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Empirical Evidence on the Use of Credit Scoring for Predicting Insurance Losses with Psycho-social and Biochemical Explanations

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An important development in personal lines of insurance in the United States is the use of credit history data for insurance risk classification to predict losses. This research presents the results of collaboration with industry conducted by a university at the request of its state legislature. The purpose was to see the viability and validity of the use of credit scoring to predict insurance losses given its controversial nature and criticism as redundant of other predictive variables currently used. Working with industry and government, this study analyzed more than 175,000 policyholders' information for the relationship between credit score and claims. Credit scores were significantly related to incurred losses, evidencing both statistical and practical significance. We investigate whether the revealed relationship between credit score and incurred losses was explainable by overlap with existing underwriting variables or whether the credit score adds new information about losses not contained in existing underwriting variables. The results show that credit scores contain significant information not already incorporated into other traditional rating variables (e.g., age, sex, driving history). We discuss how sensation seeking and self-control theory provide a partial explanation of why credit scoring works (the psycho-social perspective). This article also presents an overview of biological and chemical correlates of risk taking that helps explain why knowing risk-taking behavior in one realm (e.g., risky financial behavior and poor credit history) transits to predicting risk-taking behavior in other realms (e.g., automobile insurance incurred losses). Additional research is needed to advance new nontraditional loss prediction variables from social media consumer information to using information provided by technological advances. The evolving and dynamic nature of the insurance marketplace makes it imperative that professionals continue to evolve predictive variables and for academics to assist with understanding the whys of the relationships through theory development.

1. INTRODUCTION AND OVERVIEW

Increasingly, insurers are using behavioral predictors of loss propensity beyond the traditional sets of underwriting variables. In automobile insurance, for example, insurers have traditionally assessed potential risk based on certain easily obtained objective individual variables such as age, marital status, territory, and accident and claim history in addition to automobile characteristics. Now nontraditional variables such as credit scores, computer-monitored driving behavior (as assessed from GPS-enabled telematics devices; cf. Kremslehner and Muermann 2013; White 2012), educational attainment, occupation, and other observable behavioral choice variables are being used more frequently to determine correlates of driver insured loss propensity (see New Jersey Department of Banking and Insurance 2008 concerning the current debate over the use of occupation and education as underwriting variables).

This expansion of loss prediction variables has been facilitated by technological innovations and improved computational ability (permitting predictive modeling in real time where not previously possible), as well as the compilation of large accessible data sets ("big data"). Although the discovery of predictive personal underwriting variables arose observationally in the past (e.g., sex, age, marital status), now computational advances have made it possible to discover less clearly observationally grounded

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variables through data mining. Utilizing behavioral insights (such as those about finances and driving behavior) had to wait until sufficient individualized credit data were immediately accessible and computational speed was sufficient so that the variable could be implemented in the underwriting process in real time.[1]

Considerable additional data are being collected by both insurers and others (e.g., credit-scoring firms, GPS firms, social media firms, store loyalty programs) that, combined with new predictive modeling techniques, have the potential to uncover "nontraditional" underwriting variables providing enhanced risk assessments. As the insurance industry advances beyond traditional classification and underwriting variables, the need will increase to justify why accurate prediction works for these "nontraditional" variables and to go beyond simply complying with Actuarial Standard 12 and to verify that any correlation discovered has a basis in fact and is not without an economic, socio-psychological, or behavioral underpinning. The development of a theoretical foundation for *why* a predictor (such as credit scores or occupation and educational achievement) works can also provide a path for new underwriting variable discovery beyond an ad hoc search.

There is a need for theory development to better explain nontraditional variable predictive abilities. A theoretical foundation can help insurers, regulators, and customers understand the use of new underwriting variables, possibly facilitating the social/regulatory acceptance of these risk assessment variables. One survey showed that consumers generally agree that an individual should pay into a risk pool commensurate with the risk they bring to the risk pool.[2] If there were a better understanding of how risk was being assessed by the new predictor variables, and how this risk was related to losses, then there might be larger social acceptance of such new predictor variables.

While legislatures across the nation evaluate whether or not to allow them (NAIC 2013), credit scoring and other behavioral variables still continue to be used and developed. According to the NAIC "approximately 95% of auto insurers and 85% of homeowners insurers use credit-based insurance scores in states where it is a legally allowed underwriting or risk classification factor" (NAIC 2012a). Credit scores are, as we demonstrate empirically, strongly associated with future losses and can be incorporated as an underwriting and classification variable to improve underwriting and loss prediction. They contain behavioral information predictive of loss propensity not duplicated by traditional underwriting variables, yet they remain controversial.

We begin the next section with a focus on empirical results concerning credit scoring, a behavioral measure used to predict loss, and we conclude the article with a theoretical discussion of underlying relationship causes. The empirical research was conducted by a university, commissioned by the state's legislature, independent of the insurance industry. Its purpose was to independently investigate the relationship, if any, between credit scores and insured automobile insurance losses using consumer data. We provide actuarial (statistical) results for the relationship of credit scoring and losses and measure the strength of the relationship in both univariate and multivariate statistical settings.[3] This study of credit scoring and losses predicted from empirical data fills an information void and makes a unique contribution to the academic literature.

In Section 3 we explore an explanation of why behavioral rating variables such as credit scoring and occupation succeed in predicting losses from behavioral, socio-psychological, and biological perspectives. We present a broader theoretical perspective encompassing a larger set of human behaviors associated with predicting insured loss. Sensation seeking is posited as an important personality variable in explaining why certain more innovative behavioral variables "work" in loss prediction (going beyond Brockett and Golden 2007). In addition, we discuss a new concept to the risk management literature as a possible further explanation: "self-control" or "self-regulation." Finally, biochemical characteristics may set the stage for these evidenced personality traits and provide a linkage among risk-taking behaviors in different contexts, paving the way for developing new predictor variables based on observable behaviors, of which credit scores are only one such possibility. We discuss several biochemical factors and their potential impacts on risk taking.

In Section 4 we explore practical implications to uncover predictive variables based on behavioral and psychological theories (rather than an outcome of data mining), previously unexplored for insurance classification and pricing. Several examples illustrate this process, including some variables that are already in common usage, other variables that were recently introduced into

[1]Other sources of "newly available" data that might be tapped for predictive modeling concerning behavioral correlates of insured losses include use of social media (such as Facebook posts), data gleaned from consumer shopping behavior that can now be acquired on a large scale on individuals (from store loyalty programs), and location-based tracking and purchasing behavior. Such variables reveal a lot about an individual's personality and actions and may be shown to be connected with actuarial risk assessment in the future. See Rusli (2013) for details on the use of social media for determining credit worthiness, and the Celent Report by Beattie and Fitzgerald (2011) for uses of social media in insurance underwriting. FICO chief executive Will Lansing, looking at voluntarily posted information on social media platforms, says "If you look at how many times a person says 'wasted' in their profile, it has some value in predicting whether they're going to repay their debt" (McLannahan 2015).

[2]In a March 1991 survey conducted by the Gallup Organization and reported in *Best Review* (1991), 1000 individuals were asked to rate their agreement with the statement "People should pay differently rates for car insurance based upon the degree of risk they represent to the insurance company." On a 1–4 scale, with 4 representing strong agreement, the average score was 3.36, indicating strong general agreement.

[3]One contribution of this article is that it is the first time an independent (non–insurance industry–related) statistical analysis has been provided in the peer-reviewed academic literature. These results document the predictive power of credit scoring for automobile insurance.

the ratemaking process (e.g., usage-based insurance), and variables still on the horizon (social media, web search history). The concluding section of the article identifies further research opportunities and the importance of developing theory to help explain the effects of pragmatic applications to solve industry issues for an advancement of the science of risk management.

2. SUMMARIZING CREDIT BEHAVIOR INTO A SCORE FOR INSURANCE CLASSIFICATION AND UNDERWRITING

2.1. Credit Scoring

Indications of financial behavior (such as credit-scoring variables) have been used for decades as an aid in classification and underwriting in commercial lines and life insurance. Although not used until recently in personal lines, there have been indications for more than 65 years that financial history may be related to driving accidents. Tillman and Hobbs (1949) found that drivers with bad credit histories have repeated crashes at a rate six times higher than those with good credit history.

With the advancement of technologies, the use of massive credit files consolidating credit-related behavioral outcomes and financial choice variables at the individual level has become a viable option to use for predicting insurance losses in personal lines of insurance. The use of credit history for predicting insurance losses, however, is still very much an issue of topical importance and regulatory attention with the issue having been addressed by the legislature in 24 states and Puerto Rico in 2013 (NCSL 2014). In spite of this attention, the Property Casualty Insurers Association (PCI 2015) says

> Nearly every state has laws to ensure the fair and accurate use of credit information by insurance companies, but only two states completely prohibit the use of credit-based insurance scores (California and Massachusetts) and two ban its use for specific lines of insurance (Hawaii for auto and Maryland for homeowners). Legislators and regulators in 48 states have studied and debated insurers' use of credit information and have repeatedly reaffirmed that insurers should be allowed to use credit information in underwriting and rating decisions. (p. 2)

Those few states banning the use of credit scoring for rate setting leave insurers searching for other behaviorally based predictor variables.

To produce a "credit score" for an individual for predictive use in insurance, an individual's credit history file is examined, and a subset of variables is selected from a total array of approximately 450 variables collected in the credit record. Different insurance companies may use different subsets of these behavioral and financial variables and develop different statistical credit score models; however, all generally contain from 10–50 credit history variables that are incorporated into statistical models using insurance losses as the dependent variable.

A credit score typically is scaled to be a number between 200 and 1000 (the limits depending on the company that creates it) that reflects the strength of a person's credit history with respect to those variables that have been shown predictive of the individual's future insurance losses. This score can be created either by the credit history vendor or by the insurance company itself. Many insurance companies use their own algorithms to customize credit scores[4] based on their particular market segments.

Table A1 in the Appendix gives a list of the 31 most significant credit file variables found in the university credit-scoring study commissioned by the state's legislature[5] discussed in this article. Although not all companies use the same variable set, some variation on this fundamental set is predominant. In its simplest form, a credit score would be the output of a linear statistical model trained upon a subset of the variables in Table A1 used for predicting losses.

In spite of its usefulness as an underwriting tool, the use of credit scoring in insurance classification is controversial.[6] One reason is that it is not intuitively "obvious" why credit scoring predicts insured losses (unlike driving history to predict automobile insurance losses or building construction type to predict homeowners' insurance losses that have intuitive face validity). Additionally, although studies have consistently found a correlation between credit scores and insurance losses (cf. Monaghan 2000; Miller and Smith 2003; Wu and Guszcza 2003; Texas Department of Insurance 2005; FTC 2007; NAIC 2008; also see a summary of studies by NAIC 2013), these studies have either not been published in the peer-reviewed academic literature or were sponsored or conducted by insurance industry employees, leading some opponents of credit scoring in insurance to raise questions of objectivity.

