Nontraditional Variables in Healthcare Risk Adjustment

Sponsored by

Society of Actuaries' Health Section

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July 2013

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Contents

Acknowledgments

I am very grateful to the members of the Project Oversight Group (POG), who supported this project through their time and expertise. A special thanks to Steven Siegel, Research Actuary for the Society of Actuaries, for his insight and for moderating the many discussions with the POG panel during the course of this work. The Society of Actuaries Project Oversight Group provided review, guidance, and support. The group comprises:

John Bertko	Ian Duncan	Rafi Herzfeld
Vincent Kane	Darrell Knapp	Tom Messer
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Khristina Shields	Steven Siegel	John Stark
Sara Teppema		

A special thanks to Daniel Bailey and Ross Winkelman for their review of this report, and to Tia Sawhney for her valuable insights and review. Several findings of this report draw from and build upon her work in this area (Sawhney, 2012).

Thanks to Xingyi Qin (Wakely) for orchestrating the difficult and tedious data preparation, to Levi Mercer (Wakely) for researching several of the nontraditional variables, to Tajammul Hussain (Wakely) for researching published literature on the subject, and to Evan Morgan (Wakely) for his help with editing.

Last but certainly not least, thanks to Barbara Scott of the Society of Actuaries for expertly coordinating the multiple POG calls and schedules.

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May 7, 2013

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Risk adjustment of any kind is inherently imperfect. Read this paper to better understand the limitations of risk adjustment, how to evaluate the limitations, and the potential business impact of the limitations. Such an understanding is essential for actuaries working with risk adjusters.

- Tia Goss Sawhney, DrPH, FSA

This paper takes the refreshingly practical approach of connecting sublime improvements in predictive modeling with very tangible, meaningful impacts to bottom line margins. While most predictive modeling research focuses on gains in accuracy, it is often unclear if those gains translate into significant business differences. Syed's approach finally connects the last dots by directly relating improved accuracy to the most relevant aspect of an insurer's finances: the loss ratio. His approach starts out with a solid foundation including well accepted and easily accessible variables. Next he introduces novel insights using non-traditional but still practically accessible variables. However, his conclusions make their most meaningful impact by comparing loss ratios between insurers under various scenarios. For anyone seriously interested in health-care risk adjustment and how to effectively comprehend its impact, this paper is very much worth the time invested.

- Rafi Herzfeld, FSA, MAAA

The business of risk adjustment has come a long way since the publication of the Academy's "Monograph Number One" with the title, "Health Risk Assessment and Health Risk Adjustment—Crucial Elements in Effective Health Care Reform" in May 1993. Less than ten years later, we had hospital inpatient diagnosis-based approaches, such as the model used by the Market Stabilization Pool for small group and individual coverage in NYS in conjunction with mandated community rating. The PIP-DCG approach for Medicare + Choice, also inpatient only, soon followed. This was superseded by the CMS-HCC model developed for Medicare Advantage in 2004, which used inpatient and professional claim diagnoses, and was the most sophisticated risk tool to be used on a large-scale up to that time, and is still evolving in its use today. Like the proliferation of the advancing technology that made them possible, the complexity and sophistication of risk adjustment models has increased significantly in the past couple decades. With the passage of the Affordable Care Act (ACA), risk adjustment will be required for non-grandfathered commercial small group and individual coverage both inside and outside Exchanges. The risk adjustment approach chosen is not an easy one for the novice to understand. Many health insurers and HMOs question whether it will produce equitable results across all members and all carriers throughout the system. Using a structured and scientific approach, Syed Mehmud has examined a long list of non-traditional drivers of health cost, chosen the most relevant ones, and tested their effect on bottom-line medical cost when included in the traditional risk adjustment formula. While a couple of his results may seem counter-intuitive on first glance, Syed's approach is sound, and it certainly gives uncertain carriers a sure-fire method to answer the question for themselves. Syed has a proven track record of significant contributions to the rapidly developing science of predictive modeling and risk adjustment. With the help of Syed's most recent work and the time it will save carriers, payers can more quickly get down to the business of containing cost and insuring more members. Free from the concerns that go with monitoring and marketing around the risk profile of the insured population, it will be interesting to see what happens to cost, access, and quality over the next several years. We may even achieve the Triple Aim!

- Daniel Bailey, FSA, MAAA

Executive Summary

The Affordable Care Act (ACA) includes the mechanism of risk adjustment in commercial small group and individual markets in order to further the policy goals of premium stabilization, mitigating incentives for issuers of healthcare coverage policies (issuers) to avoid unhealthy members, and to remove any advantages or disadvantages for plans inside healthcare exchanges compared to plans outside of such exchanges. The importance of risk adjustment to these policy goals cannot be overemphasized, and details such as the variables that are included in the risk assessment formula affect the extent to which the program is successful in meeting these goals.

Risk adjustment models have included variables such as demographic (i.e. age and gender) and clinical markers based either on ICD-9 diagnosis codes and/or pharmacy codes such as the National Drug Codes (NDCs). Literature points to other variables such as geography, Body Mass Index (BMI), education, and income that also explain the variation in healthcare cost – but have hitherto not been included in risk adjustment programs mainly because such variables are not typically found in claim data. If these *nontraditional* variables explain meaningful variation in cost beyond traditional risk adjustment models – then this may provide incentives for issuers to select certain members. If such incentives lead to selection that affects the financial performance of issuers – then the policy goals of the risk adjustment program will be undermined.

Recognizing the importance of fortifying risk adjustment programs against selection based on nontraditional variables, the Society of Actuaries' Health Section sponsored an in-depth study into the relationship of nontraditional variables with health costs. This report presents the results of this study. We used the Medical Expenditure Panel Survey (MEPS) data in this research. Specific details concerning the data and preparation can be found in Section 3.2. This data is unique in that it includes a large number of individual characteristics (from BMI to whether a person has difficulty enjoying hobbies) together with healthcare claim data. There are limitations to the use of MEPS data, and these limitations are discussed further in Section 4.

The results of this research demonstrate that it is important to adjust the traditional risk adjustment model in order to recognize nontraditional variables. The report develops a new measure (Loss Ratio Advantage or **LRA**) to help quantify the potential of a nontraditional variable to affect a risk adjustment program. With the help of this measure, the report compares the importance of over thirty variables that were systematically narrowed down from a list of over fifteen hundred variables describing various characteristics of the general population (i.e. the purchasers of healthcare insurance coverage). The nontraditional variables were broadly categorized into (1) demographic, (2) economic, (3) lifestyle, (4) psychological self-assessment (i.e. how a person feels about their mental health), and (5) physical self-assessment.

The Loss Ratio Advantage or LRA indicates the *difference in loss ratios* between an issuer (i.e. Issuer **A**) that is able to select the more profitable 50% of the market based on a nontraditional variable and another issuer (i.e. Issuer **B**) that enrolls the remaining 50%. In this manner the influence of a nontraditional variable can be directly linked to financial performance. This research shows that financial performance is the correct perspective with which to study the performance of nontraditional variables, and not statistical performance, for example. Further discussion on this very important point is included in Section 1.3.

