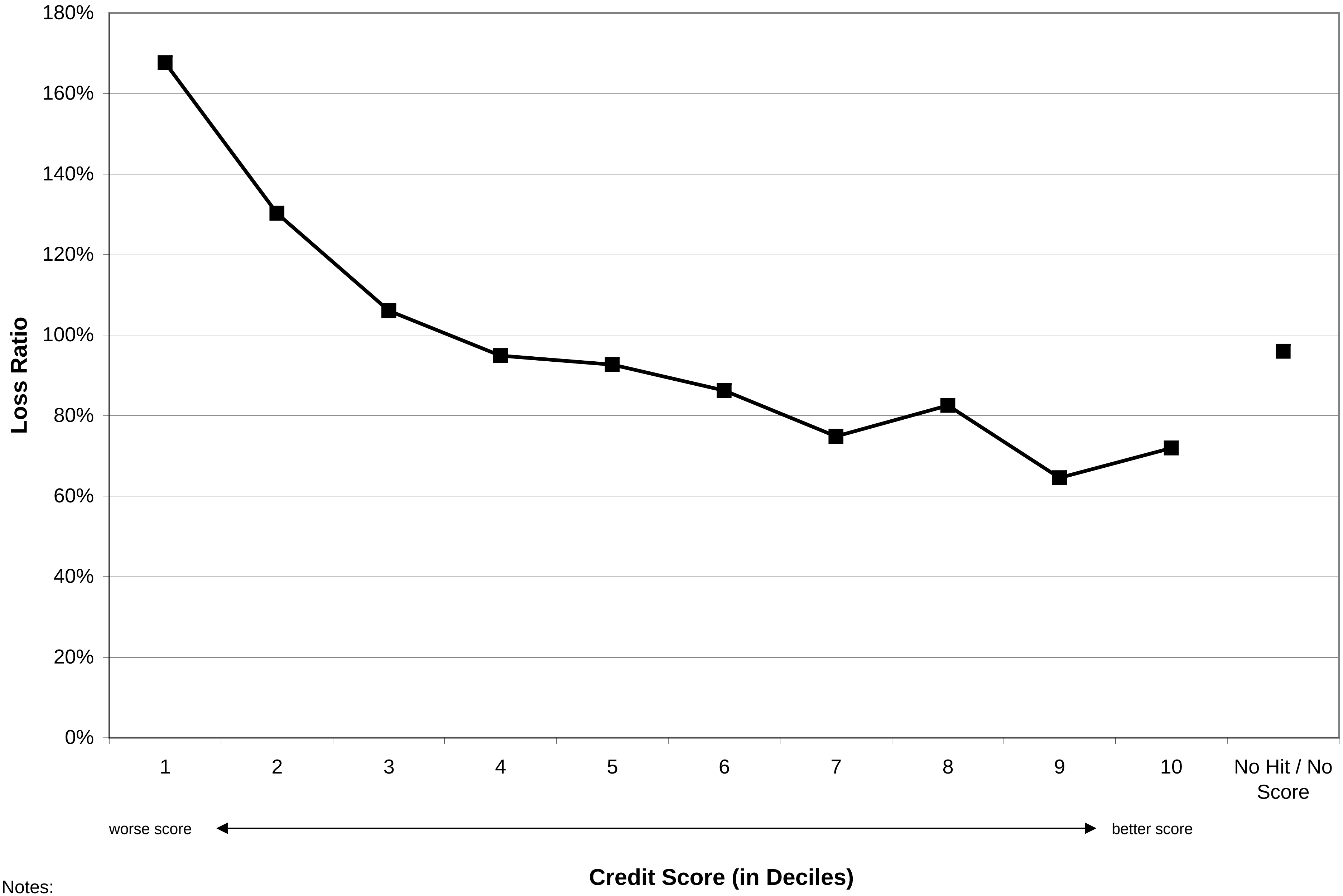
Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)

Homeowners Insurer Group E
Loss Ratio vs Credit Score



Notes:
1. Incorporates losses from all perils, including water damage, wind and hail

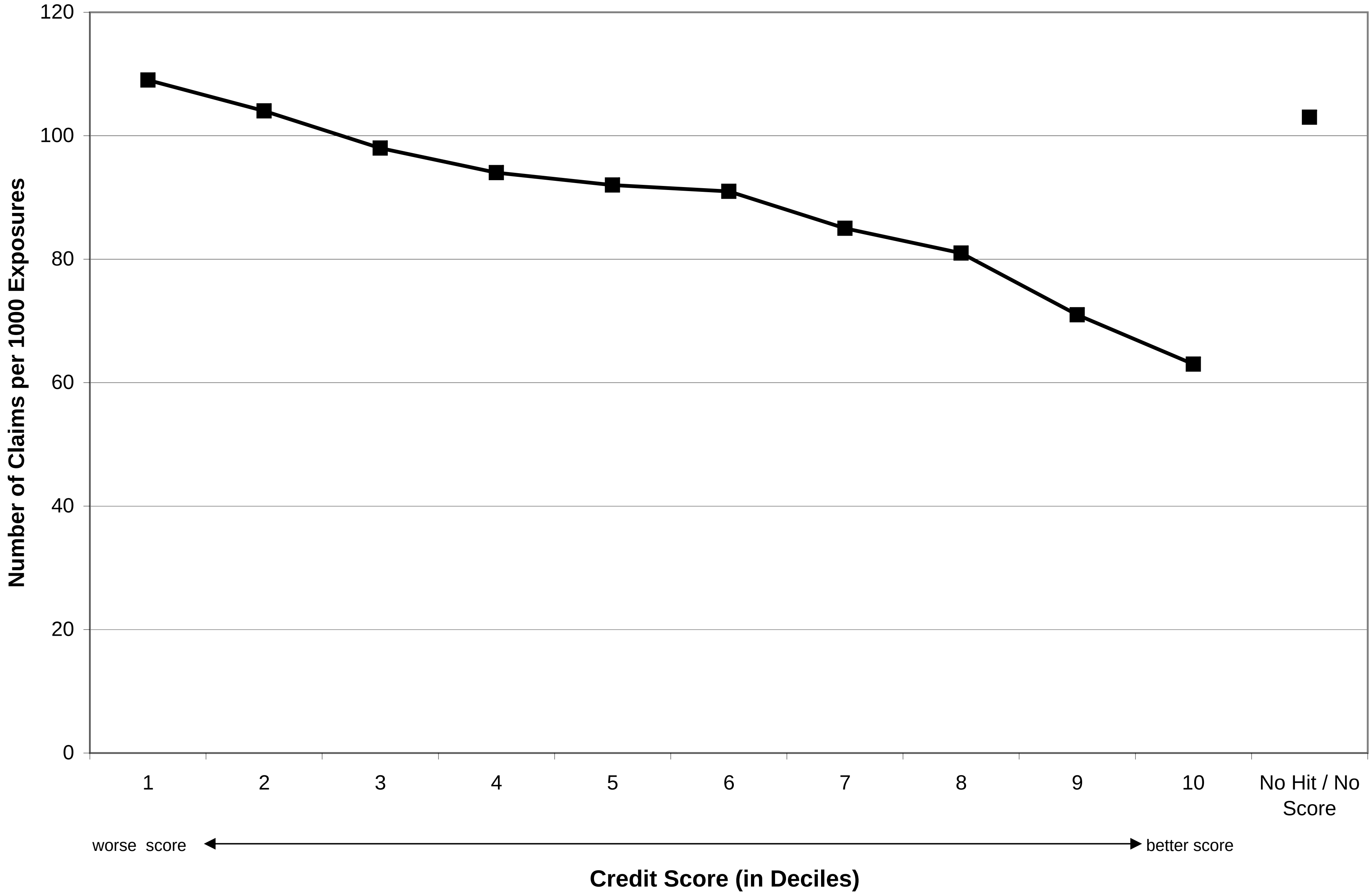
Homeowners Insurer Group H
Loss Ratio vs Credit Score



Notes:
1. Incorporates losses from all perils, including water damage, wind and hail