[4]The variables within the models are selected specifically to predict *insurance losses* (as opposed to banks using credit records to predict *default on loans*). For this reason, the term "insurance score" is often used to designate the numerical predictor of insurance losses. However, the term "credit score" is used generically in the popular press for all univariate predictive functions based on credit history (either for insurance losses or credit worthiness), and hence the term "credit score" will be used here with the understanding that we are specifically referring to the insurance credit score.

[5]Significant variables were determined from the ensemble of 445 credit variables obtainable from an individual's credit history file by running logistic regression (claim/no claim) on all policies, and regression analysis predicting the severity of the claim on the subset of policies with a claim during the year. Thus, this list includes variables useful for predicting either frequency or severity. The data set is discussed subsequently.

[6]Some potential classification variables, such as race, ethnicity, and national origin, are not legal to use when pricing and underwriting insurance in the United States. Other classification variables, such as age, sex, and place of residence, have been subject to challenge or controversy as well. For example, the use of "age" in underwriting automobile insurance is not permitted in Hawaii; the European Union banned the use of "sex" in insurance contracts (cf. Lloyds 2011); and California's Proposition 103 banned the use of residence location and credit scoring in automobile insurance.

Since both individual credit histories and insurance company losses are not publicly available information and are protected by law, it is virtually impossible for an independent researcher to perform an analysis of credit scoring and insurance losses. The state legislature provided the authors temporary access to such credit and insurance loss information under governmental mandate, thus allowing the study presented herein.[7] These data document a strong predictive relationship between credit scores and insured losses for automobiles.

Credit scores may provide information concerning the financial stability and responsibility of the insured that can impact both credit-related behavior and driving behavior, expanding on the observation by Tillman and Hobbs (1949). The rationales for the relationship likely lie in the fundamentals of human biochemistry, psychology, sociology, and behavioral science (as posited by Brockett and Golden 2007 independent of any empirical research).

2.2. Statistical Evidence of the Relationship between Credit Scores and Insurance Losses

The state legislature (Lieutenant Governor) asked nonpartisan and independent research units at the university to investigate whether or not a statistically significant relationship exists between credit score and insurance loss and to report the result of the investigation to the state legislature to inform legislation. To effect this assessment, a random sample of automobile insurance policies, including loss histories, premiums, and other variables, were obtained from several of the largest companies writing automobile insurance coverage in the state. Policy data were matched with the credit history of the named insured on the policy to create a database including both policy information and credit information (including a summary "credit score").

2.2.1. Database Composition

State insurance companies were ranked according to their premiums (dollar amount). Insurers making up the top 70% of the market were asked to provide a random sample of new or renewing automobile policies from the first quarter of 1998. This examination period was chosen for two reasons. First, most of the insurers from whom data were requested were not using credit scoring at that time in rate-making or underwriting decisions (but were thereafter). This meant that premium data collected were not confounded by credit history impacting prices or loss ratios. Second, loss information, including paid losses and reserves for losses, could be obtained for a one-year period with ease since then even slow-paying claims would have a good chance of being included in the database.

Both standard and nonstandard (high-risk) insurance company's subsidiaries data were included, with the number of policies produced by each insurer corresponding to its market share. A total of 175,647 separate policies submitted by insurance companies were transferred to a commercial credit firm providing underwriting information products for carriers writing in the U.S. property and casualty personal lines market.

The commercial firm obtained the credit history for the named insureds on these policies by matching on name, address, or Social Security number.[8] Of the policies transferred to the commercial firm from the insurance companies, 22,284 (12.7%) did not have sufficient or matchable information or credit history to create a credit score.[9] Thus, the final database contained 153,149 policies with credit scores matched and 22,284 "no hit" policies without credit scores. For nonstandard market insurance company data (high-risk auto), the "no-hit" rate was slightly higher (14.4%) than for standard insurance market company data (12.3%), reflecting that higher-risk policyholders are also more likely to have not established a sufficient credit history. Also, those in the nonstandard high-risk auto insurance market had significantly lower average credit scores (657.7) than standard market participants (733.0).

The credit data for each named insured included a total of 445 credit variables along with a summary "credit score" created by the credit score firm. There was a total original set of 153,149 policies with matched credit scores of which 124,240 were from the standard market and 28,909 were from the nonstandard market. The shape of the distribution of 124,240 credit scores was very close to bell shaped with a mean of 733, standard deviation of 104.6, and range of 295–997. The modal credit score was 745. The important point is that there was a wide distribution of credit scores that were reasonably symmetrically distributed.[10]

[7]By contractual agreement with the insurance companies involved, the actual data set had to be destroyed after the legislative report was completed.

[8]The database contained a statistically insignificant (0.0012%) number of anomalous policies that were deleted before analysis. For example, 157 policies were deleted because the stated earned premium was nonpositive, incurred loss was strictly less zero, or there was either no automobile or a negative number of automobiles covered. Also 57 policies with very large loss ratios (e.g., loss ratios in the hundreds of trillions of dollars) were deleted. Biased and nonrepresentative averages would be obtained if these anomalous policies were not deleted.

[9]The company did not go to secondary or tertiary credit vendors to try to increase the "hit" rate. This was partially due to time and financial constraints, but also because a consistent data record for each named insured was needed to perform tests on the data.

[10]Descriptive analysis was also done for the total market altogether as well as the nonstandard market separately, but these results are not presented here to conserve space. Credit scores for the nonstandard market (mean = 657.7) are significantly lower than the credit scores for the standard market (mean = 733.0). Results on this are available from the authors.

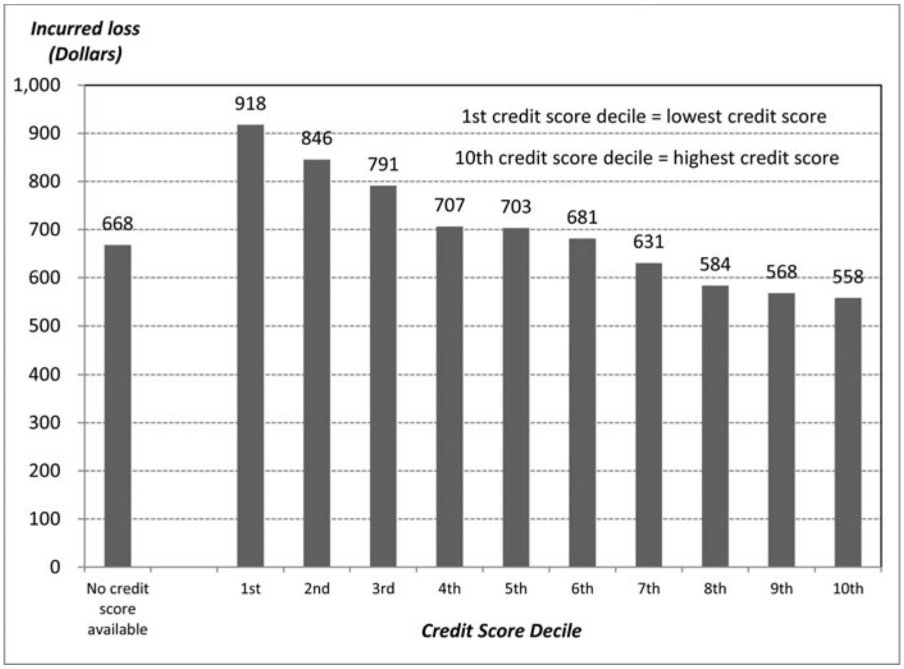

FIGURE 1. Average Incurred Loss for Policies Grouped by Credit Score Deciles.

2.2.2. Statistical Methodology and Findings

The database was sorted by credit score into 10 groups of equal size (deciles).[11] The average loss for policies with a recorded credit score in decile j, $j = 1, 2, \ldots, 10$, was calculated, and the relationship between credit score and losses was examined.[12]

Figure 1 shows the average incurred dollar loss for policies in each decile. Over the entire data set, the average loss per policy was \$695, but for those policies in the lowest (worst) 10% of credit scores, this average loss was \$918, whereas for the highest (best) credit score decile, the average loss per policy was \$558. Thus, the average loss per policy is 64.6% higher in the lowest credit score decile than in the highest credit score decile. Regression analysis confirmed a statistically significant relationship between credit scores and incurred losses ($p < 0.0001$, adjusted $R^2 = 0.92$)[13] using the midpoint of the credit score interval versus the average incurred loss for the interval.

2.2.3. Loss Ratios for Determining the Informational Value in Credit Scores

The relationship between incurred losses and credit scores shown in Figure 1 does not tell the complete story. Credit scoring has been criticized as being redundant of other underwriting variables that have also been shown to predict losses (e.g., age, sex, marital status). In order to investigate this we first ran a regression of credit score with age, with the result shown in Figure 2.

We next examined the relationship between sex and credit score. The mean (standard deviation) credit score for women was 710.9 (105.0), with $n_1 = 64{,}319$. For men the mean credit score (standard deviation) was 722.3 (107.8), with $n_2 = 69{,}866$.[14] This difference in credit scores was significant at $p < 0.0001$.

From Figure 2 and the above analysis we observe that indeed a strong relationship exists for both age and sex with credit score. This raises the question of whether credit scores actually add additional information beyond the traditional variables for predicting losses, or if credit scores simply "work" because they duplicate other predictive variables that we already know work in predicting losses. We explain next how we address this issue further using loss ratios.

Because different insurers have different underwriting guidelines and different risk profiles, the "target" loss ratio that an insurer uses to trade off risk and return for premium setting will differ from insurer to insurer depending on the strategic positioning and the returns needed to accomplish objectives (i.e., insurers writing higher-risk business may strategically require higher rates of

[11]The 22,284 policies with no credit score available were placed in their own bin and analyzed along with the other 10 groups since the legislature also was concerned about those without sufficient credit history.

[12]Analysis was also performed using 5, 10, and 20 bins of credit scores producing similar results. Only the results with 10 bins (deciles) are reported herein to conserve space.

[13]When run separately for the standard market, the results were also statistically significant ($p < 0.0001$, adjusted $R^2 = 0.85$).

[14]The total sample size used in this analysis was smaller because one large insurer did not collect gender data and needed to be excluded from this analysis.