The following graphic illustrates (albeit in a simplified way) the core concept of the LRA measure. Issuer A is able to select the 50% of the market that has the lowest *risk adjusted expenditure* based on a nontraditional variable. Issuer B enrolls the remaining 50%. Assuming Issuer A's risk score is 0.85 and expenditures are actually 0.80 of average while Insurer B's risk score is 1.15 and expenditures are actually 1.20, then allowing 20% for administration and margin, the loss ratio may be calculated as the ratio of expenditure to risk adjusted revenue. For example, for issuer A, this becomes [expenditure=0.80] / ([premium=1.2] x [risk score=0.85]) or 78% while loss ratio for insurer B is 1.20 / (1.2 x 1.15) = 87%. This calculation produces a difference in loss ratio of 9% between the two issuers. This is the LRA. In this case, it exceeds typical profit margins, and is therefore a very significant result from a business perspective. The calculations in the graphic are simplified, and the calculations used in this research are explained in Section 1.2[1].

[1] Note that in this illustration, the risk score for the lower cost health plan is overstated while that for the high cost plan is understated. This draws from the fact that risk assessment models *generally* overstate risk for the lowest cost members and understate for the highest cost members ((Winkelman & Mehmud, A Comparative Analysis of Claims-Based Tools for Health Risk Assessment, 2007)) – however this may not always hold true in any given application.

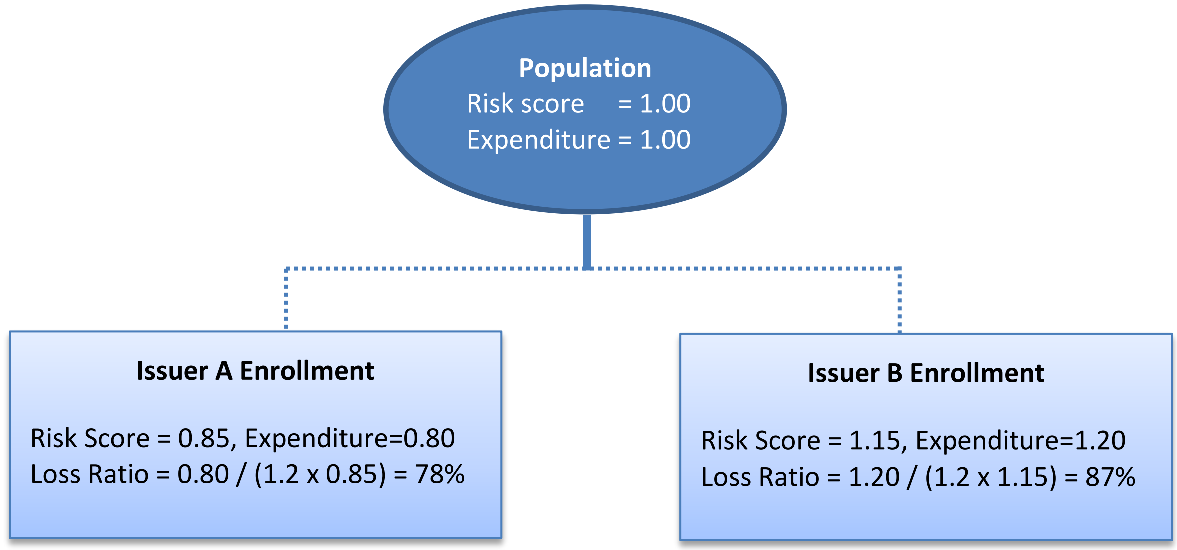


Figure 1 below shows the selected demographic nontraditional variables and their associated LRA values. Detailed results for each of these variables are presented in Section 2.

Figure 1: Loss Ratio Advantage (LRA) by demographic nontraditional variables

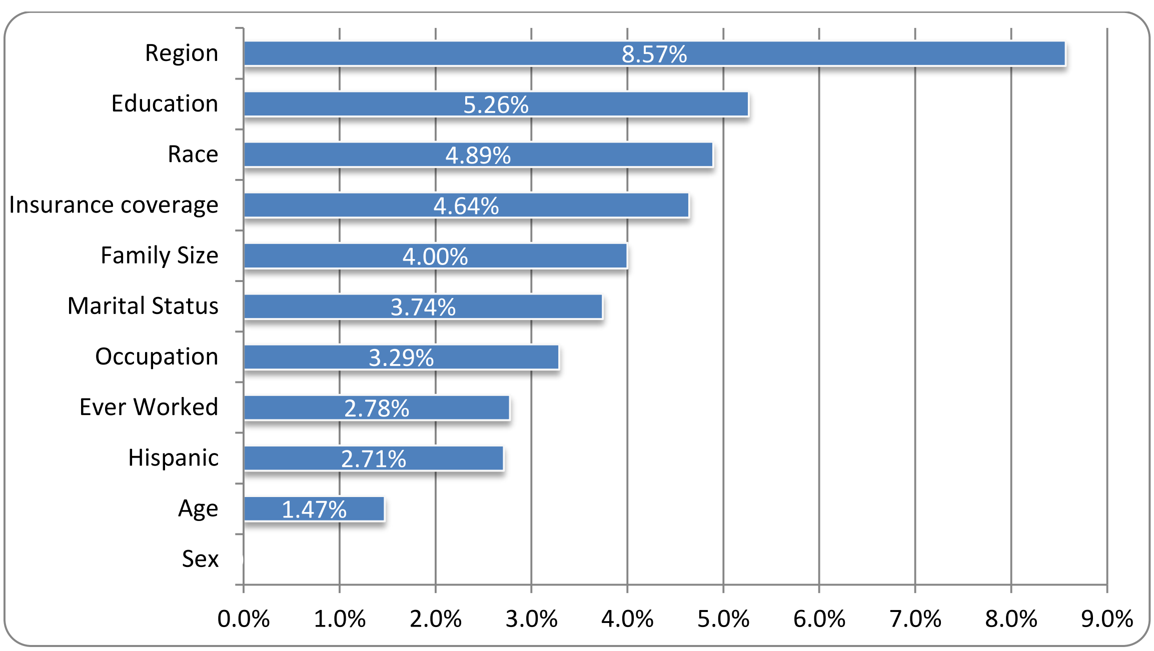


Figure 1 shows that geographic region is a powerful additional variable in the risk adjustment formula and can be used to segment customers such that one issuer has almost a 9% advantage on loss ratio than another (all other things being equal). Geography is considered as a nontraditional variable in this research since it is not typically a part of the risk assessment model calibration. 'Calibration' of a model involves ensuring that all the relevant independent variables are fitted such that the coefficients appropriately represent the application at hand. While geography is typically not an independent variable in risk assessment models, it is often times a rating variable (as it is in the ACA risk adjustment program). While having geography as a rating variable limits its potential use in selecting members, the potential may not be eliminated entirely. This point is developed further in Section 2.8.

An important point developed in this research is that fitting the residuals generated by a modeling approach (regression) may not be the best way to address evidence of bias by a nontraditional variable category (e.g. such as geographical areas). The reason is that in fixing one bias in this manner can introduce other (potentially) more serious ones – for example by age/gender categories. A nontraditional variable needs to be part of the overall model calibration in order to mitigate bias *simultaneously* by the key data groupings that are of interest. The data groupings we are keenly interested in are the ones which, if the risk score is biased with respect to estimating expenditure, may be used to segment the customer base and thereby select individuals in order to maximize profit. Please see Section 1.3 for further details on the important topic of introducing nontraditional variables in a risk adjustment model.