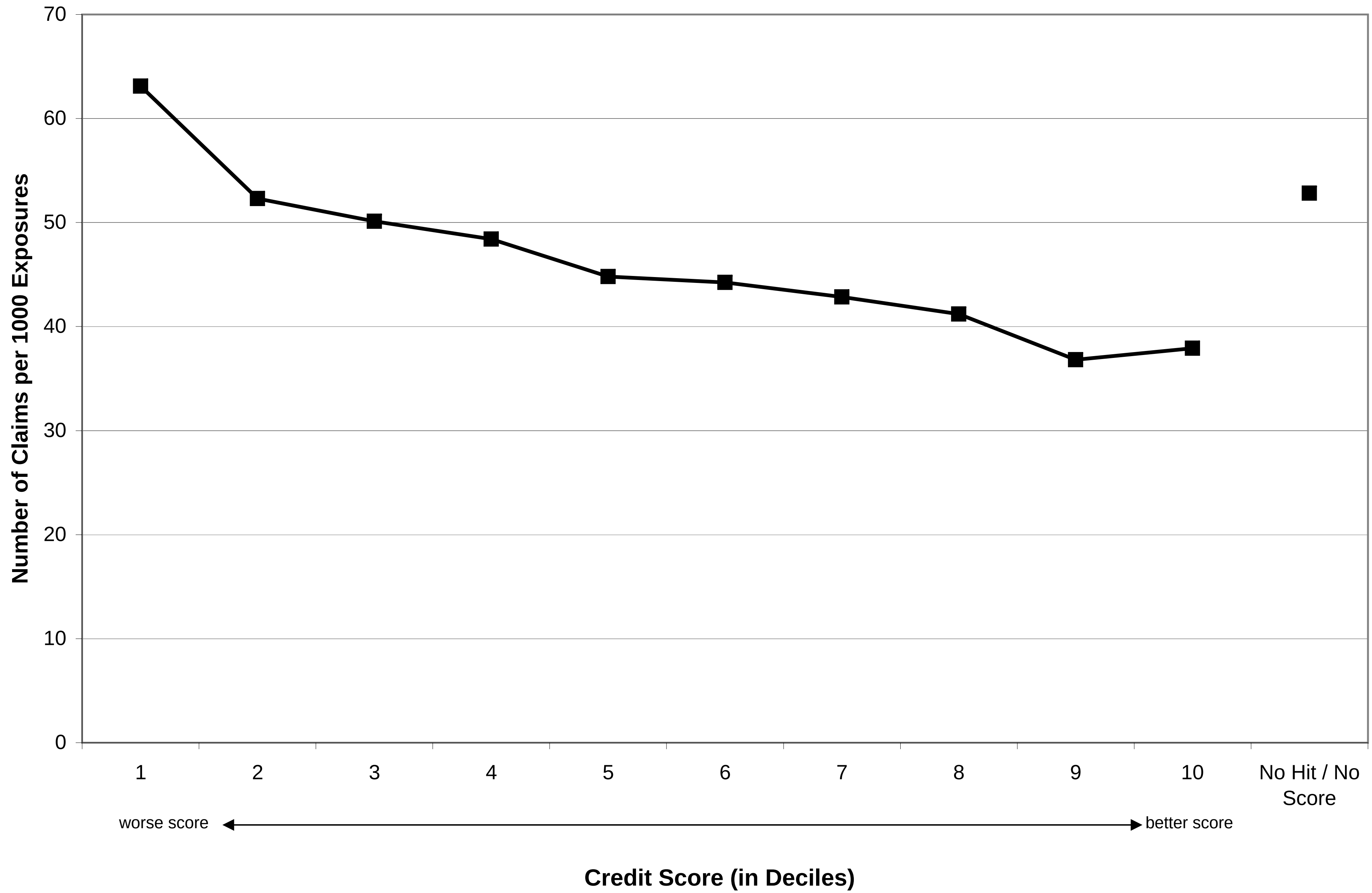
The following charts examine the relationship between
CLAIM FREQUENCY and **CREDIT SCORE**.

Personal Automobile Insurer Group B
Claim Frequency vs Credit Score

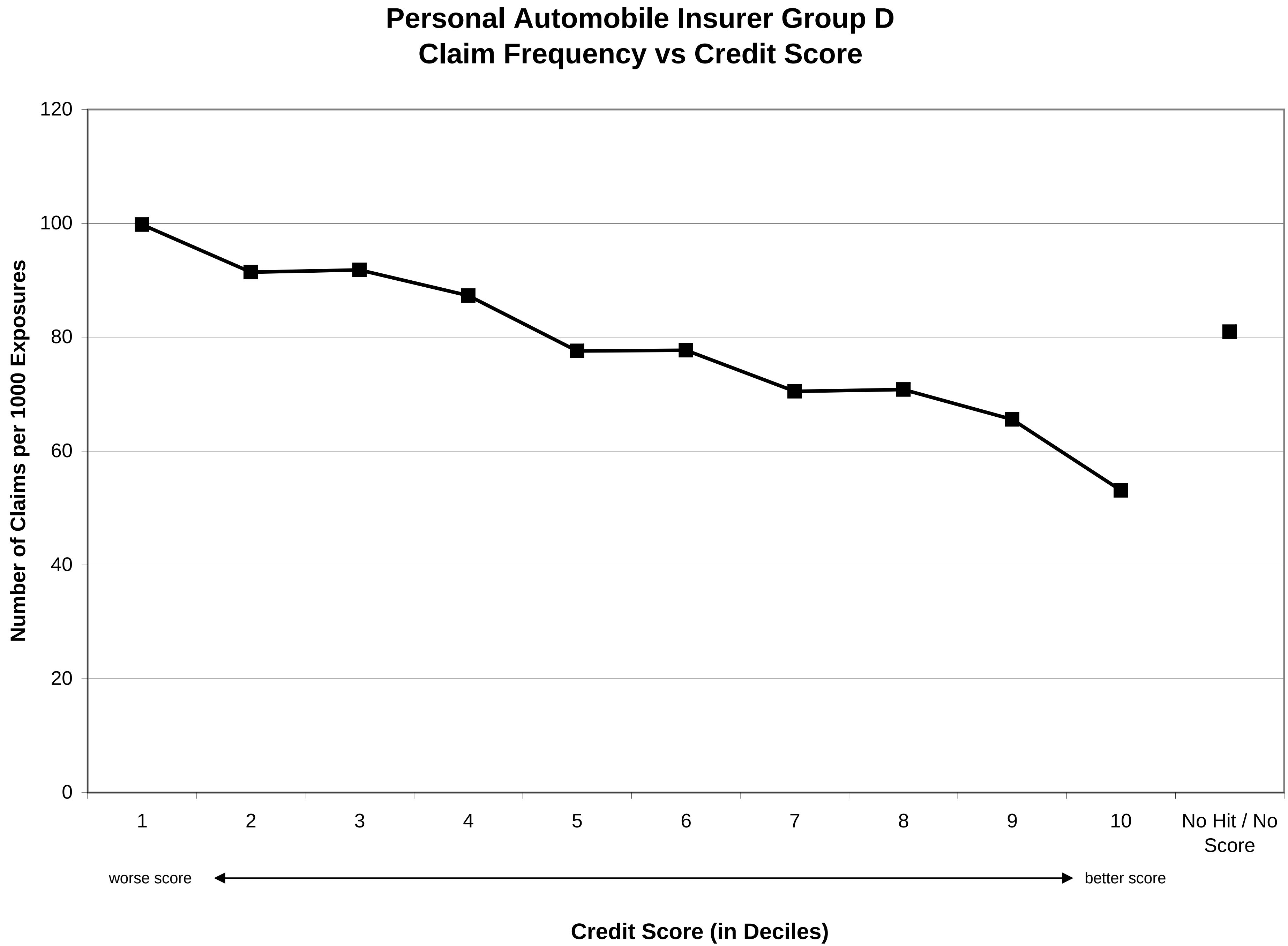


Notes:
1. Includes BI (bodily injury) and PD (property damage)