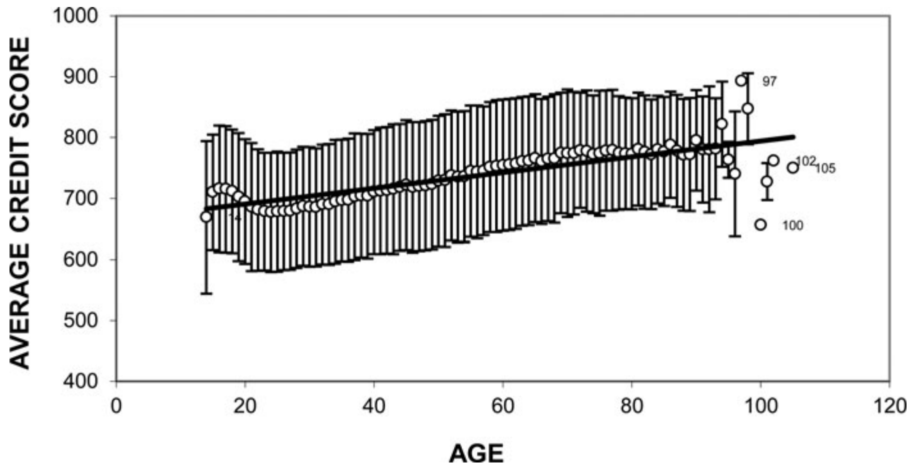

FIGURE 2. Regression of Age on Credit Score (Significant at $p < 0.0001$).

return or profit, possibly resulting in a lower target loss ratio). Simplifying, the insurer sets premiums (using underwriting criteria such as age, type of automobile, coverage, deductible, territory where driven, age and gender of driver, marital status, etc.) so as to accommodate the underwriting characteristics while targeting the insurer's anticipated loss ratio. For the companies examined in this study, the average individual insurance company loss ratio varied from 58% to 74%, with an average of 61% across all companies.

It made sense to measure the average loss ratio for large groups of policies and not for individual policyholders. This is because about 80% of policies show no claim during a given year[15] and, hence, have a loss ratio of zero, but the average loss for a large group of policies will be nonzero. If the underwriting characteristics for a group of policies indicate that an expected loss will exceed that supported by the premium (too high a loss ratio), then the premium is raised for this group of policies. If the underwriting characteristics indicate that an expected loss will be less than that supported by the premium (too low a loss ratio), then the premium can be lowered to increase market share until the expected loss ratio is, on the average for the group being priced, equal to the target loss ratio. For instance, younger drivers tend to have more accidents as a group than older drivers, and their premiums are higher accordingly.

If premiums were not adjusted upward for younger drivers, the loss ratio for the group would be higher than the target ratio. Theoretically, however, when premiums are raised for younger drivers, the loss ratio for younger drivers as a group adjusts downward. This adjustment process continues until the goal target loss ratio for an insurance company is achieved. When this occurs, the loss ratio for younger drivers should approximate the loss ratio for older drivers, since increased losses are already compensated for by increased premiums.

In a world with perfect information, insurers adjust the premium to make the loss ratio constant across all groups, with no group being charged premiums disproportionate to their anticipated losses. Any variation in loss ratio within the class should be due to random error.

It can be argued that loss ratios should be neutral to rating variables; that is, losses themselves depend on rating variables (and their effectiveness). Presumably, when rescaled by premiums, rating variables are accounted for. Therefore, if an analysis of a particular potential underwriting variable shows that it is significantly related to the loss ratio for the insurer, then this variable's influence on losses has *not* already been accounted for by previous adjustments in premiums, and the inclusion of this variable will add value to insurance classification and premium calculation (decrease residual loss risk).[16] We do find strong statistical evidence that credit scoring adds additional information beyond sex and age, at the least, suggesting that credit scoring is more than just a redundant measure already accounted for by other variables.

[15]Of the 153,149 policies with a credit score, 31,014 had a claim while 122,135 had no claim (31,014/153,149 = 0.2025).

[16]Naturally, this is only an approximation. In part this is because the gross premiums available in our database reflect not just rating variables but also exposures and expenses and whether a policy was part of a product bundle. Premiums, as given to us, have these and possibly other sources of bias or supplementation and are not the pure premium that an in-house industry analyst would have available for an insurer-specific pure premium loss ratio calculation. Such deviations from the pure premium add noise to our loss ratio calculation and, hence, make finding statistical significance in the relationship between the loss ratio and credit scores even more difficult to obtain. Thus if we find a significant relationship (which we do), then our conclusion of significance is conservative.

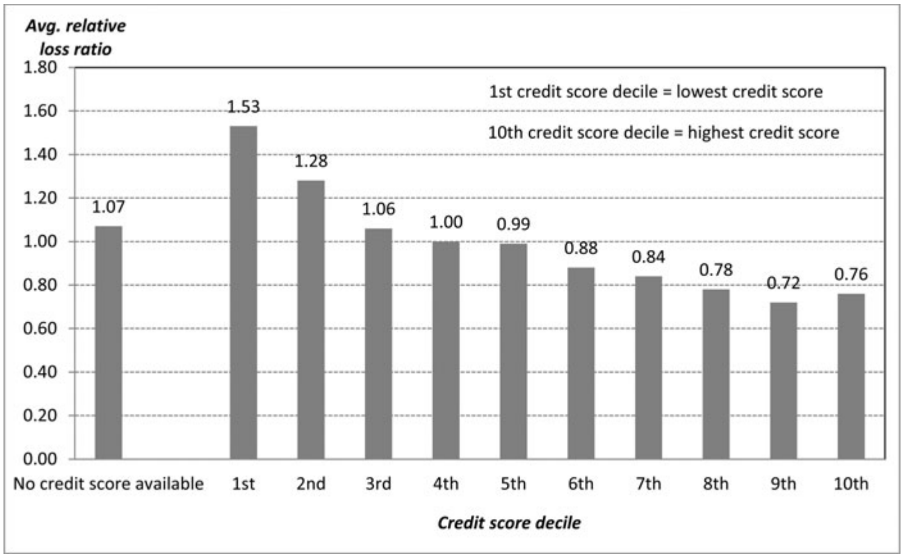

FIGURE 3. Average Relative Loss Ratio by Credit Score for Standard Market Data Set.

2.2.4. Relative Loss Ratios for Comparing across Companies

The loss ratio analysis for assessing the additional value of credit scores works for an individual company but must be modified when aggregating across companies since different insurers have different target markets, different risk profiles, and different premium pricing models, utilize possibly different rating information, and have different required rates of return built into their pricing formulas. The analysis may be misleading when aggregating statewide across insurers. For example, if one insurer or group of insurers (such as pay-by-the-month automobile insurers) had both a lower average credit score for its clientele and a higher average automobile loss ratio than industry as a whole, then an examination of credit scores versus loss ratios might indicate a relationship due to an insurer effect rather than due to an intrinsic relationship between credit score and automobile losses.

A way to mitigate this problem and reduce the insurer effect is to use a *relative* loss ratio for each policy, where the relative loss ratio is defined as the loss ratio for the policy divided by the average loss ratio for the insurer issuing the policy. In this manner, each policy is adjusted to reflect the individual insurer's characteristics. If there were no insurer differences in target loss ratios, this adjustment would not have any effect on the outcome of the statistical analysis. However, if there were company-specific loss ratio differences, using relative loss ratios rather than (absolute) loss ratios addresses this potential source of bias.[17]

In the analysis that follows, we assess the relationship between credit scoring and automobile insurance losses, after accounting for other underwriting variables, by relating the relative loss ratio to the credit score by deciles of credit score aggregation. If an aggregation of policies has been priced to reflect the expected losses for the group, then the average relative loss ratio will be 1.0 (i.e., the average loss ratio for members of the group will be the same as the target loss ratio for the issuing insurer).

Figure 3 graphically illustrates the main statistical finding related to this behavioral credit score variable for the standard market. The average relative loss ratio is shown for each of the 10 credit score deciles and for the group of policies with no associated credit score. We note also that the standard deviations of the relative loss ratios for each of the deciles, including the "no credit score available" category, from left to right are 6.1, 6.9, 6.3, 5.7, 5.1, 5.3, 5.8, 5.0, 4.9, 4.4, and 4.9. Thus, not only does the average relative loss ratio tend to decrease with increasing credit score, but the uncertainty (risk) in predicting the relative loss ratio (standard deviation) also tends to decrease with increasing credit score, increasing the value of credit scoring.

Figure 3 reveals that the three lowest credit score deciles have average relative loss ratios greater than 1.0. The six deciles containing policies with the highest credit scores have average relative loss ratios less than 1.0. For the named insureds in the lowest or worst 10% of the credit scores, the relative loss ratio for their policies averaged 53% higher than expected, whereas for the named insureds within the highest or best 10% of the credit scores, the relative loss ratio averaged 24% lower than expected.

[17]An individual insurer, having much more detailed information available at the policyholder level, including their own pricing formulas, would not have to use this relative loss ratio method when doing this analysis but could instead directly compute the residual loss information left after the standard variable predictive effect has been removed from their data. Without this detailed level of information, and because we were examining the effects of credit scoring on insured losses at the statewide level over multiple insurers with different strategic markets as directed by the state legislature, this relative loss ratio method was used here to uniformly mitigate insurer effect.

The group of policies with no credit history available had an average loss ratio of 1.07, or 7% higher than the average relative loss ratio. The same pattern shown in Figure 3 holds for the total market data and the nonstandard market data.

A similarly clear relationship between binned credit scores and average relative loss ratios was obtained when breaking credit scores into binned 5 or 20 credit score intervals containing equal numbers of policies. An additional regression analysis of the relative loss ratio with the credit score variable for the total (unbinned) set of individual policies was also highly significant ($p < 0.0001$).[18] Thus, the pattern observed in Figure 1 using incurred losses versus credit scores does not go away when using relative loss ratio instead of incurred losses. Residual information about losses is still contained in credit scores after incorporating the standard rating variables via the premium charged.[19]

Breaking loss into frequency of loss and severity of loss, two additional analyses were performed. First, a logistic regression analysis was conducted to determine whether the existence of a positive claim (incurred loss greater than zero) was significantly related to credit score. Each policy was classified as to whether a positive loss or no loss was experienced. This classification variable was then related to credit score using logistic regression (see Table A2 in the Appendix). A statistically significant relationship was found between credit score and the likelihood of a positive claim being filed ($p < 0.0001$).

Going beyond statistical significance, substantive significance is highly relevant and important. One measure of substantive importance is likelihood of filing a claim. This was investigated with a logistic regression using incurred loss or not versus credit score. As shown in Appendix Table A2 the resultant score (log odds ratio) was -0.00053. This result suggests credit scoring is of considerable substantial significance, as shown by example: Consider two individuals who are alike except that Person B has a credit score 100 points higher than Person A, so when comparing the odds of having a positive claim filed, we have $\exp(-0.00053 \times 100) = 0.94838$, illustrating person B's odds of filing a claim are 5.2% lower than Person A.

Turning to severity (as opposed to frequency), a subsequent analysis performed a regression of the relative loss ratio on both the credit score and age using only those policies having a positive claim. This analysis investigated the size of the claim as related to credit score and age. Age was added to the regression because of the potential for collinearity between age and credit score observable in Figure 2. Collinearity might bias the inference about the significance of credit scoring on the relative loss ratio if the credit score were simply proxying for age (which we know to be important) in the regression. Results of this regression are given in Table A3 in the Appendix. Again, for this regression the credit score variable was significant ($p < 0.0001$), indicating that the size of the loss for filed claims is also significantly related to credit score. Additionally, the age variable was significant, and the model itself was significant alleviating concerns about collinearity.