As a simplification, we developed a scale based on the LRA values in order to compare variables. We classified LRA metrics below 3.3% as **low** impact variables, 3.3-6.0% as **medium** impact variables, and over 6.0% as **high** impact variables. For example, Figure 1 shows that years of education has a *medium* business impact in a risk adjusted program. We can see that gender has no (i.e. zero) impact, since this variable is already included in traditional risk adjustment. Age has a small impact – which owes to the fact that the age categories used to test for bias are *different* than the ones used in the risk adjustment model. This makes an important point that simply including a variable in risk adjustment may not mitigate bias for every re-categorization of that variable, and that this needs to be explicitly tested.

Figure 2 summarizes the results for the economic category of variables. These variables mostly deal with income and also include employment status (i.e. a person's employment status at the time of data collection). The total-wage and employment status variables have a medium influence in a risk adjusted program. Further details on these variables are available in Section 2.4.

Figure 2: Loss Ratio Advantage (LRA) by economic nontraditional variables

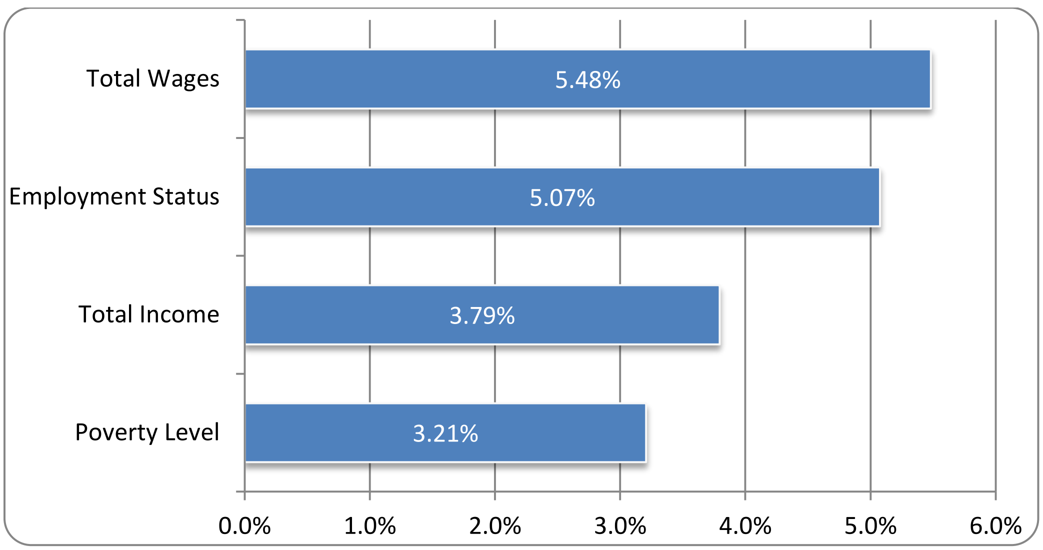


Figure 3 summarizes the results for the lifestyle category of variables. The variable that produces the largest impact on financial performance deals with whether health has stopped social activities. In the case of this variable, Issuer A selects those members who responded that 'health stopped social activities none of the time', whereas Issuer B enrolls the rest. After going through the calculations of risk adjustment and risk transfer similar to those that will be used during ACA implementation – Issuer A has a loss ratio of 80% whereas Issuer B has a loss ratio of 88.2% (hence an LRA of 88.2-80=8.2%). Other medium impact variables include whether a person felt energetic, or whether they felt that purchasing health insurance was a good investment. Further details on these rather interesting lifestyle variables are available in Section 2.5.

Figure 3: Loss Ratio Advantage (LRA) by lifestyle nontraditional variables

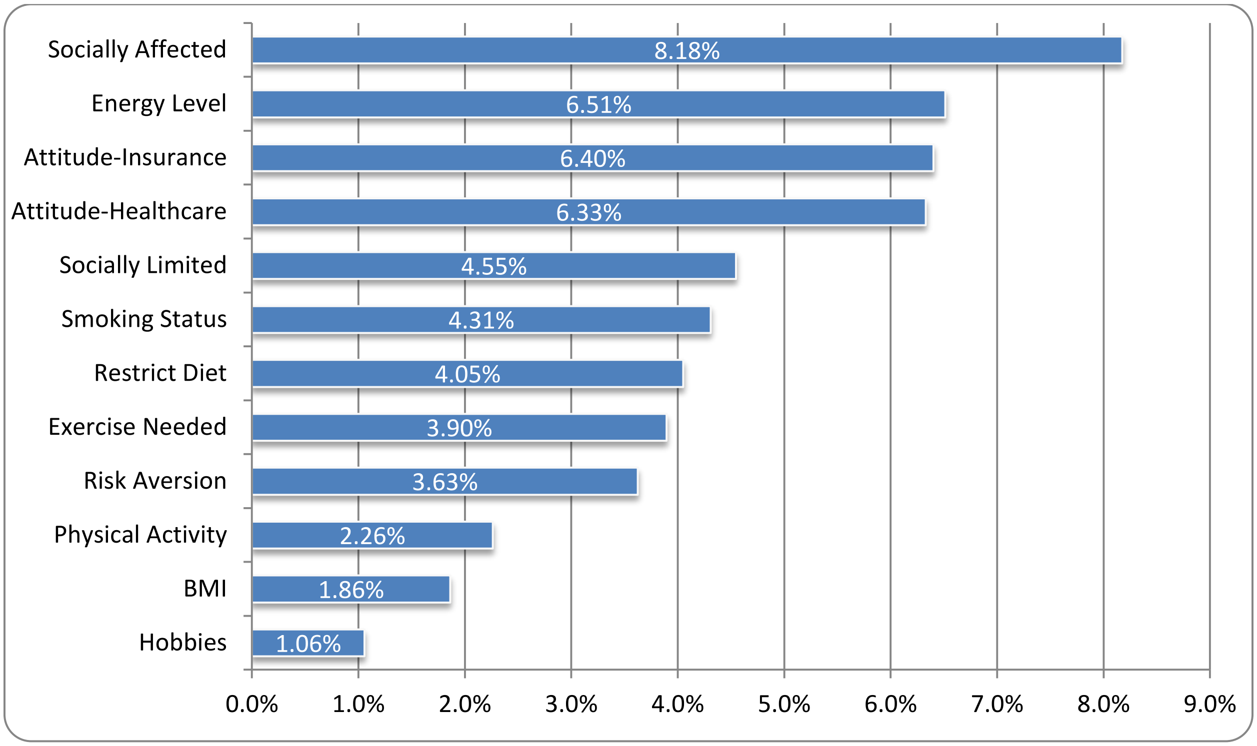


Figure 4 summarizes the results for the psychological category of variables. We have heard and read about *positive thinking* and potential associated benefits. It appears that individuals that feel calm and peace 'all of the time' also cost less than their risk scores would suggest, and thus are preferred by Issuer A; resulting in a medium impact. Also having a medium impact is a variable that indicates whether mental health limited work during the time that data was collected. Perceived mental health status also produced material differentiation between our hypothetical issuers, with Issuer A selecting those persons that perceived themselves as being in 'excellent' or 'good' mental health. Further details on these interesting psychological variables are available in Section 2.6.