Personal Automobile Insurer Group C
Claim Frequency vs Credit Score

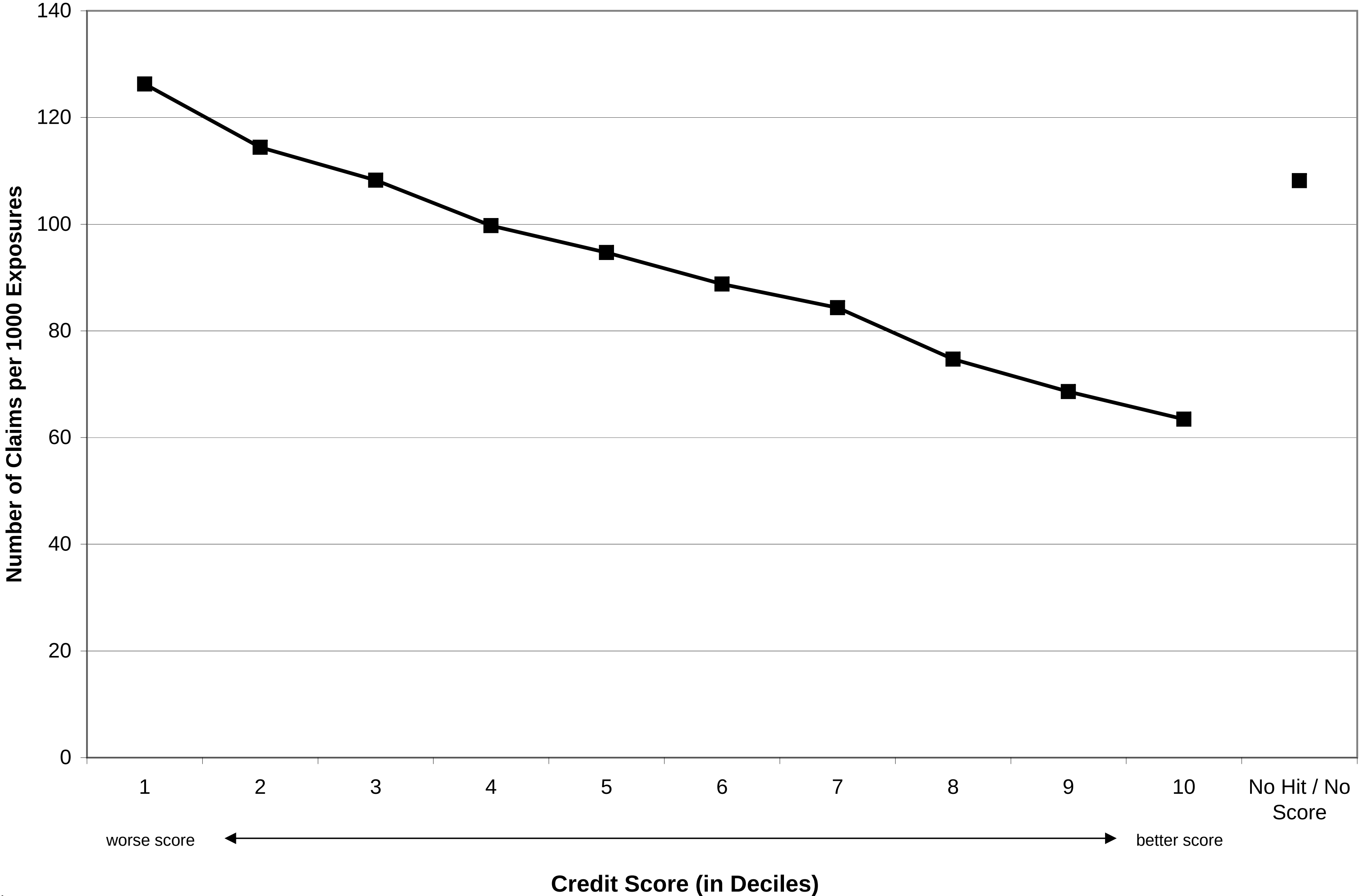


Notes:
1. Includes BI (bodily injury) and PD (property damage)



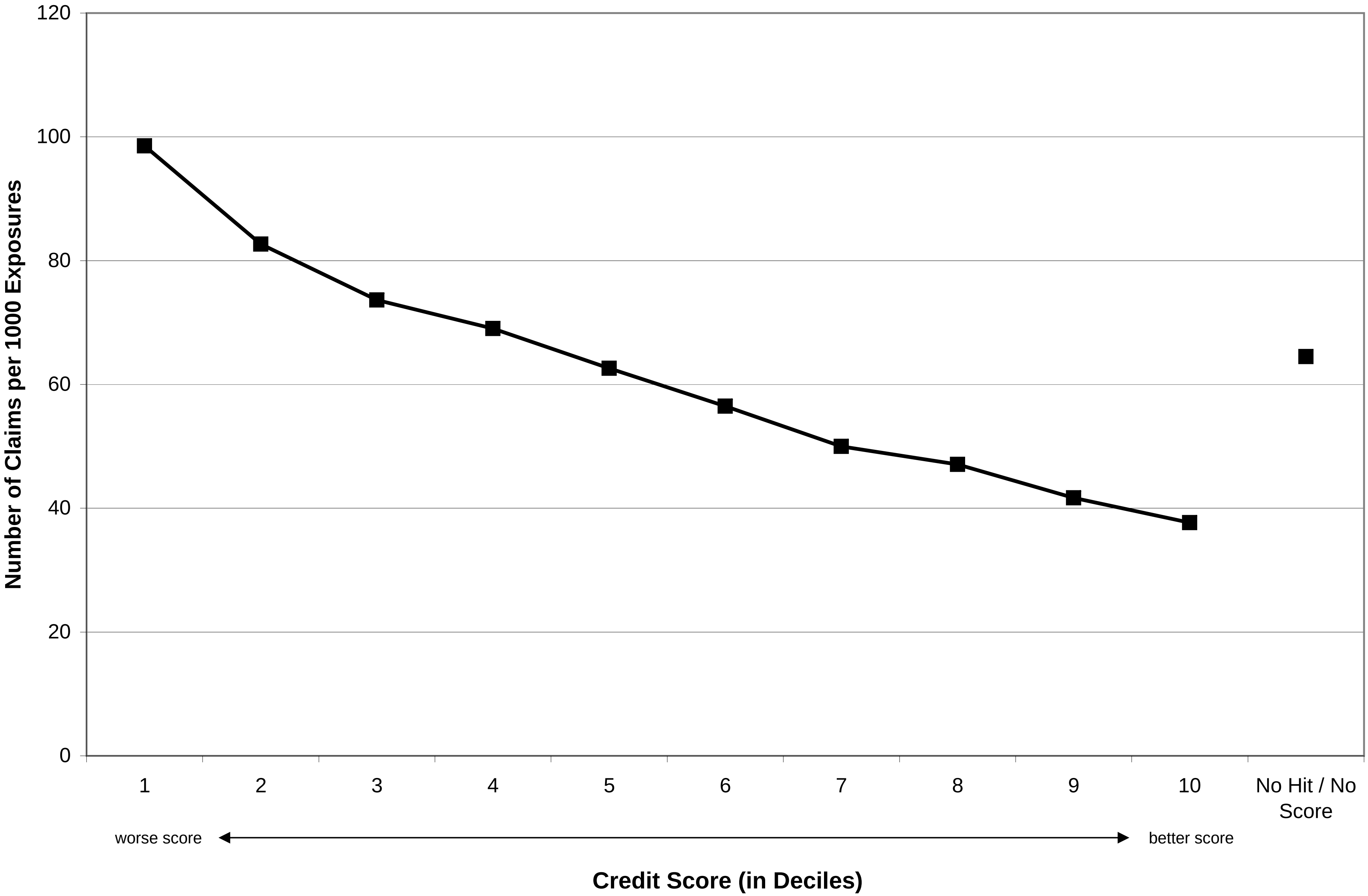
Notes:
1. Includes BI (bodily injury) and PD (property damage)