This analysis also revealed that credit scores were of substantive significance for size of claim, if one is filed. As an illustration, using the Table A3 regression coefficients, suppose two persons are insured by the same company, both aged 60 and both of whom file a claim. Given they both have losses, the ratio of the predicted relative loss ratio for Person A with a 650 credit score to the predicted relative loss ratio for Person B with a 750 credit score is 1.163. Since both are insured by the same company (same denominator target loss ratio for both) this difference in relative loss ratio must be because Person A is expected to have losses 16.3% higher than Person B. This indicates that use of credit scores provides information to the company of substantive and practical significance.

In summary, this research into the relationship between credit scores and insurance losses finds the following: (1) There is a strong relationship between credit scores and insured losses, (2) although there is overlap between credit scores and traditional rating variables, credit scoring contains information that goes beyond and is not duplicative of traditional rating variables, and (3) credit scoring is statistically and substantively significant to practice, as it is linked to both filing a claim or not and to the size of the claim were it to be filed. Residual information is captured by the credit score that is statistically and substantively significant beyond the traditional underwriting variables.[20]

[18]Note that the regression analysis based on the total unbinned dataset has about 80% of the values for the dependent variable equal to zero (since about 80% of policies show no incurred loss). One referee correctly commented to us that many property and casualty actuaries would now use a Tweedie-dependent variable in a GLM regression with a log link function to analyze data with this structure (cf. Meyers 2009, who has a link to R code, and Smyth and Jørgensen 2002). Our focus here, however, was not just to model the claims data, but in addition we needed to understandably testify to the state legislature in simple terms (graphically if possible) the nature of the relationship between credit scores and insured losses and whether credit scores added any new information about loss prediction beyond that provided by rating variables already utilized. We were able to draw conclusions supported by binned data regressions and the simpler to explain ordinary regression. We did not do a Tweetie regression but instead focused on the regressions using binned credit score data.

[19]One might expect the adjusted explained variance to be higher for the regression of credit score on incurred losses than for credit score on relative loss ratio since after incorporating the premium information (and, hence, the standard rating variables) less uncertainty is left for credit scoring to explain in the relative loss ratio analysis. This expected relationship held true for five and 20 binned credit score data and for male and female policyholders run separately. Thus, there is still substantive information about losses captured by credit scores after the traditional variables have been taken into account.

[20]We needed to use 1998 data so as to have a data set not confounded already by the use of credit scores in both underwriting and rating decisions. However, we recognize that the insurance world was different in 1998 and insurers are now using much more refined measurements of location, the vehicle, usage-based insurance, and so forth. As with any study in a dynamic industry, further research is warranted and should investigate credit scoring relative to new rating variables.

Although the goal of our empirical inquiry was expectation neutral (Is credit score statistically related to driving losses *or not*?), this issue has never been researched in a nonproprietary situation that allowed for peer-reviewed publication. These results are important for public policy makers, the public, and insurers, and they may help guide application-driven theory development related to new and innovative predictive variables (cf. Golden et al. 2012). We now examine theoretical explanations of why credit scoring works.

3. OBTAINING NEW UNDERWRITING VARIABLES PREDICTIVE OF INSURANCE LOSSES: SENSATION/NOVELTY SEEKING AND SELF-CONTROL

By understanding the foundations of the behavioral connections between seemingly disparate areas of credit behavior and driving performance it is possible to uncover other useful potential predictive variables. The identification of strong correlates of credit scores opens up new avenues to allow the actuary to improve loss prediction. Zuckerman (1990) provides an overview of the psychophysiology of sensation seeking.

Risk taking is related to loss propensity and is inherently psychological and behavioral. For example, Caspi et al. (1997) show that personality differences at young ages can predict risk-taking behavior later in life. One important psychological aspect of risk-taking behavior identified in both economic and psychological/physical risk-taking literatures is "sensation seeking" or "novelty seeking."[21] Sensation seeking is related to many aspects of general risk-taking behavior, and sensation-seeking personality types exhibit an arousal need in many of life's endeavors, including shopping, high-risk sports, high-risk sex, driving, active securities trading, and financial risk taking (for a detailed discussion on sensation seeking and risky behavior in general see Zuckerman 2007).

The dimension of "responsibility-irresponsibility" exhibits itself in several aspects of behavior related to increasing the risk of having an accident, including reckless or fast driving, running red lights, and lax vehicle maintenance (cf. Bair et al. 2012), distracted driving, inattention to details of the driving environment, and others, that may also relate to sensation seeking. Sensation/novelty-seeking personality has been posited to be fundamentally related to both increased automobile insured losses and to risky financial credit in Brockett and Golden (2007). This article goes beyond Brockett and Golden's treatment by discussing sensation seeking and risk taking in more detail, as well as presenting other risk-taking–related personality types not in the actuarial literature and discusses roles of biochemical influences.

3.1. Sensation Seeking/Novelty Seeking

Sensation seeking is defined by Zuckerman (1979, p. 10) as "the need for varied, novel, and complex sensations and experience and the willingness to take physical and social risks for the sake of such experience." It can be assessed with a psychological inventory questionnaire (Zuckerman Sensation Seeking Scale-V; cf. Zuckerman 1979). Zuckerman's "sensation seeking" trait is closely related to Cloninger's (1987) "novelty seeking." In fact, the two terms are often used interchangeably. Both Zuckerman and Cloninger regard sensation/novelty seeking as a fundamental dimension of temperament with strong relationships to antisocial behavior (cf. Zuckerman and Cloninger 1996).[22] Theoretically, sensation seeking links to "responsibility-irresponsibility."

3.1.1. Correlates of Sensation Seeking: Self-Regulation and Control

Another important personality trait related to risk-taking activities is "self-control," which has deeply rooted implications for insurance losses. Individual differences in ability to self-regulate (self-regulatory competence/control) may further explain engagement in risky activities. Self-regulation/control is also related to sensation seeking. The psychology literature has studied the interaction between self-control and the sensation-seeking personality traits and found that positive self-control can mitigate sensation seeking in various scenarios (Steinberg et al. 2008).

Empirical evidences suggest that poor self-regulatory competence leads to greater endorsement of and participation in risky activities (Magar et al. 2008). For example, self-regulation has been shown to be negatively associated with risky sexual behavior, substance use, and delinquency (Raffaelli and Crockett 2003; Wooda et al. 1993). In one popular model, self-control is considered as a "capacity to override natural and automatic tendencies, desires, or behaviors" to pursue goals and to follow socially prescribed norms and rules (Bauer and Baumeister 2011, p. 65).

[21]See Brockett and Golden (2007) for a brief discussion of sensation seeking and automobile driving behavior and sensation seeking and financial risk taking. The sensation-seeking behavior and driving behavior are so strongly linked that Grinblatt and Keloharju (2009) use the number of final convictions for speeding as a proxy for the sensation-seeking personality type.

[22]Other variables, such as age, sex, and marital status, have also been related to sensation seeking and "responsibility" (see Brockett and Golden 2007). These variables are already used in insurance rate making and have been accepted without asking why they work. There are some stereotypical explanations (e.g., marriage may indicate stability, as does age, education, etc.).

The so-called "self-control" problem can arise from the "present-bias" or time-inconsistent preference of individuals: When evaluating trade-offs between two future events, as the dates of the events become closer, individuals appear to assign an unreasonably higher relative weight to the event that takes place earlier (O'Donoghue and Rabin 1999).

Present bias captures individuals' common tendency to yield to short-run impulses (e.g., running a red light) at the cost of the long-run outcomes (tickets with further delays, accidents, death), confronting people with the self-control problem. It undermines one's ability to implement long-run plans involving immediate costs with delayed benefits—typical scenarios of precautionary activities being pervasive in the insurance context. For example, individuals having the self-control to follow vehicle maintenance schedules have lower accidents/insurance claims (Bair et al. 2012). Impulsivity can lead to accidents and self-control mitigates.

Previous research has found that individuals differ in their degree of self-control, as well as the awareness of the problem (cf. Voh and Baumeister 2011; Wong 2008). Self-control can also occur in a nonconsciousness way (Papies and Aarts 2011) and can be measured via a scale, such as the "Self-Regulation Questionnaire" (Brown et al. 1999). Individuals' self-control problems and their awareness can have profound impact on insurance losses, insurance market dynamics, and public policy effectiveness (Ai et al. 2013).

3.1.2. Sensation Seeking and Insurance

> Sensation seeking is related to risk taking in all kinds of risk areas. In fact, the sensation seeking trait may be the common factor that accounts for the relationships among different kinds of risk taking. (Zuckerman 2007, p. 65)

From an insurance perspective, manifestation of sensation-seeking personality type can include reckless driving and excessive consumption of alcohol (Zuckerman 2007). Sensation seekers also have a higher intension to speed (Cestac et al. 2011), have more traffic citations (Lonczaka et al. 2007), and are involved in more automobile crashes (Dunlop and Romer 2010). Brockett and Golden (2007) showed that sensation seeking was a fundamental correlate of both risk taking in driving and in financial decision making, thus providing an up-to-then missing connection between credit scores and observable losses to the insurer. Consequently they provide explanations as to why the sensation seeking trait (and its proxy variable "credit score") is statistically (and predictably) related to insured losses. As the results of the statistical analysis of credit scores and insured losses showed in the first sections of this article, "personal responsibility," as captured by the credit score, is not collinear with traditional underwriting variables used by insurers and, hence, provides a new and independently useful predictor of risk.

3.1.3. Theoretical Psychological Characterizations of Sensation Seekers

In other disciplines, there has been extensive research into the personality type exhibited by the sensation seeker/novelty seeker (see Roberti 2004). As the name implies, sensation seekers prefer increased stimulation levels. Individuals with a high optimum stimulation level (OSL) are better able to respond to ambiguities in their environment. They are more likely to seek variety and change, and they are more open-minded than those with low OSL (Raju 1980).

Horvath and Zuckerman (1993) demonstrated that high-sensation seekers may show an increased reduction of perceived risk and increased assurance in their ability to avoid negative outcomes. They suggest that risk appraisal is a consequence of risky behavior, which can be strongly predicted by perceived peer behavior. That is, sensation seekers will engage in the risky behavior without assessing the risk ahead of time, and sensation seekers are more likely to participate if their friends do. Risk taking reinforces further risk taking for sensation seekers.[23]

Higher sensation seeking is associated with frequent involvement in risky behavior, which, in turn, is associated with higher perceived benefits of risk taking and perceived peer participation in risky behaviors. Separate studies conducted by Siegel and Cousins (1994), Rolison and Scherman (2003), and Rosenbloom (2003) all supported this sequence.

Further, Rosenbloom (2003) found that the higher the individual's level of sensation seeking, the lower the individual estimates the risk involved in the risky activity.[24] High-sensation seekers typically overestimate their skills and abilities, and the more an activity is evaluated as dangerous, the more they will be attracted to it. This attraction to danger is connected to the degree of control they perceive they have (and prior "survival" success).