Figure 4: Loss Ratio Advantage (LRA) by psychological nontraditional variables

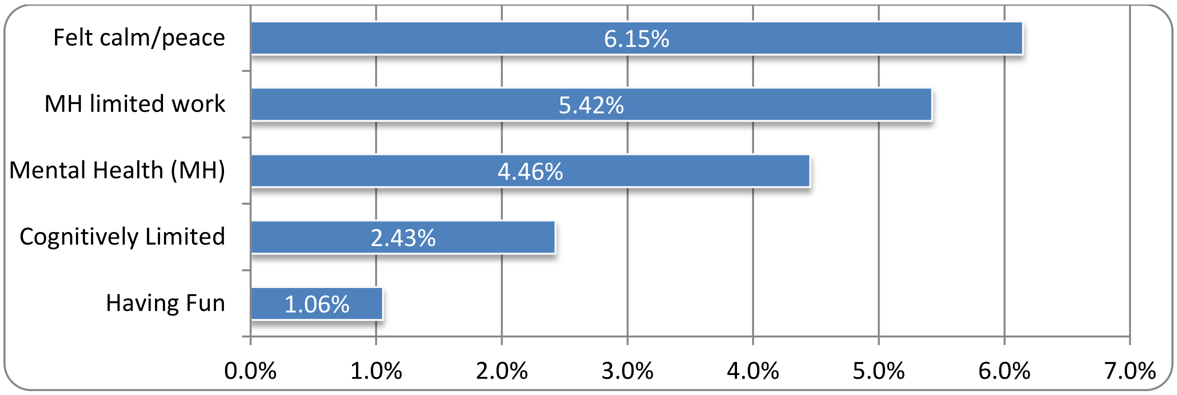
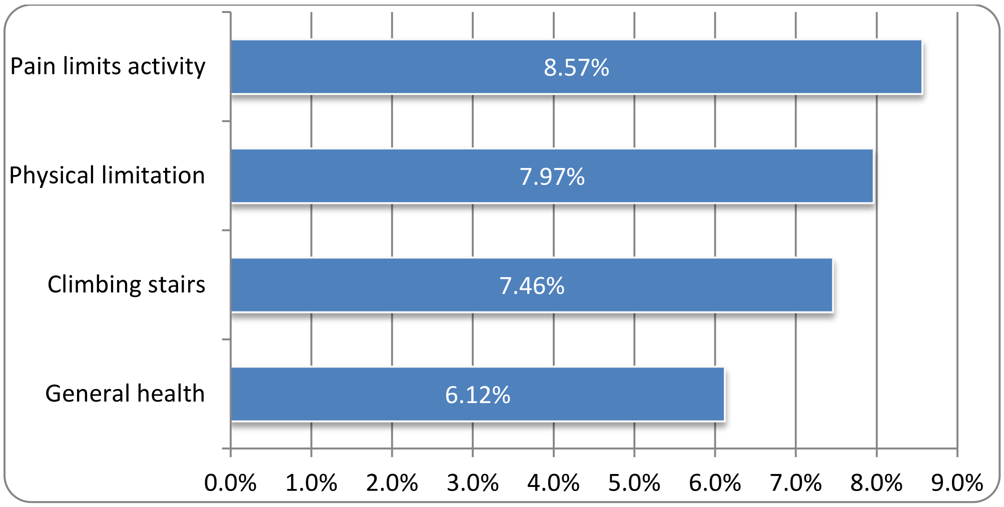


Figure 5 summarizes the results for the physical category of variables. Most of the variables selected for presentation in this report produce medium or high impact. As one might intuitively expect – variables that deal with physical status are the most important and the most directly linked with healthcare costs. There were many other physical status variables that we studied and are not included in this report. Most of these variables communicated similar information and so we tried to limit redundant conclusions. A physical status variable describing whether pain limited normal activity produced the highest differentiation between issuers in a risk adjusted market. Issuer A preferred enrolling members that indicated pain did not limit their normal work at all.

This forms a theme in this research, a theme that is generally but not always true. Issuer A prefers to enroll individuals indicating a better physical, mental, or socio-economic status. In this manner, issuer A is typically cutting a check to issuer B in a risk adjusted environment, yet still coming out ahead on loss ratio comparisons. However this is not always true – as in the case of the geography variable. Geography produces one of the highest loss ratio differentials, yet in that case, Issuer A receives a payment from Issuer B. Note that the result should not be interpreted as saying that an issuer that makes a payment fares better; this seems generally true only in the case where the issuer is also utilizing a nontraditional variable to segment the population and select customers. Further details on these interesting physical variables are available in Section 2.7.

Figure 5: Loss Ratio Advantage (LRA) by physical nontraditional variables



It is infeasible to include all of the nontraditional variables discussed above in a risk adjustment formula. The practical limitation is that if any variable is included in the formula – then information on that variable needs to be collected and input to the formula. It is practically impossible to consistently collect information such as 'does an individual have trouble climbing a flight of stairs' in a database for risk adjustment[2]. In this research we propose a model that includes (1) coverage type (i.e. whether an individual was uninsured or commercially insured), (2) total wages, and (3) geography in the risk adjustment formula. This information may be more feasibly collected than most other variables discussed in this report, and also has a significant impact in mitigating selection potentials for these three nontraditional variables. This model may not mitigate selection potential for any other nontraditional variables; however, data on such variables may not be available to issuers anyway.

Section 2.8 covers geographical adjustments and concludes that it is important to consider rating area adjustments – not only from the perspective of geographic proximity or health network adequacy – but also in terms of patterns in risk adjusted costs. Such patterns may inform development of rating areas for purposes of a risk adjustment program.

[2] An important tangent here is to consider the information that will become available with ICD-10 codes. ICD-10 codes, which are scheduled to go into effect later this year, contain much more granular information (e.g. fall down a flight of stairs). It may be important to consider revising risk assessment models given more granular information on medical conditions.

It is important to make a few remarks about how to interpret results from this study. This study is not a 'cookbook' in terms of how to strategize marketing activities or any other selection effort. Nor should the results be relied upon by policy makers to adjust risk adjustment programs without checking to see if the results hold when data for a specific application is considered. While this study used a specific data source and risk adjustment model, results for an issuer or policy maker will vary by the data, model, and methodology that are used. The most important outcome of this work is the conceptual framework and high level conclusions rather than specific numbers. The author hopes that this work is extended by other researchers, and applied towards risk adjustment programs in order to improve them and mitigate selection incentives that may otherwise persist.

This study is not a 'cookbook' in terms of how to strategize marketing activities or any other selection effort.

Last but certainly not least – one issue discussed in this report is the importance of model calibration. Ignoring nontraditional variables for a moment, a basic traditional variable such as age/gender can present a strong incentive for selection if a model is not well-calibrated to the application at hand. The largest selection potential discovered in this research does not involve a nontraditional variable – rather it has to do with not properly calibrating the model in terms of age and gender of members. This issue is discussed further in Section 2.1.

While this report is lengthy, hopefully it is also interesting and exciting. Please feel free to contact the author who would love to hear any comments, questions, or suggestions.