Personal Automobile Insurer Group F
Claim Frequency vs Credit Score

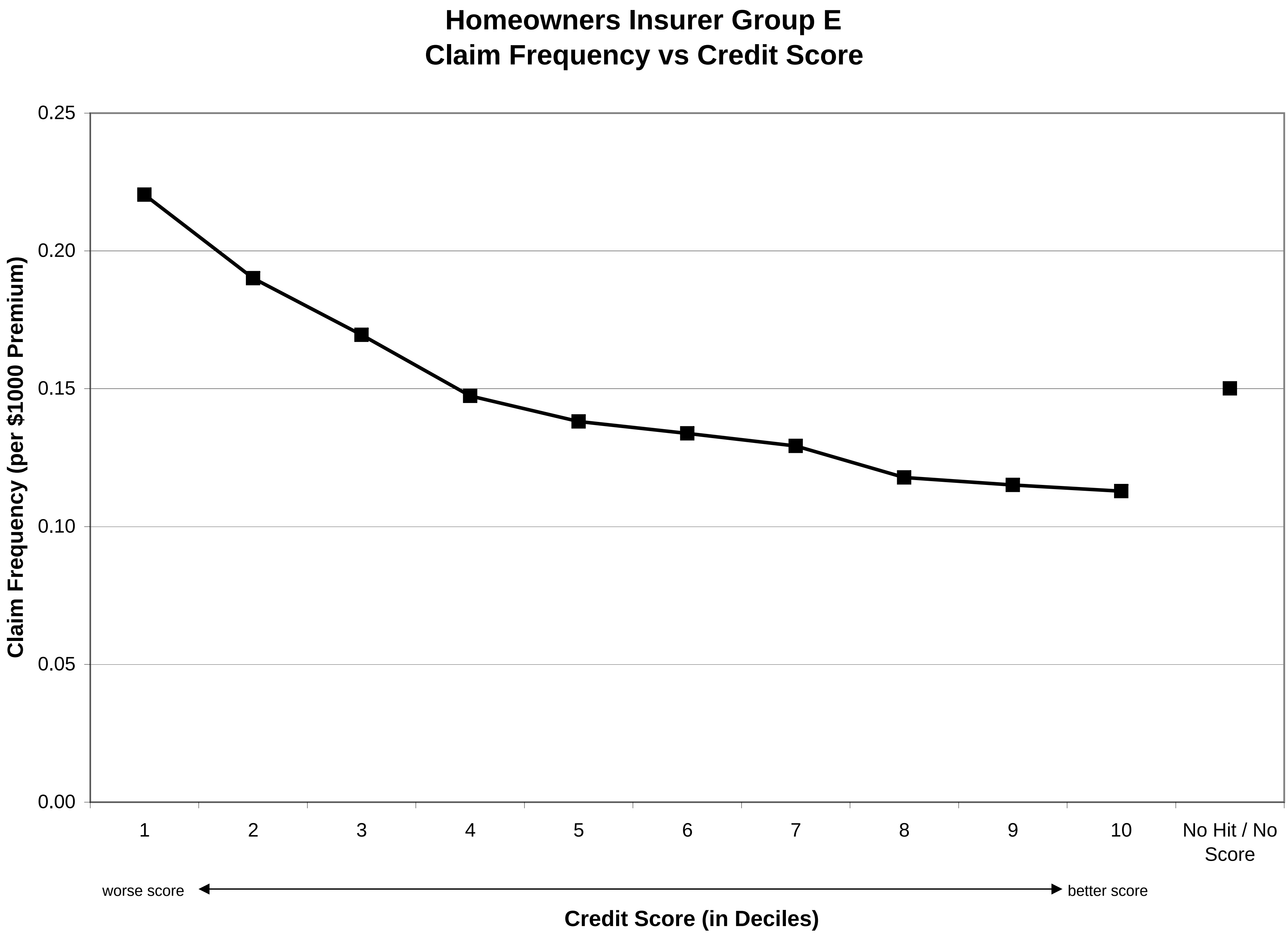


Notes:
1. Includes BI (bodily injury) and PD (property damage)

Personal Automobile Insurer Group G
Claim Frequency vs Credit Score

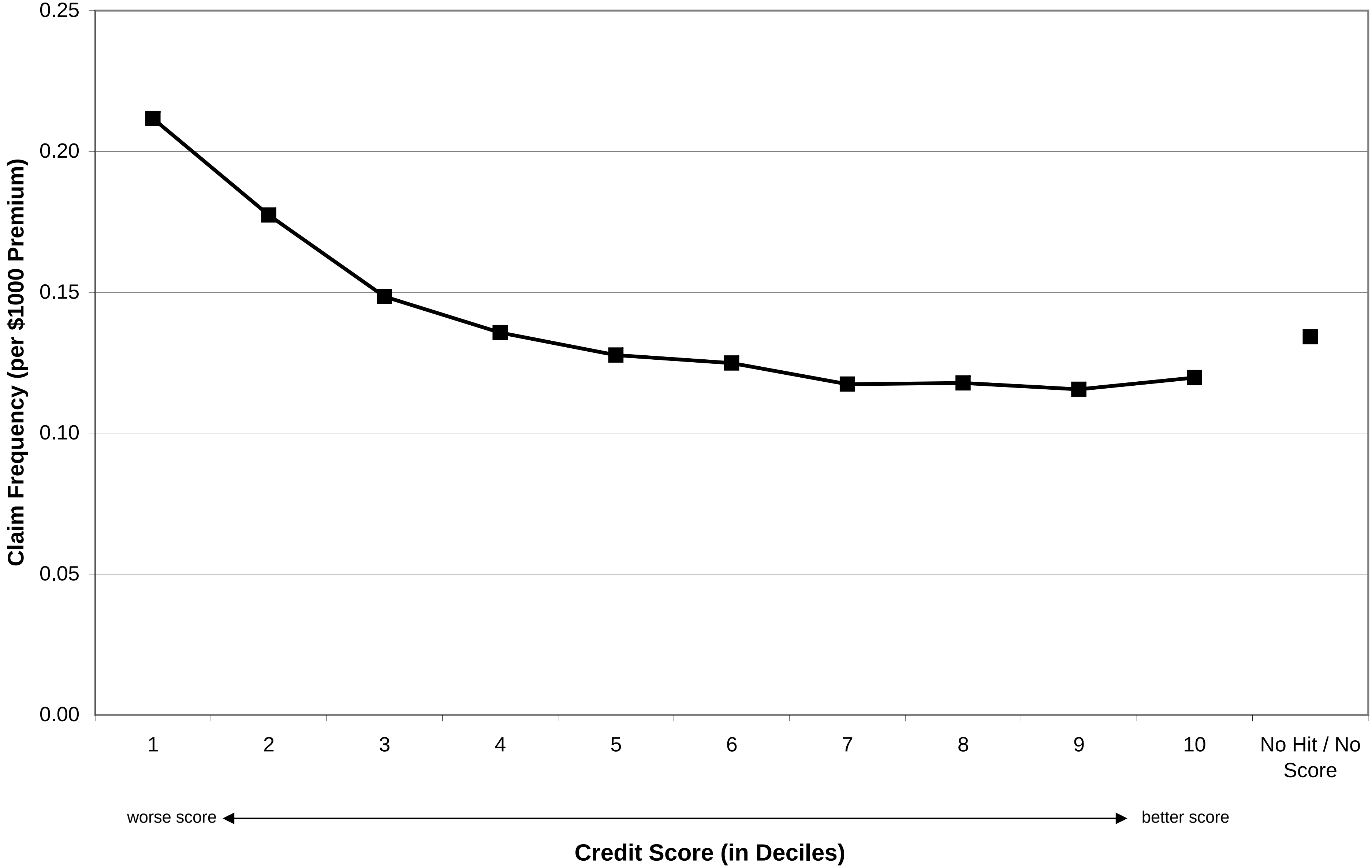


Notes:
1. Includes BI (bodily injury) and PD (property damage)