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[23]This is more than the simple Bayesian analysis of risk: The unknown risk being successively updated by successes and failures, it can be a known risk with known consequences that are ignored: "The bullet missed me this time, it will continue to do so (irrespective of probability) in the future." Also, peer input is important here.

[24]The economic concept of risk aversion based on a utility theoretic formulation for the individual is often used to explain risky choice since the lower risk averter will engage in higher-risk activities. This conceptualization (risk aversion) does not really address the problem of insurance loss prediction, however, since it only gives a name to a phenomenon without giving measurement. The behavioral traits of sensation seeking and "self-control" or "self-regulation" have observable correlates (and measures) that can be used in insurance underwriting. Moreover, individual utility-based risk aversion does not address the peer behavior findings of Horvath and Zuckerman (1993) or the intrinsic misapprehension of risk in sensation seekers as detailed in Rosenbloom (2003). It also does not explain the attraction to danger without corresponding utility payoff.

The individual's propensity to participate in risky behaviors and perception of the risk involved mediates how they frame the problem and view the outcomes of prior risky behaviors (Sitkin and Weingart 1995). The level of deliberation prior to participating in an activity influences participation in risky activities whether or not the behavior has potential for either negative or positive outcomes. Low levels of deliberation (impulsivity) place the individual at risk for participating in activities with a greater chance of negative outcomes. Higher levels of deliberation are associated with participating in a risky activity successfully (Fischer and Smith 2004). Thus, deliberation is a moderator of impulsively.

3.1.4. Age and Sensation Seeking

Sensation seeking, which is highest in adolescence, is part of the developmental basis of reckless behavior in adolescence as seen in driving, sexual behavior, drug use, and minor criminal acts (see also the biological section of this article). Although strongly associated with teen years, participation in risky behaviors does not end for everyone as they age. Chronological age does not always correspond to risk-taking propensity (behavioral) age, and, across one's chronological aging, risk taking may be expressed in different ways (including "age-appropriate" ones). In a study of skydivers, Celsi et al. (1993) determined that initial and continued participation in high-risk activities was explained by an evolution of motives leading to risk acculturation that, in turn, led to normalization of the risk. Thus, age alone does not explain risk taking (e.g., mountain climbing seniors). Hence, identifying risk-taking individuals by means other than age can be productive for insurance loss prediction.

3.1.5. Sensation Seekers' Hobbies, Interests, and Activities

Relevant to uncovering new (observable) underwriting variables, sensation seeking also relates to educational achievement, occupational choice and hobbies, as well as risk perception and risk appraisal (and is connected to demographic characteristics). These connections can support the now emerging (but controversial) use of these variables by insurers (such as GEICO) in automobile insurance underwriting. In Roberti's (2004) review he found that sensation seekers were more likely to make job choices that were more adventurous and provided novel, stimulating demands, and sensation seekers change employment more often. Sensation seeking is also related to entrepreneurship (Nicolaou and Shane 2008). Thus, the current use of occupation as an underwriting variable is supported by the sensation-seeking literature and sensation seeking's well-established connection to insured losses.

Other habits of sensation seekers can include licit and illicit drug use, risky sexual encounters, criminal behavior, an increased tendency to participate in high-impact sports, team sports, and risky activities, such as rock climbing, skydiving, or scuba diving (Zuckerman 2007). Sensation seekers do not perceive their environment as threatening, they rate their personal risk as low, and they self-report that they are likely to engage in risky behaviors. These psycho-behavioral characteristics of risk taking by sensation seekers are also related to impulsivity and aggression, with men engaging in more overall risky behavior than women (Harris et al. 2006). There also appears to be a genetic correlation between sensation seeking and impulsivity (Hur and Buchard 1997.

3.1.6. Financial Risk Taking

Sensation seeking has been shown to be fundamental in explaining risk taking in everyday financial decision making (Wong and Carducci 1991). High-sensation seekers also exhibit more risk-taking behavior in financial matters, including more frequent equity trading than low-sensation seekers (Grinblatt and Keloharju 2009). Sjöberg and Engelberg (2009) found that the students of finance had a positive attitude to economic risk-taking and gambling behavior and have a high level of sensation seeking. Harlow and Brown (1990a, 1990b) drew students' blood and measured biochemical markers (e.g., MAO level), finding a relationship between biochemistry, sensation seeking, and financial risk taking. Raylu and Ori (2002) reviewed the relationship that exists between sensation seeking and gambling activities.

Figure 4 summarizes risk-taking characteristics of sensation-seeking personality persons and the related effects as developed from the literature.

3.2. Biochemical Influences on Sensation Seeking

We next provide a plausible biological basis for the sensation-seeking personality supporting the argument that sensation seeking will be a trait common across many life situations, including financial-related variables (like credit scores), occupational choices, education attainment levels, and driving behavior (such as those exhibited by insurance losses) and those behavior variables monitored in newly created usage-based insurance products. There is no single biological factor that influences sensation seeking behavior; rather, it is the combination and interaction of multiple factors. For example, high levels of testosterone, norepinephrine, prolactin, and dopamine and low levels of MAO are found in sensation seekers. Connections between risk taking, sensation seeking, and neuropsychological characteristics are discussed in Llewellyn (2008). The next set of subsections address some of the

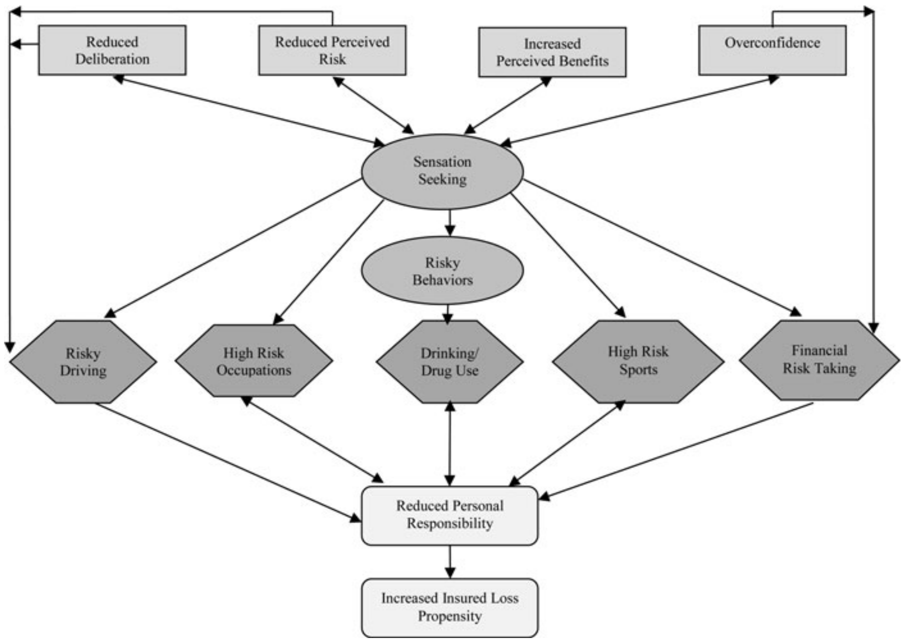

FIGURE 4. Psychobehavioral Profile of Sensation Seeking/Novelty Seeking.

most important relationships between biochemical and psychobehavioral traits as related to sensation seeking and risky behavior potentially impacting insurance losses.[25]

3.2.1. Testosterone

High levels of testosterone, a male hormone, are correlated with many aspects of sensation seeking. It is well established that high testosterone levels in men influence their behavior (hence, some age correlates of risk taking for young male drivers). Also, high levels of testosterone are correlated with many aspects of sensation seeking. Gerra et al. (1999) found that testosterone is positively correlated with novelty seeking, sensation-seeking, and aggression and that testosterone decreases with age. Dabbs and Morris (1990) showed that antisocial behaviors, such as delinquency, substance use/abuse, and multiple sexual partners, are associated with testosterone levels. Interestingly, socioeconomic status (SES) provides a moderating variable in this relationship. In other words, a weaker testosterone-behavior relationship was found among high SES subjects.

Additionally testosterone level, which is genetically determined, affects behaviors that are related to occupational achievement. In addition to higher antisocial behaviors, men with higher levels of testosterone reveal lower intellectual ability and lower educational achievement during their youth with lower-status adult employment (Dabbs 1992). Marriage and employment have been found to mediate antisocial behaviors (Booth et al. 1999).[26]

3.2.2. Dopamine and Serotonin

Dopamine, a genetically transmitted neural chemical, stimulates exploration and promotes positive arousal and rewards associated with stimulation (Jonah 1997). The psychobiological model developed by Depue and Collins (1999) explains the effects of differences in dopamine transmission on the personality trait of extraversion, which encompasses a cluster of traits known variously as sensation seeking, risk taking, novelty seeking, or boredom susceptibility. Benjamin et al. (1996) studied mostly male siblings and found that the dopamine D4 receptor gene is associated with novelty seeking, and this association is the result of genetic transmission.

Conversely, serotonin is negatively related to risk taking. It mediates sensation seeking (Netter et al. 1996) by modulating dopamine facilitated behaviors (Depue and Collins 1999). Zuckerman and Kuhlman (2000, p. 1021) aptly described these two biochemicals in this way: "If serotonin is the brakes, dopamine is the accelerator in the drive to risky behavior."

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[25]Many of the biochemical levels discussed are genetically influenced (as in various twin studies, such as those described in Fulker et al. 1980).

[26]Not every study comes to the same conclusion. Rosenblitt et al. (2001) found that male testosterone was not associated with the total Sensation Seeking Scale-V score; however, male cortisol levels were negatively associated with sensation-seeking behaviors. Their findings suggest that sensation-seeking behaviors are associated with hormones rather than testosterone, and the "rush" of sensation seeking behaviors may affect cortisol levels. Aluja and Torrubia (2004) found a positive relationship between testosterone and sensation seeking only when using correlations and extreme group comparisons.

3.2.3. Norepinephrine

Norepinephrine increases the sensation-seeking individual's response to stimuli (Jonah 1997). Its level decreases with age and is correlated with novelty seeking, sensation seeking, and aggression (Gerra et al. 1999). Antelman and Caggiula (1977) determined that the interaction between norepinephrine and dopamine in stress-related stimuli affects many behaviors, including aggression. For example, financially induced stress (e.g., bankruptcy, default, or late payment activity) can produce consequences affecting driving and other risk-taking behavior through a biological mechanism.

3.2.4. Cortisol

Cortisol is a hormone related to stress. Roberti (2004) examined biological characteristics related to sensation seeking and noted that humans have lower levels of cortisol in response to stress. The lower level of cortisol in high-sensation seekers is possible evidence of increased activity in dopamine systems and decreased activity in serotonergic systems. Low levels of cerebrospinal fluid cortisol found in high sensation seekers provide further evidence that cortisol levels are related to sensation seeking. Gerra et al. (1999) found a positive correlation between aggression and cortisol but not between novelty seeking and cortisol.