1. Conceptual Framework

This research report presents a large number of results. In order to fully understand them it will be useful to carefully review the development of the conceptual framework that includes the selection of nontraditional risk adjustment variables, model development, statistical metrics, and presentation of results. Section 1 presents the key concepts and questions that are explored in this report. More importantly, it provides the conceptual and statistical tools needed to understand the standard layout of results that is used throughout this report. In this regard, reviewing Section 1.3 may be especially important prior to reviewing results in Section 2.

1.1 Motivation & Purpose

Risk assessment models have an important role in the healthcare system today, and tomorrow. Medicare and Medicaid plans currently use risk assessment models to adjust capitation payments to private sector contractors. Health care reform legislation mandates the use of risk adjustment in the commercial healthcare market in order to stabilize premiums and remove the incentive for health insurers to select healthy individuals. The importance of the risk adjustment mechanism in achieving the policy goals of the Affordable Care Act (ACA) cannot be overemphasized.

Issuers of healthcare policies will be pricing their 2014 products assuming that the purchasers will be an 'average risk'. As the phrase implies, an average risk is an individual that is expected to cost the same as the average of all of the individuals in that age cohort in a market. Around June of 2015, the issuer will receive a payment if purchasers were actually higher than average risk, or have to make a payment if they were lower than an average risk. In this manner an issuer can price to an average risk year over year – this promotes premium stabilization – while not having to worry about who takes up coverage since revenue is adjusted after the benefit year. This process mitigates the incentive for risk selection. The risk adjustment program should also decrease implicit conservatism that issuers may otherwise build into their rates in expectation of enrolling individuals with unknown health status (HHS, 2012).

To summarize, the following is a list of major policy goals of a risk adjustment program (ACA or otherwise):

- Mitigate incentives for health plan issuers to avoid unhealthy members (selection)

- Promote stable premiums
- Remove any advantages or disadvantages for plans inside the exchange relative to plans outside it; hence payments and charges are applied to all non-grandfathered individual and small group plans inside and outside exchanges (HHS, 2012)
- Foster competition in the market on the basis of medical and administrative efficiency and quality of service and care, rather than on the ability to select risk (Rosenblatt, et al., 1993)
- Promote financial soundness in the system by avoiding spiraling losses to issuers that experience adverse selection
- Compensate health plan issuers fairly and equitably for the risks they assume (Rosenblatt, et al., 1993)

Like most actuarial exercises, risk adjustment is not perfect – in this case, the imperfections, if not properly understood and addressed, may undermine the policy goals of the ACA risk adjustment program. In this report, we explore an important question with potentially serious implications. What happens when a risk adjustment mechanism does not adequately remove the incentive for selection? Health actuaries are well aware of the so-called 'death spiral' that may occur when an issuer experiences significant ongoing adverse selection. Can that happen even in a risk adjusted market?

The way it can potentially happen is if the risk adjustment mechanism does not adequately compensate an issuer for the assumed risk. For example, consider the hypothetical case of a chronic disease such as diabetes. A risk adjustment model such as the Department of Health and Human Services' ACA condition category model (HHS model) assigns a risk weight to this condition. The risk weight is about 1.3 for adults in a 2014 platinum plan. This implies that a person with diabetes is expected to cost about 1.3 times more than an average person without diabetes in the same demographic cohort and metallic plan. This is an average expectation, but in reality, individuals with a specific healthcare condition have costs that are typically distributed across a spectrum from low to high cost. There will be individuals with diabetes who will not cost much more than an average individual without the condition, and there will be those that will cost much more than 1.3 times the cost of an average individual without diabetes. If there were ways to identify these two different theoretical sub-groups of individuals, then a strong incentive for selection would persist even after the revenue is risk adjusted.

In concept, an issuer that is able to attract membership on the healthier side of the spectrum for any specific condition will be credited with revenue based on the expected cost of that condition, however, the actual cost to that issuer will be lower (leading to an increase in profitability). Conversely an issuer that is left with the remaining individuals who are more morbid will not be fully compensated for the assumed risk. Competition in markets may suffer if issuers exit due to adverse selection (or for other reasons), and premium rate disruptions could occur as membership for existing issuers changes significantly as a result. Such a worst case scenario illustrates how both of the main policy goals of risk adjustment may be undermined if the door is left ajar for selection activities and significant selection occurs.

The mechanism of risk adjustment attempts to mitigate or eliminate (close the door on) selection by adjusting revenue based on health status. In traditional risk adjustment models health status is typically determined through demographic (i.e. age and gender only) and clinical information, specifically diagnosis codes and medications recorded in claim data for an individual. While there have been a fair number of developments in the relatively new science of risk adjustment in the last decade, the use of demographic and clinical information has essentially remained the same. In this report, we collectively refer to this information as *traditional risk adjustment variables (age, gender, and diagnosis/pharmacy codes)*. The door on selection is not fully closed though, as these traditional variables do not explain all the variation in healthcare cost. On a concurrent basis, the best risk adjustment models explain about 20-50% of the variation in cost (Winkelman & Mehmud, 2007). In other words, this is less than half of the way to a full explanation. If a model could be devised that could do better – an issuer could identify and target customers while receiving a higher revenue credit through a traditional risk adjustment program relative to the assumed risk.

At this juncture, it is useful to say a few words about why we consider nontraditional variables to be an important area of research in risk adjustment. There are two distinct stakeholder perspectives on the issue, as follows.

1. **Issuer Perspective**: Understanding the impact of nontraditional variables is as much about avoiding losses as it is about creating gain. The ACA risk adjustment is intended to be a zero-sum exercise, but if incentives for selection via nontraditional variables persist and are utilized only by a few participants, then participants not using them will suffer. Conversely, if the variables

are used similarly across the marketplace, then the potential for adverse effect on a given issuer would be greatly mitigated.

2. **Policy Perspective**: It is important to understand the impact of nontraditional variables and to consider these in any update of a risk adjustment methodology so that policy goals are preserved.

This report was written keeping in mind both of these perspectives, and the author hopes that the information contained herein is constructive towards those goals.

The title of this report is *Nontraditional Variables in Risk Adjustment*, and these potentially present a path toward a better performing risk adjustment model. In this report we test the potential of these variables to explain claim cost variation above and beyond traditional risk adjustment. The nontraditional variables were grouped, using judgment, into one of five categories. Each variable was analyzed in exactly the same manner. The categorization merely serves to organize results and to suggest general characteristics that may be impactful from a business perspective. Specifically we tested characteristic variables from the following broad categories:

1. **Demographic**: While traditional models utilize age and gender, we built models that included race, years of education, smoking status, occupation or industry, and family size. In addition, geography is an important variable in that it is readily available *and actionable* in terms of devising marketing strategies to attract certain populations.
2. **Economic**: Income is an important variable to consider in this research. Cost-sharing subsidies are based on income levels in healthcare reform, which in turn impacts the ACA risk models via an assumed induced utilization. We explore the extent to which relative income explains the variation in cost.
3. **Lifestyle**: Variables include whether the person was advised to restrict high fat/high cholesterol foods, usually had a lot of energy, whether health had limited social activities, or was advised to exercise more.
4. **Psychological Outlook**: We tested variables such as whether a person considered their mental health status to be good, fair, or poor; or felt calm or peaceful, etc.
5. **Physical Outlook**: Perception and attitudes towards personal health may drive medical cost, and we tested variables such as whether perceived health status was poor, whether the person had

difficulty in walking three blocks, or whether the person feels that ills can be overcome without medical help.