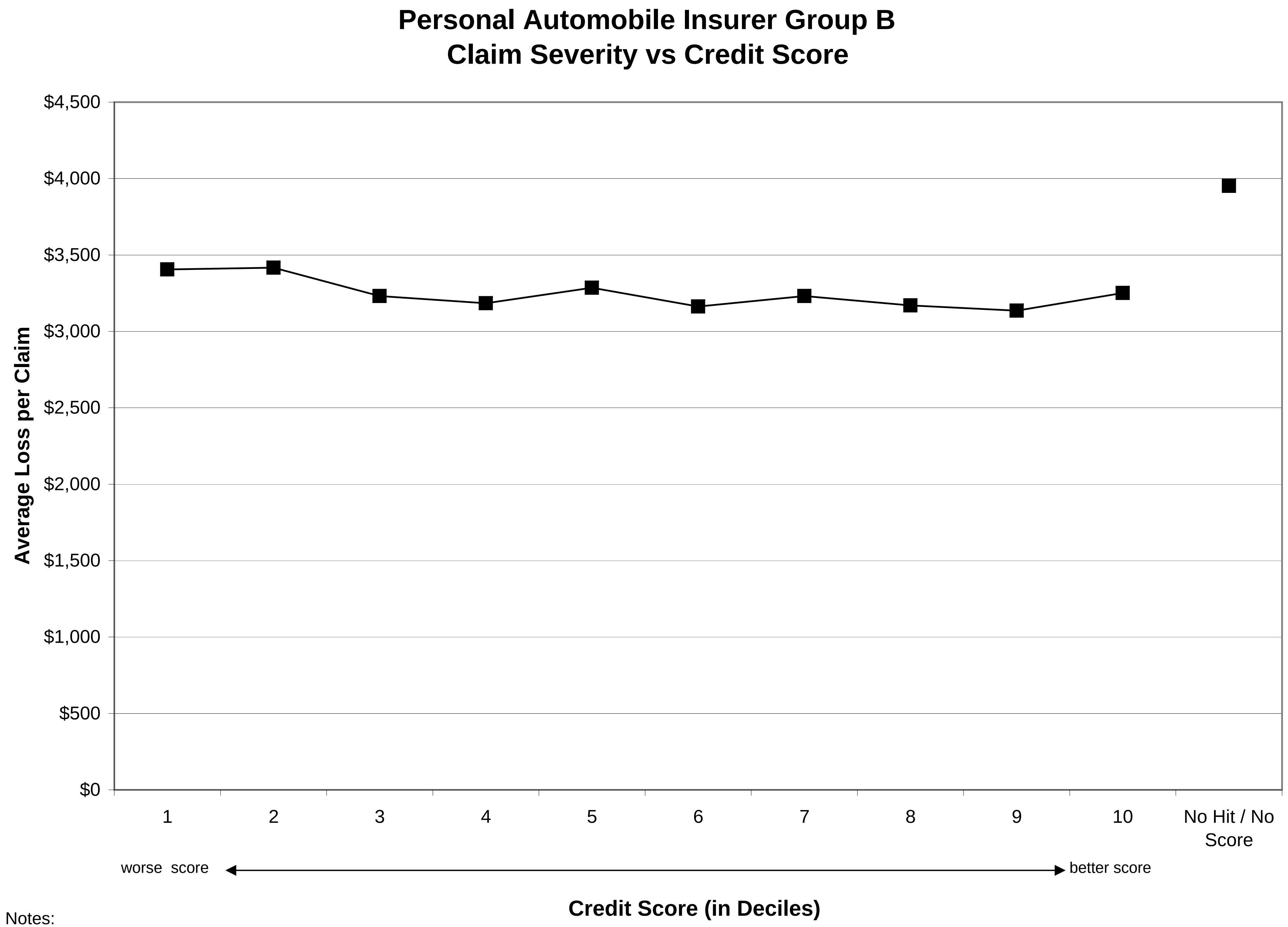
Notes:
1. Incorporates claims from all perils, including water damage, wind and hail

Homeowners Insurer Group H
Claim Frequency vs Credit Score



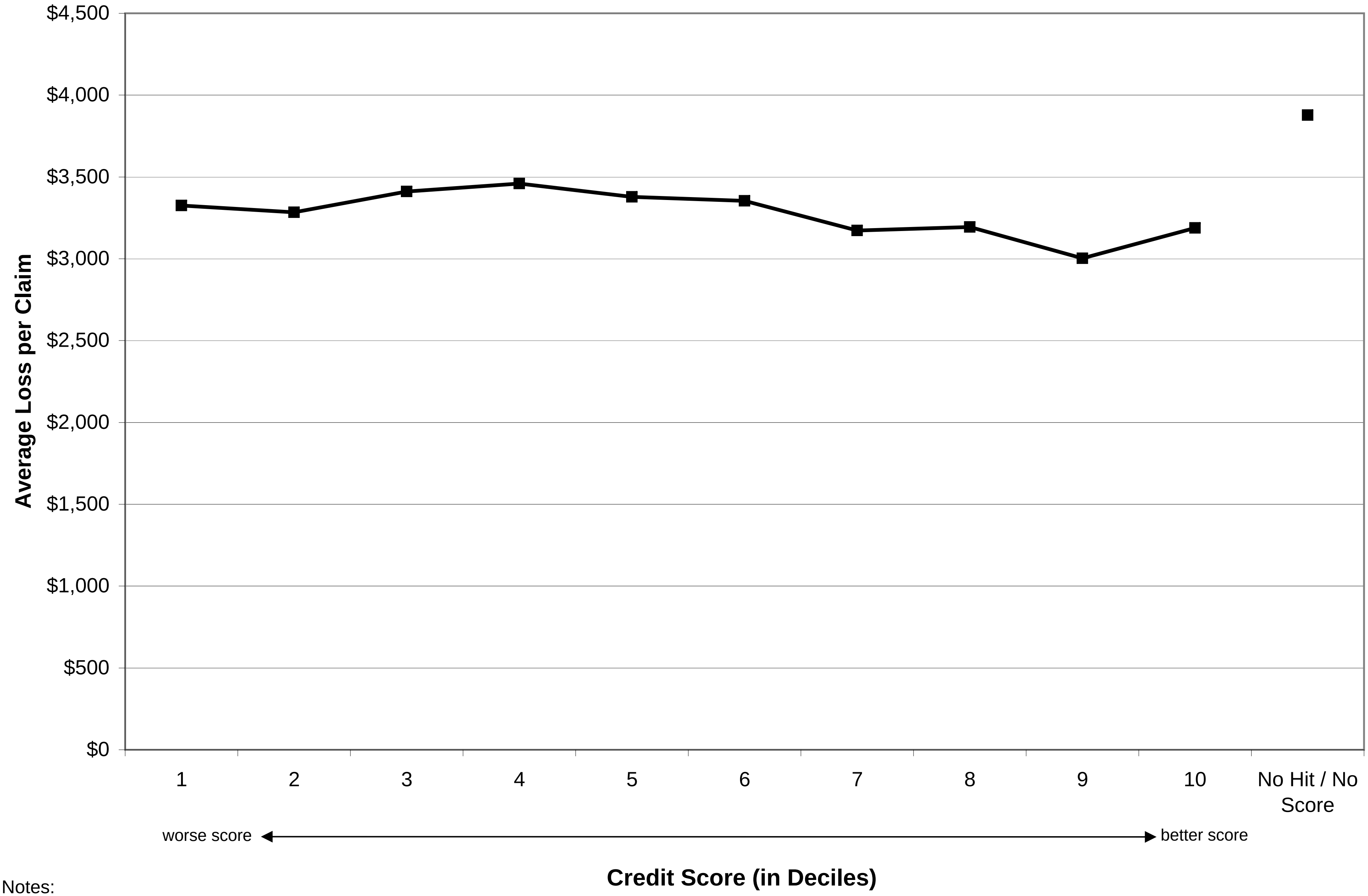
Notes:
1. Incorporates claims from all perils, including water damage, wind and hail

The following charts examine the relationship between **CLAIM SEVERITY** and **CREDIT SCORE**.