3.2.5. Prolactin

Gerra et al. (1999) found that prolactin is positively correlated with novelty seeking and sensation seeking. Hansenne and Ansseau (1999) demonstrated a positive correlation between harm avoidance and prolactin but found no correlation between prolactin and novelty seeking, reward dependence, and age.

3.2.6. Monoamine Oxidase (MAO)

Biologically speaking, low levels of monoamine oxidase (MAO), an enzyme regulating serotonin and cortisol, are found in high sensation seekers. MAO is highly stable and is evident in individuals from their earliest ages. Zuckerman (1996) develops his "psychobiological model for impulsive unsocialized sensation seeking" (Zuckerman, 1996, p. 125) where he describes MAO as a biochemical marker related to childhood externalizing behaviors and impulsivity in adults. Infants as young as three days old can show behavioral signs of high or low MAO levels. Interestingly, MAO levels are also low in adolescents and higher in women than in men (consistent with empirical automobile insurance risk assessments that risks are higher in adolescents and lower in women).

Depue and Collins (1999) found that changes in MAO activity are associated with increased probability of impulsivity and sensation seeking. Fulker et al. (1980) determined that low levels of MAO and high levels of norepinephrine increase sensation seeking and create a greater capacity for prolonged periods of high stimulation. In a large-scale review of literature on risky driving and sensation seeking, Jonah (1997) concluded that MAO regulates the production of dopamine and norepinephrine by keeping them in balance.

Two widely used tools for measuring the psychological profile of sensation seeking (Zuckerman's *Sensation Seeking Scale-V* and Cloninger's *Temperament Personality Questionnaire*) show negative correlations with MAO, suggesting a biological basis with high heritability for this personality dimension (Zuckerman and Cloninger 1996). MAO levels are related to educational achievement and occupation, as well as to financial decision making, risk taking, age, sex, and other "traditional" underwriting factors. This connection may partially explain GEICO's desire to use occupation and education level (see New Jersey Department of Banking and Insurance 2008) for risk determination. MAO-A may regulate serotonin and norepinephrine, while MAO-B may be tied to the regulation of dopamine. Thus, MAO-A levels provide a link to sensation-seeking and risk-taking behavior such that one variable (occupation, education, credit score) can proxy for another (insured losses from risk taking, impulsivity, or lack of control).

These biological mechanisms underpin the sensation-seeking personality type, justifying it as a trait in humans. Moreover, they are found to drive risk-taking behavior across multiple life domains, as seen in sensation seekers, providing a linkage among them. These are clearly sensation-seeking correlates to be explored further for developing new insurance classifications.

4. OPPORTUNITIES FOR IDENTIFYING NEW BEHAVIORAL PREDICTOR VARIABLES

Insurers are constantly seeking observable covariates of the individual that they can predicatively relate to insurance risk. Steinberg et al. (2008) show that sensation seeking is related to both age and impulsivity, and, hence, behaviors surrounding sensation-seeking personality types can provide a source of such observable related covariates. Correlates such as age, education, sex, and marital status are readily observable and relate to loss frequency (and sensation seeking), but other variables such as credit scores, financial trading volume, occupation choices, education attainment, and participation in high-risk sports are less readily observed, and you need to know where to look to discover such underwriting variables (e.g., New Jersey Department of Banking and Insurance 2008).

Sensation seeking has been shown to be strongly associated with many other currently used classification variables such as age, sex, marital status, education, number of traffic citations, previous accidents, and income. Many of these variables have been identified and employed in practice for a long time because of observed correlations without asking why these variables "work" for loss prediction. For example, it may not be clear on the surface why sex or age should matter in assessing driving losses, yet the statistical evidence is clear that they do. Sensation seeking, self-control theory, and psychosocial and biochemical factors provide an explication of why these traditional predictors work, just as they do for why credit scores link to insurance losses.

In states where credit scoring is banned, other variables related to sensation seeking could be incorporated into automotive underwriting, such as participation in high-risk sports or hobbies, private aviation, academic performance, occupation choice and stability, financial trading activities, income level, and social history including drug or alcohol use in the past. The use of these types of information is viable since such information is available and already currently used in other lines of insurance (such as life and health; cf. Black and Skipper 2000). In these other lines of insurance, such predictor variables have an apparent connection to the risk; however, as we have seen, they also are connected with sensation seeking and are candidates for use in personal lines such as automobile and homeowners insurance.

Personal history is used in life insurance and health insurance and is an especially attractive potential variable to use due to the multiple correlates of sensation-seeking behavior across various domains of an individual's lifestyle. Personal history may be very relevant for automobile insurance underwriting as well, given its link to sensation seeking. For example, foreign travel is used in underwriting life and health insurance, but Lepp and Gibson (2008) have also found that those individuals higher in sensation seeking were more likely to travel internationally and to have traveled to riskier destinations and chose explorer and drifter roles.

As the use of social media becomes ubiquitous, data and data-mining techniques useful for exploiting these newly identified underwriting opportunities are abundantly available. Social media is a very good vehicle for determining the extent to which an individual loads on the sensation-seeking trait since individuals post their activities, hobbies, habits, lifestyle characteristics (including risk taking), and travel, as well as other personal information that the literature has shown to be highly correlated with sensation seeking. According to a 2011 Celent report (Beattie and Fitzgerald 2011, p. 15), "Just as insurers recognize a link between credit health and risk in auto insurance, social data may offer similar insights for insurers who set out to crack the data." They predicted that social media data use will be incorporated into core underwriting activities in the future. Data mining of social networks and social media are already used in certain areas of insurance. For example, insurers data mine social media to discover fraud in workers' compensation (NAIC 2012b) and for subrogation negotiations (Kenealy 2013).

Technological advancements allow for the development of credit scoring in real-time underwriting and focus on driver behavior. Advancements in the ability to data mine very large data sets is leading to the development of additional behavioral underwriting variables. Illustrative of these are "Pay-as-You-Drive" plans that track mileage driven and to where (Ferreira and Minikel 2010). This is promoted as a consumer cost benefit opportunity (and provides relevant driving information to the firm). Indeed, a range of usage-based products using telematics devices (cf. Kremslehner and Muermann 2013) has been introduced (e.g., State Farm's "Drive Safe and Save" program and Progressive's "Snapshot Discount" program). As a *Wall Street Journal* article states, "The companies say that basing premiums on how and how much one drives will allow them to accurately target discounts at careful drivers, and charges more spirited customers an appropriately higher amount" (White 2012).

5. CONCLUSIONS

The evidence presented in this empirical study of credit scoring and automobile insurance losses is clear: Credit scores predict insurance losses in automobile insurance at a statistically significant level. In fact, they are among the most useful predictor variables available to underwrite and price automobile (and homeowners) insurance. Rationales as to why these predictors work are socio-psychological, behavioral, and biological/biochemical.

There are important biological aspects of risk-taking behavior not elucidated in Brockett and Golden (2007), giving a more complete underlying rationale for why risk-taking behavior transcends a particular characteristic (such as credit score). These include an array of hormones and other biochemical characteristics, such as MAO, dopamine, testosterone, norepinephrine, cortisol, serotonin, and prolactin. Depending on the directional quantities, these biochemicals can impede (e.g., serotonin) or stimulate risk-taking behavior (e.g., testosterone).

We note that one consideration constantly raised in the debate over the acceptability of usage of credit scores in insurance is that of individual controllability and accountability. To what extent must predictor variables be under the control of the individual before they are permissible to use in rating? Is it "unfair" to charge larger premiums for something outside the control of the individual? These considerations apply also to traditional rating variables such as sex, age, and to a lesser extent territory and marital status.

If we accept that sensation seeking has a connection to insurance losses, and that sensation seeking has associated biochemical process, does this raise the controllability and accountability argument that credit scores should not be used because poor drivers cannot change their driving behaviors because they cannot control their underlying bio-chemical process? This is certainly an interesting area for discussion and for future research. Failure to charge individuals for the level of risk they bring to the insurer creates a cross-subsidization of higher-risk individuals by lower-risk individuals and creates an adverse economic incentive. Economists would argue we will overconsume underpriced goods, and in the case of subsidized risk-taking activities (whether biologically or consciously induced) one would expect the exhibited level of risk in society to increase should such subsidization be mandated.

Further, there is evidence that marriage and employment can mediate antisocial behaviors associated with sensation-seeking behavior (Booth et al. 1999). Also, Donohew and Bardo (n.d.) have discussed prevention programs for excessive risk taking in sensation-seeking adolescents. Additional research into how to control the negative outcomes associated with sensation seeking (such as increased insurance losses) while allowing for the positive aspects is needed.

Credit scores contain much more information about an individual's behavior than simply their ability to pay debt in a timely manner. For example, Dokko et al. (2015) show that self-reported measures of trustworthiness and survey-based, subjective measures of trustworthiness are highly correlated with financial credit scores. Similarly, occupational choices and educational attainment (as used by GEICO in underwriting automobile insurance) provide more information than just delineating a vocational selection or a commitment to knowledge acquisition. Credit scores, occupation, educational attainment, and other nontraditional underwriting variables tap a fundamental aspect of the personality, with similar underlying psychosocial and biological attributes that can be useful for multiple applications where responsibility is a critical component.

We suggest several other personality variables that may correlate with sensation seeking, may help explain it, and may also be of independent usefulness to predict loss behavior. A person's competency in self-regulation may be prime among these. For example, if a person cannot self-regulate their behavior, they would not be able to deliberate prior to risky behavior (hence, impulsiveness), they may lack self-control (again, leading to risk taking even without knowledge of such), and they may have tendencies toward an appearance of irresponsibility. These are behavioral (observed actions) and personality traits, as well as individual characteristics that are also influenced by biochemistry (DNA at the base of it). Much remains for insurers and public policy makers to explore in the area of risk taking and its correlates (including occupation, education, and hobbies).

In the spirit of developing a more theoretical approach to understanding credit scoring and other potential insurance loss predictors, we call for an Application Driven Theory approach (Golden et al. 2012). The concept of Application Driven Theory suggests that we develop theory from important pragmatic applications and industry issues. We call for future research to further explore and develop an underlying theory of risk taking and financial behavior related to risk management practice.

We can observe the empirical application/applied success of various predictor variables commonly used, but we do not necessarily understand why they predict losses. In understanding and beginning to form theories around why a particular variable predicts, researchers can help insurers reduce losses, consumers gain from lower prices and better risk pooling, and society benefit through more informed public policy actions. Again, more theoretical development is needed for "successful" loss predictor variables.

In addition, the advent of social media information allows insurers (and public policy makers) to gather more and better publically available information about consumers. Usage-based telematic variables, social media information, personal history, and high-risk hobbies or sports have been demonstrated to correlate with insurance losses, and we need a better understanding of why these predictors work. Sensation seeking, self-control/regulation, and other socio-psychological traits point a direction for uncovering new predictors and, at the same time, may provide a vehicle for better regulatory and consumer acceptance for the use of predictors, since they will no longer be a "black box."