In this research we narrowed down an initial list of over fifteen hundred variables to two hundred, using a rigorous process of selection (Section 3.2.4). We further narrowed this list to around thirty-three variables, and this report presents the answers to five key questions that we explored for each of the variables.

1.2 Research Questions

The results presented in this report address each of the following five key questions:

1. **What is the relationship between a nontraditional variable and total health costs?**
2. **Is the relationship statistically significant?**
3. **Does the relationship persist after we risk-adjust costs using traditional variables? Is the relationship still statistically significant?**
4. **How do we quantify the potential and incentive for using a nontraditional variable in a risk adjusted environment?**
5. **How do we adjust a risk adjustment methodology to remove such an incentive?**

Together these questions constitute a fairly comprehensive look at a nontraditional variable and its value in a risk adjustment program, both from a public policy and a private issuer perspective. There are a number of conceptual steps that go into answering these questions, and it will be helpful to go through a detailed example. Section 1.3 develops the key findings of this research in the case of a particular nontraditional variable: *family income as a % of poverty level (*also referred to in Section 1.3 as *income level* or as *family income)*.

1.3 A Step-by-Step Example: Income Level

There is considerable literature (see Section 1.4) that suggests that healthcare utilization is in fact related to income and other indicators of socioeconomic status. The variable of income is not typically used in risk adjustment and so we consider it a nontraditional variable for purposes of this research. As you navigate through the analytic build-up that follows, keep the following overarching question at the back of your mind: *can income be used to attract a certain membership such that costs* *are lower relative to risk adjusted revenue (and therefore resulting in an improved loss ratio for the issuer)*?

In our research, we used data from the Medical Expenditure Panel Survey (MEPS), a unique database that includes member-level healthcare cost and utilization information together with a plethora of socioeconomic variables, including income[3]. For each of the carefully selected variables, we tested and quantified the potential to improve a traditional risk adjustment model[4]. The first step in the analysis is to answer the following question:

Question 1: What is the relationship between income level and total health costs?

Table 1.3.1 shows how total health costs vary as family income increases from poor to high income.

Table 1.3.1 – Variation in Mean Cost by Family Income Category[5]

Category	%	Cost
1 POOR/NEGATIVE	6.8%	0.8989
2 NEAR POOR	2.7%	0.8557
3 LOW INCOME	11.1%	0.8494
4 MIDDLE INCOME	33.9%	0.9468
5 HIGH INCOME	45.5%	1.1003
ALL	**100%**	**1.0000**

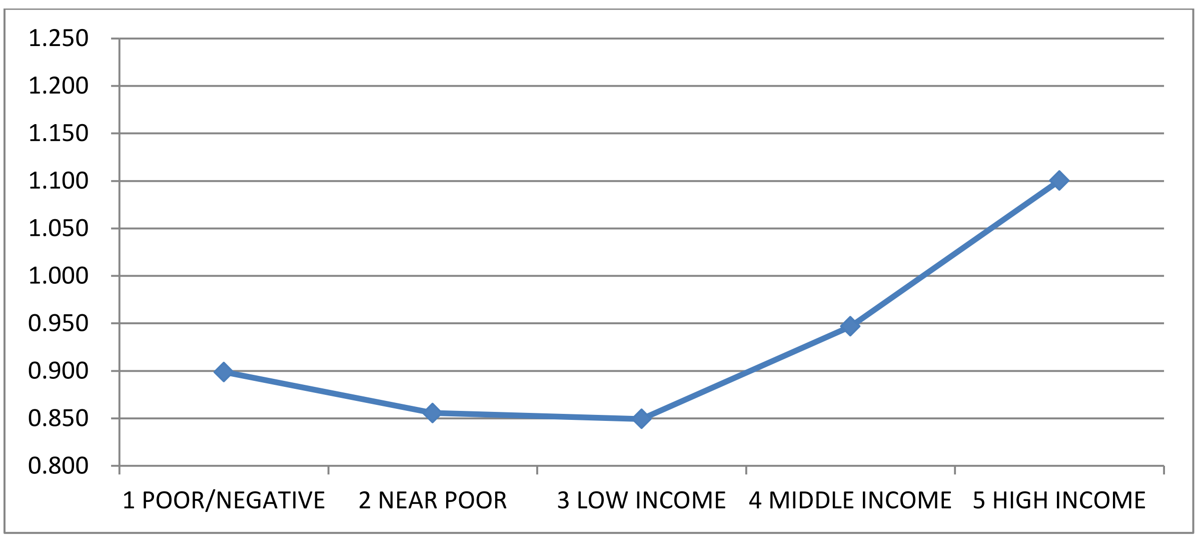
Income in Table 1.3.1 is defined in terms of the family income as a percentage of the Federal Poverty Level (FPL). Family income is categorized as 'Negative or Poor' (less than 100% of FPL), near poor (100-125% of FPL), low income (125-200% of FPL), middle income (200-400% of FPL), and high income (400%+ of FPL). There is an extensive discussion of what constitutes total individual healthcare

[3] Additional details on MEPS are provided in Section 3, and on the income variable in Section 2.4.4
[4] For further information on this process please review Section 3.2.4, *Variable Winnowing*
[5] The reader will note that the categorization does not result in an even distribution (e.g. top two income categories represent most of the population). The reason is that we are excluding Medicaid populations from analysis as we are trying to focus on the commercial segment, and re-categorization of data is not possible with the data source that was used.

cost for purposes of this research in Section 3.2.1. It is referred to simply as 'cost' through the rest of this report.

The first column presents the proportion[6] of people falling into the corresponding income category. The second column presents actual costs[7], which have been normalized such that they average to 1.0 over the study sample. The study sample includes only Commercial and Uninsured populations. The sample is also restricted to those under sixty-five years of age. At first glance it appears that the relationship between income and costs is complicated (sort of saddle-shaped when we graph it, see Figure 1.3.1). However this apparent complexity owes to the fact that there is also the confounding variable of age/gender. For example the high income individuals/families tend to be older on average and total health cost is correlated with age.

Figure 1.3.1 – Relationship of Cost with Income Category



Note that the relationship between cost and income is described in terms of the difference in mean cost across income levels. Initially our research focused on describing the relationship in terms of a goodness of fit measure when a variable, such as income, is regressed on total cost.

[6] The proportions are derived from sample data, but are weighted such that they represent national estimates for the population comprising Commercial and the Uninsured

[7] A total healthcare cost variable was developed for this research keeping mind the limitations of MEPS data. Details on the development of this variable are presented in section 3.2.1.

The literature on risk adjustment, actuarial or otherwise, includes a proliferation of references to the *coefficient of determination*, or R^2. This statistical metric is used to determine the accuracy or *goodness-of-fit* of a risk assessment model, and is in fact one of the HHS criteria for evaluating state alternative ACA risk adjustment models. R^2 has a value between 0-1, with 1 representing that the model explains the variation in the dependent variable perfectly. The HHS model has an R^2 performance of about 30% according to the 2014 HHS Notice of Benefits and Payment Parameters (NBPP) (HHS, 2012). Can we use R^2 to evaluate the relationship between cost and income instead? Can we also use this metric to describe the incremental value of the nontraditional variable in a risk adjusted program?