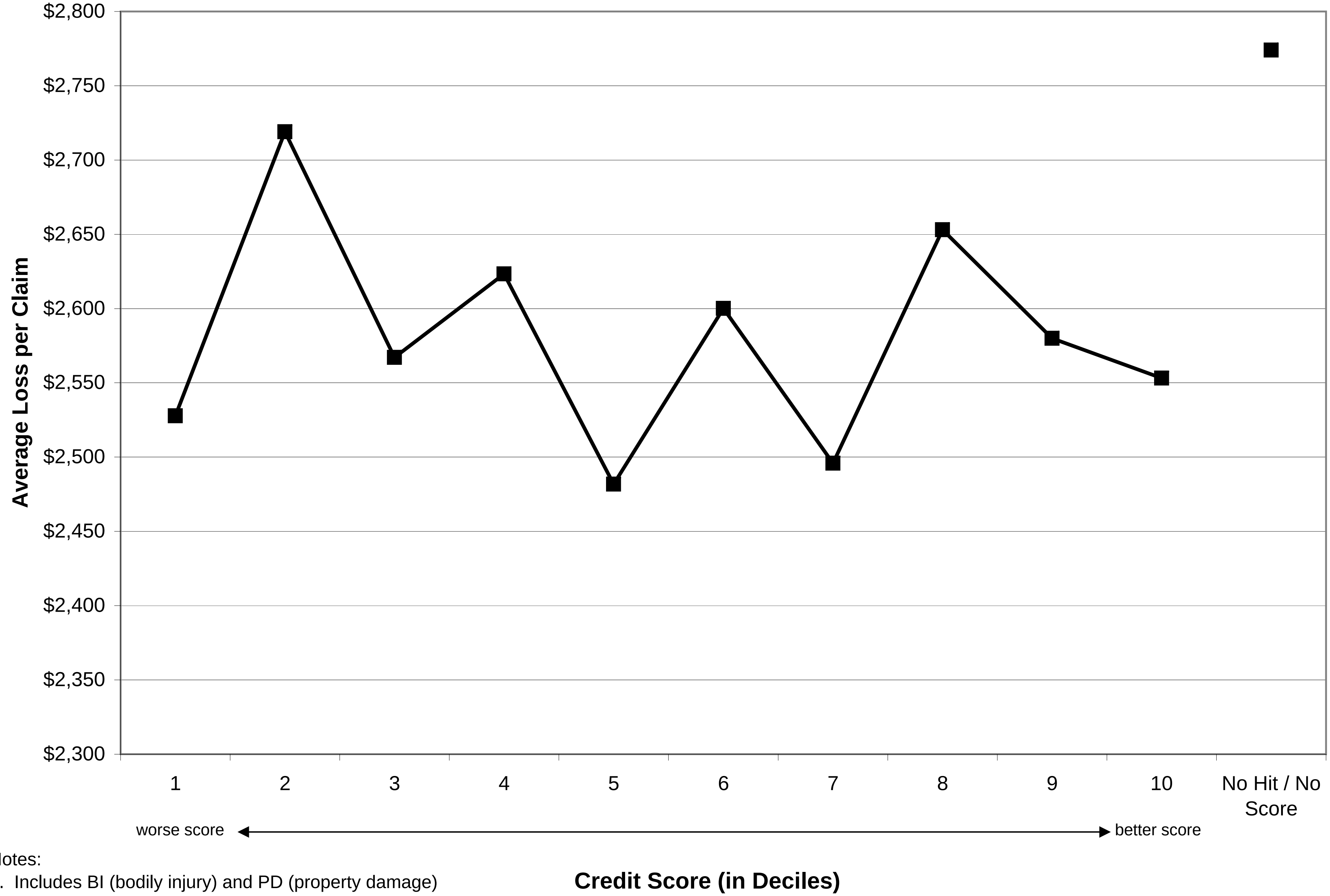
Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)

Personal Automobile Insurer Group C
Claim Severity vs Credit Score

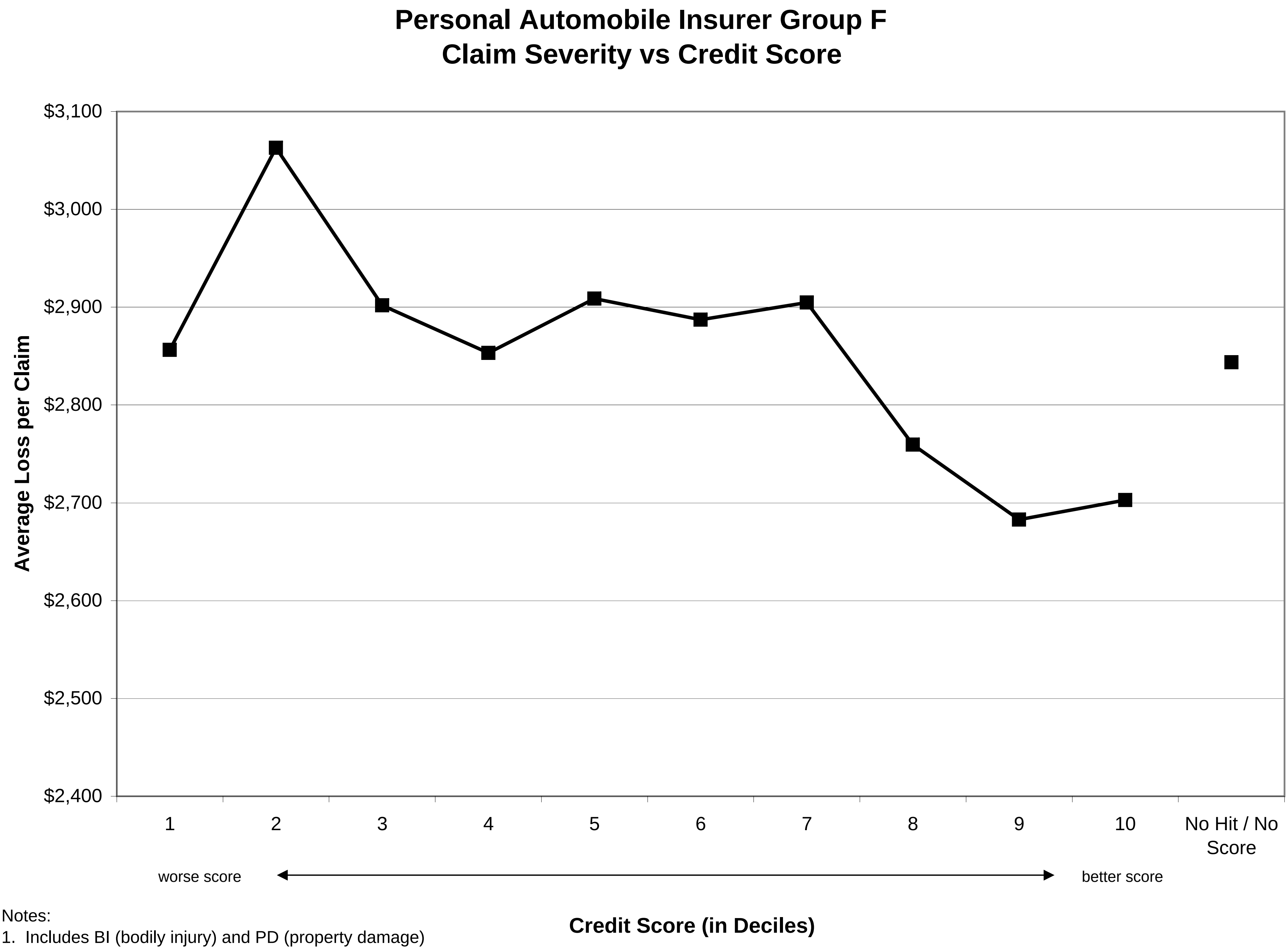


Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)