As Tillman and Hobbs noted in 1949, "a man drives as he lives" (p. 329). Understanding personal history and consumer lifestyle choices may be the key to advancing underwriting variable selection in this dynamic world.

REFERENCES

Ai, J., L. Zhao, and W. Zhu. 2013. Equilibrium and Welfare in Insurance Markets with Time-Inconsistent Consumers. *American Risk and Insurance Association Annual Meeting.*

Aluja, A., and R. Torrubia. 2004. Hostility-Aggressiveness, Sensation Seeking, and Sex Hormones in Men: Re-exploring Their Relationship. *Neuropsychobiology* 50: 102–107.

Antelman, S. M., and A. R. Caggiula. 1977. Norepinephrine-Dopamine Interactions and Behavior. *Science* 195(4279): 646–653.

Bair, S.-T., R. J. Huang, and K. C. Wang. 2012. Can Vehicle Maintenance Records Predict Automobile Accident? *Journal of Risk and Insurance* 79: 567–584.

Bauer, I., and R. Baumeister. 2011. Self-regulatory Strength. In *Handbook of Self-regulation: Research, Theory, and Applications*, 2nd ed., ed. K. Voh and R. Baumeister, Ch. 4, pp. 64–82. New York: Guilford Press.

Beattie, C., and M. Fitzgerald. 2011. Using Social Data in Claims and Underwriting. Celent Industry Trends Report. http://www.celent.com/reports/using-social-data-claims-and-underwriting.

Benjamin, J., Lin Li, C. Patterson, B. D. Greenberg, D. L. Murphy, and D. H. Hamer. 1996. Population and Familial Association between the D4 Dopamine Receptor Gene and Measures of Novelty Seeking. *Nature Genetics* 12: 81–84.

Best Review. 1991. Gallup Poll Risk. *Best Review (Property/Casualty Ed.)* 91 (11): 12.

Black, K., Jr., and H. D. Skipper, Jr. 2000. *Life and Health Insurance. 13th ed*. Upper Saddle River, NJ: Prentice Hall.

Booth, A., D. R. Johnson, and D. A. Granger. 1999. Testosterone and Men's Depression: The Role of Social Behavior. *Journal of Health and Social Behavior* 40(2): 130–140.

Brockett, P. L., and L. L. Golden. 2007. Biological and Psychobehavorial Correlates of Credit Scores and Automobile Insurance Losses: Towards an Explication of Why Credit Scoring Works. *Journal of Risk and Insurance* 74(1): 23–63.

Brown, J. M., W. R. Miller, and L. A. Lawendowski. 1999. The Self-regulation Questionnaire. In *Innovations in Clinical Practice: A Source Book*, vol. 17, ed. L.VandeCreek and T. L. Jackson, pp. 281–289. Sarasota, FL: Professional Resource Press.

Caspi, A., D. Begg, N. Dickson, H. L. Harrington, J. Langley, T. E. Moffitt, and P. A. Silva. 1997. Personality Differences Predict Health-Risk Behaviors in Young Adulthood: Evidence from a Longitudinal Study. *Journal of Personality and Social Psychology* 73(5): 1052–1063.

Celsi, R. L., R. L. Rose, and T. W. Leigh. 1993. An Exploration of High-Risk Leisure Consumption through Skydiving. *Journal of Consumer Research* 20(1): 1–23.

Cestac, J., F. Paran, and P. Delhomme. 2011. Young Drivers' Sensation Seeking, Subjective Norms, and Perceived Behavioral Control and Their Roles in Predicting Speeding Intention: How Risk-Taking Motivations Evolve with Gender and Driving Experience. *Safety Science* 49(3): 424–432.

Cloninger, C. R. 1987. A Systematic Method for Clinical Description and Classification of Personality Variants. *Archives of General Psychiatry* 44: 573–588.

Dabbs, J. M., Jr. 1992. Testosterone and Occupational Achievement. *Social Forces* 70(3): 813–824.

Dabbs, J. M., and R. Morris. 1990. Testosterone, Social Class, and Antisocial Behavior in a Sample of 4,462 Men. *Psychological Science* 1(3): 209–211.

Depue, R. A., and P. F. Collins. 1999. Neurobiology of the Structure of Personality: Dopamine, Facilitation of Incentive Motivation, and Extraversion. *Behavioral and Brain Sciences* 22: 491–569.

Dokko, J., Geng Li, and J. Hayes. 2015. Credit Scores and Committed Relationships. *Finance and Economics Discussion Series 2015-081*. Washington, DC: Board of Governors of the Federal Reserve System. http://dx.doi.org/10.17016/FEDS.2015.081.

Donohew, L., and M. Bardo. n.d. Designing Prevention Programs for Sensation Seeking Adolescents. http://www.tanglewood.net/projects/teachertraining/Book_of_Readings/Donohew.pdf.

Dunlop, S. M., and D. Romer. 2010. Adolescent and Young Adult Crash Risk: Sensation Seeking, Substance Use Propensity and Substance Use Behaviors. *Journal of Adolescent Health* 46(1): 90–92.

Federal Trade Commission (FTC). 2007. Credit-Based Insurance Scores: Impacts on Consumers of Automobile Insurance. http://www.ftc.gov/os/2007/07/P044804FACTA_Report_Credit Based_Insurance_Scores.pdf.

Ferreira, J., Jr., and E. Minikel. 2010. Pay-as-You-Drive Auto Insurance in Massachusetts: A Risk Assessment and Report on Consumer, Industry, and Environmental Benefits. http://web.mit.edu/jf/www/payd/.

Fischer, S., and G. T. Smith. 2004. Deliberation Affects Risk Taking beyond Sensation Seeking. *Personality and Individual Differences* 36: 527–537.

Fulker, D. W., S. B. G. Eysenck, and M. Zuckerman. 1980. A Genetic and Environmental Analysis of Sensation Seeking. *Journal of Research in Personality* 14: 261–281.

Gerra, G., P. Avanzini, A. Zaimovic, R. Sartori, C. Bocchi, M. Timpano, U. Zambelli, R. Desiignore, F. Gardini, E. Talarico, and F. Brambilla. 1999. Neurotransmitters, Neuroendocrine Correlates of Sensation-Seeking Temperament in Normal Humans. *Biological Psychology/Pharmacopsychology* 39: 207–213.

Golden, L. L., W. W. Cooper and P. L. Brockett. 2012. Application Driven Theory: Rigorously Combining Applied and Basic Research Relevant to Accounting and Marketing. *Journal of Accounting and Marketing* 1(1): 1–2, 1:e103. doi:10.4172/jamk.1000e103.

Grinblatt, M., and M. Keloharju. 2009. Sensation Seeking, Overconfidence, and Trading Activity. *Journal of Finance* 64(2): 549–578.

Hansenne, M., and M. Ansseau. 1999. Harm Avoidance and Serotonin. *Biological Psychology* 51: 77–81.

Harlow, W. V., and K. C. Brown. 1990a. *The Role of Risk Tolerance in the Asset Allocation Process: A New Perspective*. Charlottesville, VA: Research Foundation of the Institute of Chartered Financial Analysts.

Harlow, W. V., and K. C. Brown. 1990b. Understanding and Assessing Financial Risk Tolerance: A Biological Perspective. *Financial Analysts Journal* (November/December): 50–62.

Harris, C., M. Jenkins, and D. Glaser. 2006. Gender Differences in Risk Assessment: Why Do Women Take Fewer Risks than Men? *Judgment and Decision Making* 1(1): 48–63.

Horvath, P., and M. Zuckerman. 1993. Sensation Seeking, Risk Appraisal, and Risky Behavior. *Personality and Individual Differences* 14(1): 41–52.

Hur, Y.-M., and T. J. Bouchard. 1997. The Genetic Correlation between Impulsivity and Sensation Seeking Traits. *Behavior Genetics* 27(5): 455–463.

Jonah, B. A. 1997. Sensation Seeking and Risky Driving: A Review and Synthesis of the Literature. *Accident Analysis and Prevention* 29(5): 651–665.

Kenealy, B. 2013. Insurers Finding Ways to Use Social Media in Underwriting, Claims Handling. *Business Insurance* June 3. http://www.businessinsurance.com/article/99999999/NEWS070109/130609971?tags = |332|65|342#full_story.

Kremslehner, D., and A. Muermann. 2013. Asymmetric Information in Automobile Insurance: Evidence from Driving Behavior. http://dx.doi.org/10.2139/ssrn.2048478.

Lepp, A., and H. Gibson. 2008. Sensation Seeking and Tourism: Tourist Role, Perception of Risk and Destination Choice. *Tourism Management* 29(4): 740–750.

Llewellyn, D. J. 2008. The Psychology of Risk Taking: Toward the Integration of Psychometric and Neuropsychological Paradigms. *American Journal of Psychology* 121(30): 363–376.

Lloyds. 2011. European Court of Justice Bans Insurers' Use of Gender. March 25. http://www.lloyds.com/the-market/communications/regulatory-communications-homepage/regulatory-communications/regulatory-news-articles/march-2011-european-court-of-justice-bans-insurers-use-of-gender.

Lonczaka, H. S., C. Neighbors, and D. M. Donovan. 2007. Predicting Risky and Angry Driving as a Function of Gender. *Accident Analysis & Prevention* 39(3): 536–545.

Magar, E. C.E., L. H. Phillips, and J. A. Hosie. 2008. Self-Regulation and Risk Taking. *Personality and Individual Differences* 45(2): 153–159.

McLannahan, B. 2015. Being 'Wasted' on Facebook May Damage Your Credit Score. *Financial Times*. October 15. http://www.ft.com/cms/s/0/d6daedee-706a-11e5-9b9e-690fdae72044.html#axzz3odUFS28o.

Meyers, G. 2009. Pure Premium Regression with the Tweedie Model. *Actuarial Review*, 12–13. http://www.casact.org/newsletter/index.cfm?fa = viewart&id = 5756.

Miller, M. J., and R. A. Smith. 2003. *The Relationship of Credit-Based Insurance Scores to Private Passenger Automobile Insurance Loss Propensity*. EPIC Actuaries. http://www.ask-epic.com/Publications/Relationship%20of%20Credit%20Scores_062003.pdf.

Monaghan, J. E. 2000. The Impact of Personal Credit History on Loss Performance in Personal Lines. *Casualty Actuary Society Forum (winter)*: 79–19-05.

NAIC (National Association of Insurance Commissioners). 2008. Review of the Use of Credit-Based Insurance Scoring by Insurers. http://www.naic.org/documents/committees_c_d_related_docs_08_credit_study.pdf.

NAIC (National Association of Insurance Commissioners). 2012a. Credit-Based Insurance Scores: How an Insurance Company Can Use Your Credit to Determine Your Premium. http://www.naic.org/documents/consumer_alert_credit_based_insurance_scores.htm.