We researched extensively to discover a way to reasonably express the relationship between a nontraditional variable and healthcare cost in terms of statistical metrics yielded by a least-squares regression procedure. We came to a crisp conclusion paid for by a significant amount of time and effort! Regression-related metrics alone, such as R^2, are inadequate in evaluating the relationship between cost (with or without risk adjustment) and a nontraditional variable. The reason is simple - changes in the value of this metric are inconsistent with the real economic impact of the nontraditional variable as expressed by the Loss Ratio Advantage. R^2 is known to be sensitive to outlying values at the expense of lesser effects, whereas small but statistically significant differences in average cost can have a large business impact on the loss ratio of an issuer.

Model accuracy is not the correct lens through which to evaluate a nontraditional variable in risk adjustment

The point in the above paragraph is important enough to warrant an analytic example. The Wakely Risk Assessment model includes a concurrent sub-model, with a performance of around 45.3**5**% (R^2) as measured on a commercial database using demographic (age and gender) and diagnosis-based clinical markers. If we remove demographic markers and *only* use clinical information, the R^2 performance becomes 45.3**0**%. Does this *miniscule* drop in statistical performance of the risk adjuster indicate that demographics are not important to consider along with diagnosis information?

Of course not! A closer inspection reveals that by not considering demographics (age/gender), the predictive ratios (i.e. ratio of predicted cost to actual cost) are biased by demographic categories. If demographics are not included in a risk assessment model, bias by demographic categories may lead to issuers having a very strong incentive to select younger/middle-aged individuals (as cost will be lower relative to risk adjusted revenue). **Correcting for bias that may lead to adverse selection should be a**

***primary* modeling goal in risk adjustment (consistent with the policy goal), and not simply improving the model accuracy (for example, the R^2 metric).**

It is for these reasons that (1) we do not use R^2 as a metric to evaluate the impact of nontraditional variables in this research (although we calculate and present this value), and (2) nontraditional variables can have a significant impact on issuer loss ratios, even though their marginal contribution to the statistical performance of a risk adjuster may be very small or even negligible. Omitting age and gender from the risk adjustment formula may not affect the accuracy of a concurrent risk model as measured by R squared, but it will have a significant business impact on risk-adjusted markets, and our research shows that there are nontraditional variables that can have a similar effect.

Considering age and gender as 'nontraditional' variables provides a powerful argument for adjusting traditional risk assessment models to reflect variables such as income and geography.

It is highly instructive to consider demographics (age and gender) as 'nontraditional' variables for a moment. We will expand upon this in Section 2.1, but demographics are not much different from other variables, such as income or geography. Yet while age/gender is a permanent fixture in virtually every risk assessment model, income and geography are not. In this research, we remove age and gender from the risk assessment model, re-calibrate the model, and measure the potential impact of age/gender. These results are presented in Section 2.1. Comparing age/gender to other nontraditional variables on a consistent basis provides a powerful argument for producing a more general risk assessment model. The results show that the business impact of including or excluding age/gender (from a risk assessment model) is not superior to many other nontraditional variables. If age and gender are widely accepted for inclusion in risk models based on the argument that they mitigate model bias, then several other nontraditional variables should also be considered for inclusion[8]. Later in this section, we build the conceptual framework and the financial metric needed to quantify the business impact of traditional and non-traditional variables.

[8] Note that mitigating bias and improving accuracy are not the only considerations for including or excluding variables from a risk adjustment methodology. Legal and privacy considerations are also important. Certain variables (e.g. race) may be challenging to include in a model due to other considerations.

We turn our attention now to the second research question:

Question 2: Is the relationship between income and cost statistically significant?

Answering this question involves a statistical test to determine whether the observed relationship of cost with income is statistically significant. The results of this test are presented in the third column in Table 1.3.1. To talk more meaningfully about this test we specify the null (H_0) and alternate hypothesis (H_1) as follows:

H_0: The null hypothesis is that the average cost by an income category is in fact higher (or lower) than the average cost for the population (which is 1.0).[9]

H_1: The alternate hypothesis is that the average cost by an income category is in fact lower (or higher) than the average cost for the population.

The next steps involve computing the *t*-statistic and calculating the likelihood of a chance variation yielding a test statistic as extreme as the one for the null hypothesis. In other words, the probability of exceeding the *t*-statistic represents the likelihood of the survey yielding a sample that *by chance or coincidence* has a different average cost for a category of respondents. Details of statistical significance testing are presented in Section 3.5.1, and the test indicates that the mean cost by every income category is statistically significant and therefore not likely an artifact of data sampling.

Question 3: Does the relationship between income and cost persist after we risk-adjust cost? Are the average differences by cost still statistically significant?

Risk adjusted cost by nontraditional category is the most important perspective with which to analyze a nontraditional variable. Prior to adjusting cost, we need to present it on a similar basis as risk scores. We *normalize* cost by dividing a cohort's cost by the overall average cost, and in this manner both the average cost and risk score is defined as a 1.0. Table 1.3.2 presents mean risk score by income category, as well as the mean cost adjusted for risk score.

Before going to Table 1.3.2, let us review our understanding and handling of risk scores. In Table 1.3.2 the risk-adjusted cost is calculated as **(i.e. Adj. Cost = Cost - Risk Score + 1)**. This is not the only

[9] Typically, the null hypothesis would assume that effect is no different than the average (or 1.0). In the one-tailed test however, we are studying whether the mean is significantly greater than average or significantly less.

possibility for calculating risk-adjusted cost. For example one could compute it as the ratio of normalized cost and average risk score. The table below illustrates both methods of risk-adjusted cost. The methods yield similar, but not the same answers. Method 1 is the correct method in the specific situation where one is adjusting cost for the assessed risk score.

	Member Months	Risk Score	Cost PMPM	Cost Normalized	Method 1 [Cost-Risk+1]	Method 2 [Cost / Risk]
Plan A	1,000	1.030	$450.00	1.091	1.061	1.059
Plan B	1,000	0.970	$375.00	0.909	0.939	0.937
Total/Avg.	2,000	1.000	$412.50	1.000	1.000	0.998

Let us think through the example carefully and conceptually. The average (normalized) cost for Plan A is 1.091. Risk score accounts for about 3% of the variation from the average for Plan A. The cost for Plan A is $450.00. The risk score prediction (or estimate) is that Plan A should cost $424.88 (risk score 1.030 x average cost $412.50). This means that while Plan A's costs are $37.50 PMPM higher than the average ($450.00 - $412.50), $12.37 of this increase is explained by Plan A having a higher than average risk score. The remaining increase is unexplained and therefore the risk-adjusted cost is *average cost plus the portion (of the variation) not accounted for by the risk assessment model*, or **$437.63** (i.e. $412.50 + ($37.50 - $12.37)). If we normalized this cost (i.e. divide by average cost), we get 1.061 as in Method 1 (and not 1.059 as in Method 2). Note further that Method 2 yields risk-adjusted costs that do not average to 1.0 overall (an added benefit of Method 1 over Method 2 is in not having to re-scale the average to a 1.0). If we perform another scaling adjustment (i.e. dividing by the average score for Method 2, or 0.998), the risk adjusted cost for Method 2 becomes 1.0611 (whereas Method 1 gives 1.0609). The risk-adjusted cost in dollar terms becomes $437.69, which is closer to the correct answer (i.e. $437.63), but is *six cents too high*. One may easily construct additional examples where the difference between Methods 1 and 2 is larger. Hopefully this discussion illustrates how important it is to understand the real meaning of a risk score (which is akin to a cost estimate, and not always treated as an adjustment factor to a cost estimate). As stated earlier, this is a subtle but an important distinction. Practitioners should exercise great care when performing calculations that involve both actual costs and risk scores.