Personal Automobile Insurer Group D
Claim Severity vs Credit Score

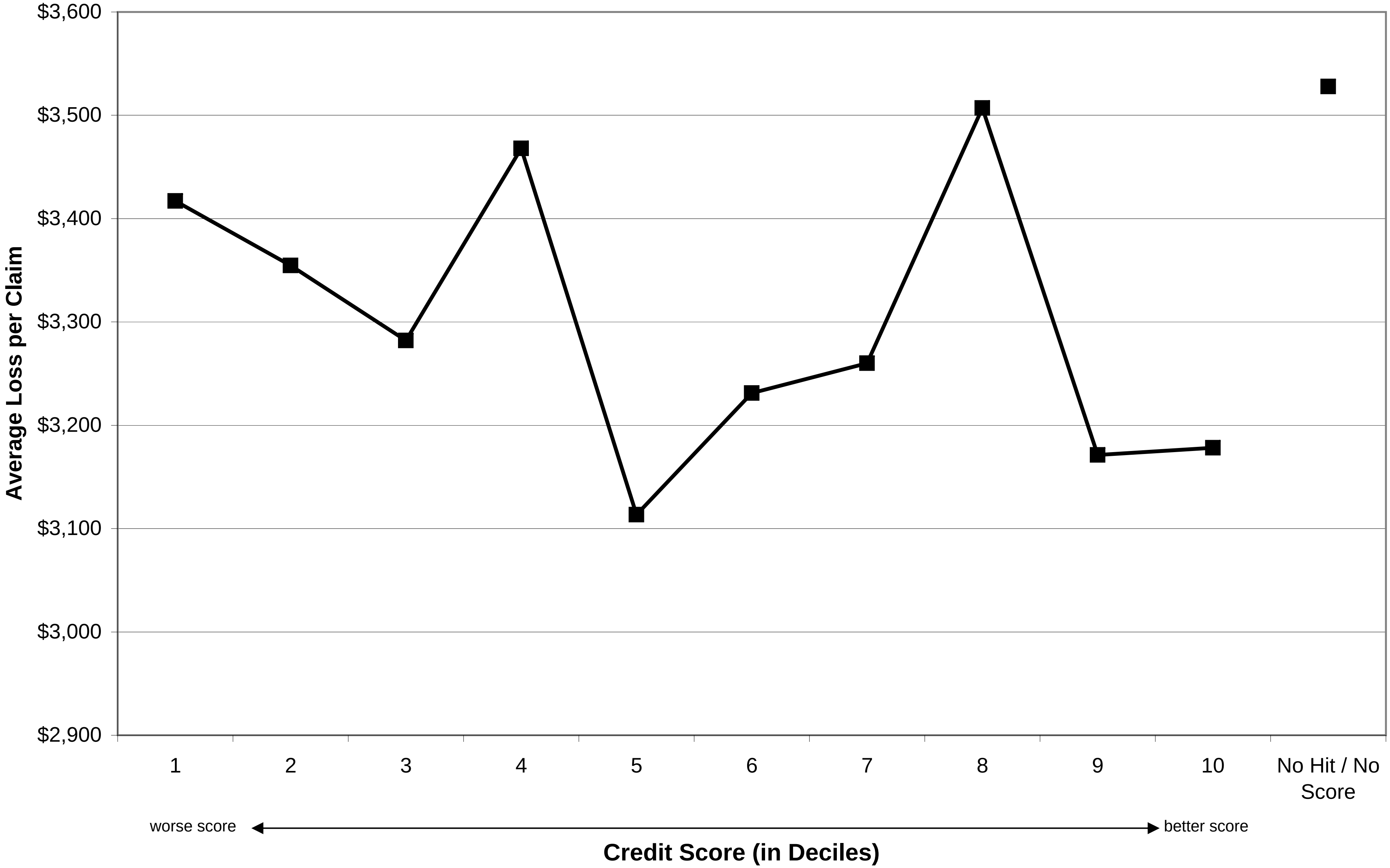


Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)

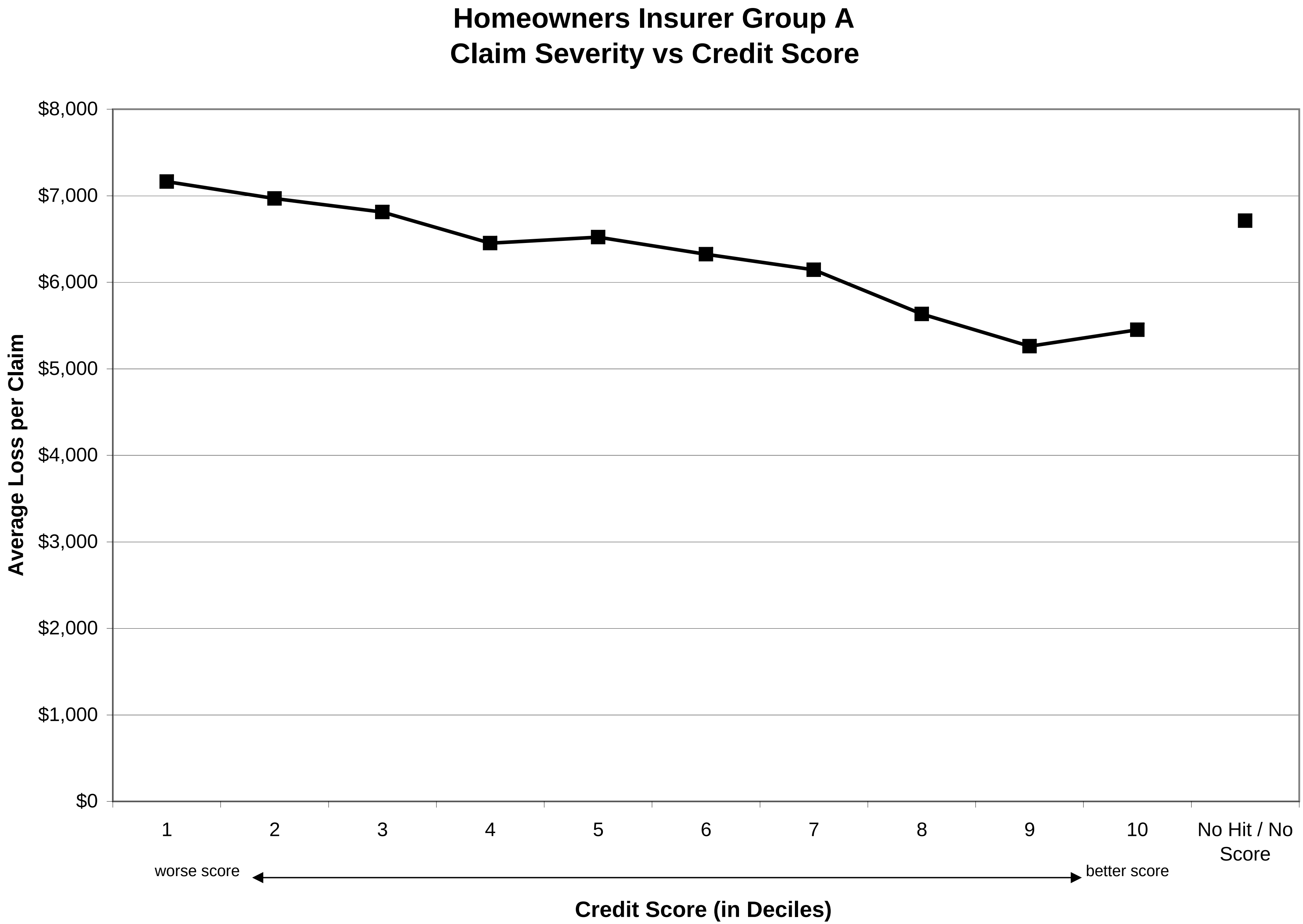


Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)