NAIC (National Association of Insurance Commissioners). 2012b. The Use of Social Media in Insurance. www.naic.org/store/free/USM-OP.pdf.

NAIC (National Association of Insurance Commissioners). 2013. Studies, Reports and Surveys Examining the Use of Credit Scoring, Occupation or Education in Insurance. http://www.naic.org/documents/committees_c_d_auto_insurance_study_wg_related_studies_examining_use_credit_scoring.pdf.

NCSL (National Conference of State Legislatures). 2014. Use of Credit Information in Insurance 2013 Legislation. http://www.ncsl.org/research/financial-services-and-commerce/use-of-credit-information-in-insurance-2013-legis.aspx.

Netter, P., J. Hennig, and I. S. Roed. 1996. Serotonin and Dopamine as Mediators of Sensation Seeking Behavior. *Neuropsychobiology* 34: 155–165.

New Jersey Department of Banking and Insurance. 2008. The Use of Occupation and Education Factors in Automobile Insurance. http://www.state.nj.us/dobi/division_insurance/pdfs/ed_occ_april2008.pdf.

Nicolaou, N., and S. Shane. 2008. The Influence of Sensation Seeking in the Heritability of Entrepreneurship. *Strategic Entrepreneurship Journal* 2(1): 7–21.

O'Donoghue, T. D. and M. Rabin. 1999. Doing It Now or Later. *American Economic Review* 89: 103–124.

Papies E., and H. Aarts. 2011. Nonconscious Self-regulation, or the Automatic Pilot of Human Behavior. In *Handbook of Self-regulation: Research, Theory, and Applications*, 2nd ed., ed. K. Voh and R. Baumeister, Ch. 7, pp. 125–142. New York: Guilford Press.

PCI (Property Casualty Insurance Association of America). 2015. *Credit Based Insurance Scoring FAQ*. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&ved=0ahUKEwi07onC2MvNAhXDYiYKHb5NDQUQFggeMAA&url=http%3A%2F%2Fwww.pciaa.net%2Fdocs%2Fdefault-source%2Fdefault-document-library%2Finsurance_scoring_faq.pdf%3Fsfvrsn%3D2&usg=AFQjCNEjLS3Z7Sev_XH5HtQS06kXl1wSog&sig2=PlA5AXr9o2r18WoMO8H7ow&cad=rja.

Raffaelli, M., and L. J. Crockett. 2003. Sexual Risk Taking in Adolescence: The Role of Self-Regulation and Attraction to Risk. *Developmental Psychology* 39(6): 1036–1046.

Raju, P. S. 1980. Optimum Stimulation Level: Its Relationship to Personality, Demographics, and Exploratory Behavior. *Journal of Consumer Research* 7(3): 272–282.

Raylu, N., and T. Oei. 2002. Pathological Gambling: A Comprehensive Review. *Clinical Psychology Review* 22: 1009–1066.

Roberti, J. W. 2004. A Review of Behavioral and Biological Correlates of Sensation Seeking. *Journal of Research in Personality*: 38: 256–279.

Rolison, M. R., and A. Scherman. 2003. College Student Risk-Taking from Three Perspectives. *Adolescence* 38(152): 689–704.

Rosenblitt, J. C., H. Soler, S. E. Johnson, and D. M. Quadagno. 2001. Sensation Seeking and Hormones in Men and Women: Exploring the Link. *Hormones and Behavior* 40: 396–402.

Rosenbloom, T. 2003. Risk Evaluation and Risky Behavior of High and Low Sensation Seekers. *Social Behavior and Personality* 31(4): 375–386.

Rusli, E. 2013. Bad Credit? Start Tweeting: Startups Are Rethinking How to Measure Creditworthiness beyond FICO. *Wall Street Journal*, April 1. http://online.wsj.com/article/SB10001424127887324883604578396852612756398.html.

Siegel, A. W., and J. H. Cousins. 1994. Adolescents' Perceptions of the Benefits and Risks of Their Own Risk Taking. *Journal of Emotional and Behavioral Disorders* 2(2): 89–98.

Sitkin, S. B., and L. R. Weingart. 1995. Determinants of Risky Decision-Making Behavior: A Test of the Mediating Role of Risk Perceptions and Propensity. *Academy of Management Journal* 38(6): 1573–1592.

Sjöberg, L., and E. Engelberg. 2009. Attitudes to Economic Risk Taking, Sensation Seeking and Values of Business Students Specializing in Finance. *Journal of Behavioral Finance* 10(1): 33–43.

Smyth, G. K. and B. Jørgensen. 2002. Fitting Tweedie's Compound Poisson Model to Insurance Claims Data. *ASTIN Bulletin* 32(1): 143–157.

Steinberg, L., D. Albert, E. Cauffman, M. Banich, S. Graham, and J. Woolard. 2008. Age Differences in Sensation Seeking and Impulsivity as Indexed by Behavior and Self-report: Evidence for a dual Systems Mode. *Developmental Psychology* 44(6): 1764–1778.

Texas Department of Insurance. 2005. Supplementary Report to the 79th Legislature: The Use of Credit Information by Insurers in Texas: The Multivariate Analysis. http://www.tdi.state.tx.us/reports/documents/credit05sup.pdf.

Tillman, W. A., and G. E. Hobbs. 1949. The Accident-Prone Automobile Driver: A Study of the Psychiatric and Social Background. *American Journal of Psychiatry* 106: 321–331.

Voh, K., and R. Baumeister (eds.). 2011. *Handbook of Self-Regulation: Research, Theory, and Applications. 2nd ed*. New York: Guilford Press.

White, J. B. 2012. Auto Insurance Enters the 'Pay-per-View' Era. *Wall Street Journal*, June 12. http://online.wsj.com/news/articles/SB10001424052702303901504577462382411135766.

Wong, A., and B. J. Carducci. 1991. Sensation Seeking and Financial Risk Taking in Everyday Money Matters. *Journal of Business and Psychology* 5(4): 525–530.

Wong, W. K. 2008. How Much Time-Inconsistency Is There and Does It Matter? Evidence on Self-awareness, Size, and Effects. *Journal of Economic Behavior and Organization* 68: 645–656.

Wooda, P. B., B. Pfefferbauma, and B. J. Arnekleva. 1993. Risk Taking and Self Control: Social Psychological Correlates of Delinquency. *Journal of Crime and Justice* 16(1): 111–130.

Wu, C.-S. P., and J. C. Guszcza. 2003. Does Credit Score Really Explain Insurance Losses? Multivariate Analysis from a Data Mining Point of View. *Casualty Actuarial Society Forum* Winter: 113–138.

Zuckerman, M. 1979. *Sensation Seeking beyond the Optimum Level of Arousal*. Mahwah, NJ: Erlbaum.

Zuckerman, M. 1990. The Psychophysiology of Sensation Seeking. *Journal of Personality* 58(1): 313–345.

Zuckerman, M. 1996. The Psychobiological Model for Impulsive Unsocialized Sensation Seeking: A Comparative Approach. *Neuropsychobiology* 34: 125–129.

Zuckerman, M. 2007. *Sensation Seeking and Risky Behavior*. Washington, DC: American Psychological Association.

Zuckerman, M., and C. R. Cloninger. 1996. Relationships between Cloninger's, Zuckerman's and Eysenck's Dimensions of Personality. *Personality and Individual Differences* 21(2): 283–285.

Zuckerman, M., and D. M. Kuhlman. 2000. Personality and Risk-Taking: Common Biosocial Factors. *Journal of Personality* 68(6): 999–1029.

Discussions on this article can be submitted until April 1, 2017. The authors reserve the right to reply to any discussion. Please see the Instructions for Authors found online at http://www.tandfonline.com/uaaj for submission instructions.

APPENDIX. CREDIT SCORING VARIABLES AND STATISTICAL RESULTS

TABLE A1
Credit Variables Useful for Predicting Insured Automobile Losses

Total number of accounts
Total number of open, paid, closed, or inactive accounts
Total number of accounts opened within 6 months of the profile date
Total number of bankruptcy account lines ever
Total number of satisfactory accounts in the last 24 months
Total number of collection accounts, if external collection (i.e., collection agency, medical, utility) amount must be greater than $250
Total number of bankruptcy public records
Overall balance/limit ratio on all open accounts reported within 6 months of the profile date
Age, in months, of most recently opened account
Months since most recent 30–180 day delinquency or derogatory item on any account
Total number of inquiries made for credit purposes
Total number of inquiries for credit purposes made within 6 months of the profile date
Months since most recent inquiry for credit purposes was made
Total number of auto or auto lease inquiries made for credit purposes
Maximum number of months of consecutive balance activity in the payment history, across open bankcard accounts in the last 24 months for accounts open at least 6 months and reported in the last 6 months
Total number of open bank accounts reported within 6 months of the profile date
Total number of open captive auto finance accounts reported within 6 months of the profile date
Total number of installment accounts ever 30 or more days delinquent or derogatory
Total number of installment accounts with maximum delinquency ever of 90–180 days
Total number of installment accounts 30 or more days delinquent or derogatory in the last 6 months
Worst status ever on installment accounts opened within 36 months of the profile date
Percentage of total open installment accounts to total open accounts
Average outstanding credit limit or loan amount on all open real property accounts reported within 6 months of the profile date
Total number of open, paid, closed, or inactive revolving accounts
Total number of revolving accounts, including external collections
Total number of revolving accounts with maximum delinquency of 60 days in the last 6 months
Overall balance/limit ratio on all open revolving accounts opened within 12 months of the profile date
Age, in months, of oldest revolving account
Total number of open retail revolving accounts with balance greater than zero reported within 6 months of the profile date
Total number of retail revolving accounts with maximum delinquency ever of 30 days
Worst present status on an open retail revolving account

TABLE A2
Logistic Regression for Claim Frequency (Accident/No Accident)

Accident indicator	n
0 (no accident)	122,135
1 (accident)	31,014
Intercept coefficient	−0.9914
Statistical significance $p \leq$	0.04
Score (log odds ratio)	−0.00053
Statistical significance $p \leq$	0.0001
Total N	153,149
Chi-square of likelihood ratio	78.3499
Odds ratio of score	0.999

TABLE A3
Regression Analysis of Relative Loss Ratio versus Credit Score and Age Conditioned on Policies Having Positive Claim ($n = 28{,}228$)

Model					
Source	DF	Sum of Squares	F Value	$p <$	
Model	2	19,529	79.30	0.0001	
Error	28,225	3,475,376			
Parameter Estimates					
Variable	DF	Estimated Coefficient	Standard Error	t Value	$p <$
Intercept	1	9.650	0.45380	21.26	0.0001
Age	1	0.021	0.00413	5.08	0.0001
Credit score	1	−0.008	0.00064	−12.5	0.0001

Note: The sample size was a subset (28,228) of the 31,014 policies with an accident because policies that had missing data on one or more of the variables were excluded. There were 137,220 policies containing all variables used here, of which 108,991 did not have a claim.