Personal Automobile Insurer Group G
Claim Severity vs Credit Score

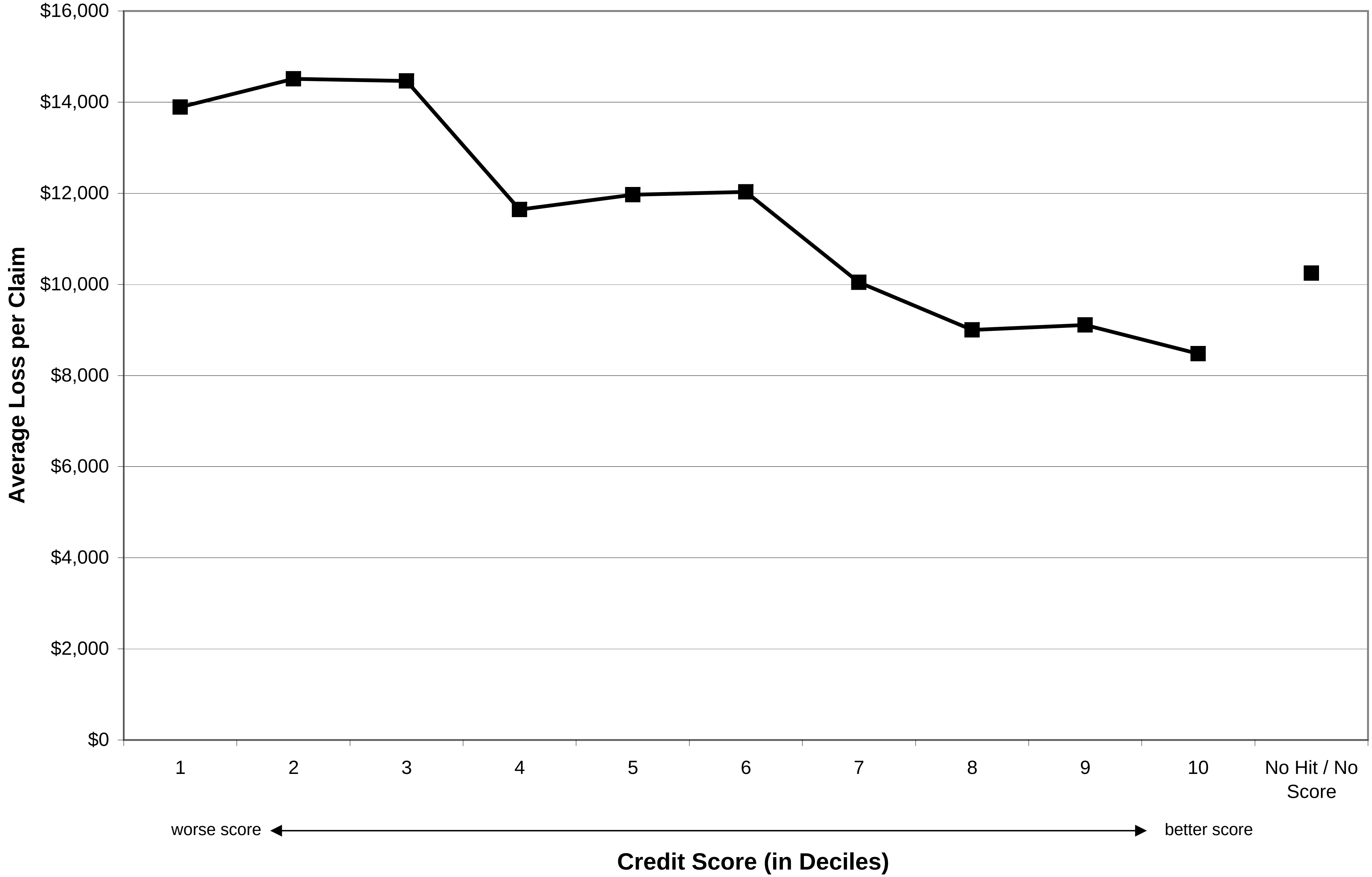


Notes:
1. Includes BI (bodily injury) and PD (property damage)
2. Losses are capped at basic limits ($20,000/$40,000/$15,000)



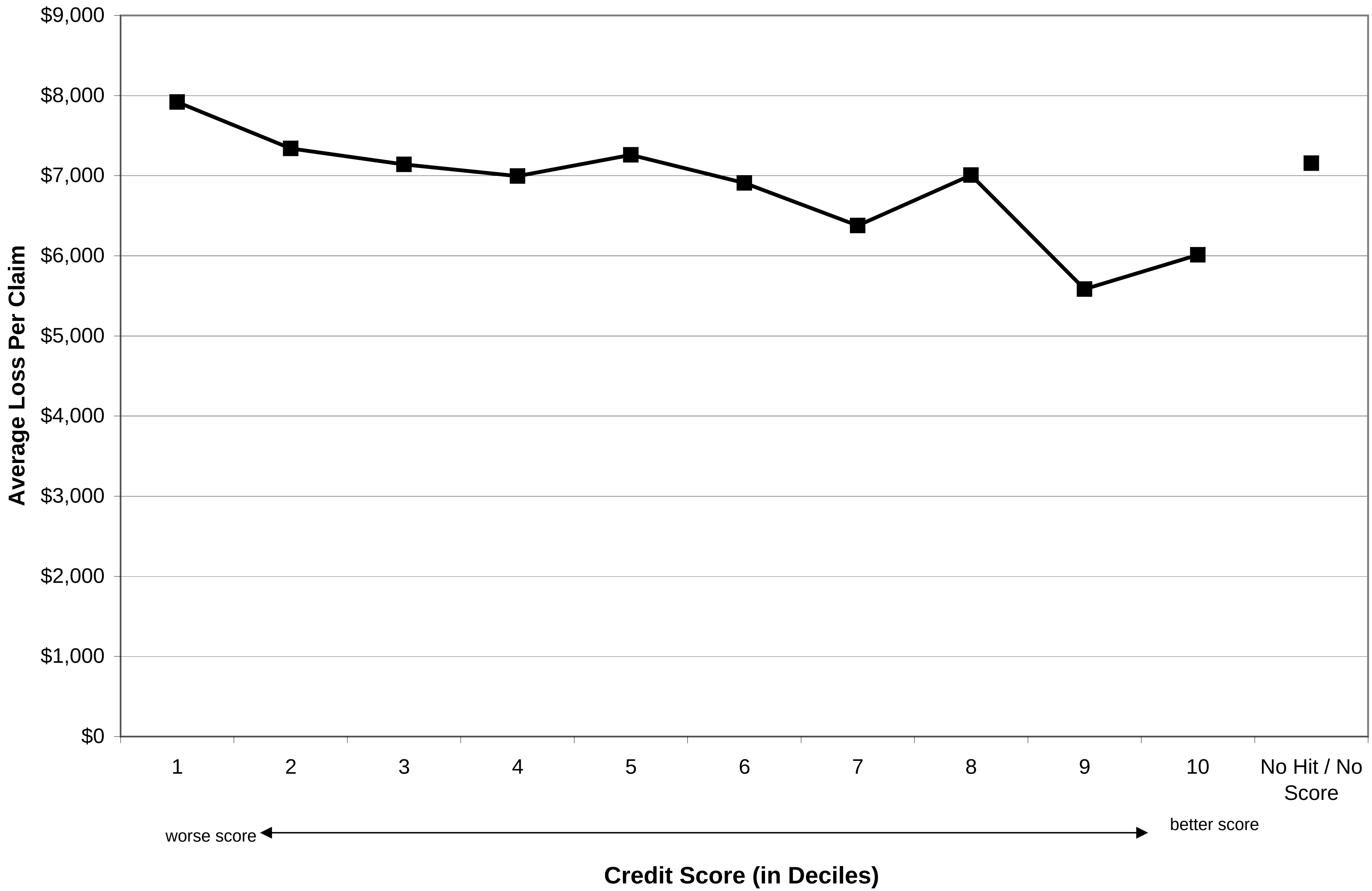
Notes:
1. Incorporates losses from all perils, including water damage, wind and hail

Homeowners Insurer Group E
Claim Severity vs Credit Score



Notes:
1. Incorporates losses from all perils, including water damage, wind and hail

Homeowners Insurer Group H
Claim Severity vs Credit Score



Notes:
1. Incorporates losses from all perils, including water damage, wind and hail