Risk-adjusting cost involves a subtle but important distinction.

Now let us get back to Table 1.3.2 which shows actual costs adjusted by the risk scores.

Table 1.3.2 – Variation of Actual Costs and Risk Scores by Income

Category	%	Cost	Risk Score	Adj. Cost	Sig.
1 POOR/NEGATIVE	7.0%	0.899	0.882	1.017	x
2 NEAR POOR	3.0%	0.856	0.877	0.979	x
3 LOW INCOME	11.0%	0.849	0.900	0.950	✓
4 MIDDLE INCOME	34.0%	0.947	0.958	0.989	x
5 HIGH INCOME	45.0%	1.100	1.081	1.019	✓
ALL	100.0%	1.000	1.000	1.000	

We can see that the mean cost and risk scores are more or less correlated, which tells us that the risk assessment model is doing a fair job of tracking the total healthcare cost of individuals. Statistical significance testing further reveals that even after adjusting for underlying morbidity risk, the differences in mean cost by income category are significant for the low income (Level 3) and high income (Level 5) categories of poverty level. The average risk-adjusted cost for the other categories is not statistically significantly different than the population average (i.e. 1.00). However while statistical significance by <u>each category</u> of the nontraditional variable is a useful test, *it is unnecessarily stringent*. In order for the results for a variable to be meaningful for purposes of influencing selection bias, we only need to show that the mean risk-adjusted cost is different for the *lowest* and *highest* categories of income level. The income level variable shows significance for this test (see Section 2.4.4 for further details).

While it is known that cost is correlated with income (see Section 2.4), we do not see a pronounced relationship in Table 1.3.2 because we are only considering the subset of data that will potentially enroll in ACA plans (i.e. commercial and the uninsured). This subset does not represent the full spectrum of income levels, and is sparse at the lower income levels as measured as a percentage of the federal poverty level. There is a more powerful income variable for the commercial and the uninsured segment of the population, and that is presented in Section 2.4.2.

Question 4: How do we quantify the potential and incentive for using a nontraditional variable in a risk-adjusted environment?

This is the key question of this research, and one that necessitated development of a new tool or measure that is proposed in this section (called **Loss Ratio Advantage, or LRA**). Table 1.3.2 shows the relationship of risk-adjusted cost with income levels. However, we need another conceptual layer in order to quantify the strength of an incentive to (a) either use this (or similar) nontraditional variable in the risk assessment formula or towards selection activities (e.g. selectively marketing products) [*issuer perspective*], or conversely (b) adjust the risk adjustment methodology to include variables that mitigate the incentive for selection [*policy perspective*]. The economic impact of a nontraditional variable is a function of both the difference in the value of risk adjusted cost as well as how those values are distributed within the population. The latter part of that sentence is rather important (and not immediately obvious), since a variable may be able to identify a subset of a population that is 10 times more profitable to enroll, but if that cohort is only 0.5% of the total population, then the business impact is minimal. Hence, the investment necessary to use that variable in practice might not be worth the cost.

LRA is the measured potential of a risk adjustment variable to produce loss ratio differentials in a market.

We construct a simplistic example, without any loss of generality, to quantify the potential economic impact of a nontraditional variable. We focus on the bottom line impact to an issuer, in terms of loss ratios, and not a statistical metric such as the *R* squared goodness-of-fit. Statistical metrics focusing on accuracy often have little or no bearing on the business importance of a nontraditional variable which is driven chiefly by *bias*.

Assume that our study population is covered by two issuers (**Issuer A** and **Issuer B**). Assume that 50% of the members are covered by each issuer. This assumption is fundamental to our research approach since it allows us to consistently compare the importance of each nontraditional variable. Assume further that Issuer **A** is able to use this nontraditional variable to selectively target and enroll preferred members that have the lowest risk-adjusted cost. Issuer B must then enroll the remaining half of the population. Both issuers have similar administrative overhead and are otherwise identical, except for Issuer A's ability to target and selectively enroll preferred members based on certain (nontraditional) information.

In one sense, this construct represents the maximum influence that a nontraditional variable may have (since in reality an issuer may not be able to (a) identify all of the individuals in a population in such a manner, and (b) enroll every one of the identified individuals). In another sense, this is *not* the maximum impact a variable may have since an issuer may be able to produce more extreme loss ratio differences in a market by enrolling more or less than 50% of the identified population. On balance, this construct provides a reasonable and consistent comparison of the potential impact across all of the nontraditional variables studied in this report.[10]

We develop a key new measure in this section called the ***Loss Ratio Advantage (LRA)***. LRA may be defined as the potential of a nontraditional risk adjustment variable to produce loss ratio differentials in a market. The first step in doing so is to develop the final revenue for Issuer A and B in accordance with the Affordable Care Act (ACA) regulations. According to the rules of ACA risk adjustment in 2014, both issuers set prices assuming an average risk population (i.e. 1.0 risk), and their ultimate premium for 2014 will be equal to:

2014 Final Premium = Premium without Risk Selection + Risk Adjustment Transfer

Risk adjustment transfers are to be calculated using the following statutorily defined formula:

$$T_i = \left[\frac{PLRS_i \times IDF_i \times GCF_i}{\sum_i (s_i \times PLRS_i \times IDF_i \times GCF_i)} - \frac{AV_i \times ARF_i \times IDF_i \times GCF_i}{\sum_i (s_i \times AV_i \times ARF_i \times IDF_i \times GCF_i)}\right] \overline{P_s}$$

Where:
$\boldsymbol{T_i}$=Transfer for plan i
$\overline{\boldsymbol{P_s}}$=State Average Premium
$\boldsymbol{PLRS_i}$=Plan i's plan liability risk score
$\boldsymbol{IDF_i}$= Plan i's induced demand factor
$\boldsymbol{ARF_i}$=Plan i's allowable rating factor
$\boldsymbol{AV_i}$=Plan i's metal level AV
$\boldsymbol{GCF_i}$=Plan i's geographic cost factor
$\boldsymbol{s_i}$=Plan i's share of State enrollment, and the denominator is summed across all plans in the risk pool in the market in the state

[10] For specific applications (e.g. where a variable affects only a certain demographic and not the entire population, or where there are limitations in terms of the members an issuer can enroll, etc.), it may be necessary not to assume a uniform 50-50 split in development of the LRA. The method described in this paper is general, and may need to be adjusted to the application of interest in order to produce more relevant comparisons.

The formula above seems complicated however it can be simplified substantially. Once again, without any loss of generality (and a desirable loss of complexity for purposes of this research), we assume that all individuals are enrolled within the same metal tier and rating area, and in one qualified health plan each for Issuer A and B. In this manner, the induced demand factor (IDF), geographic cost factor (GCF), and actuarial value (AV) terms in the formula cancel out. What is left is an adjustment for the allowable rating factor. The state average premium can simply be assumed as average total healthcare cost (normalized cost=1.0) plus an additional 20% for administration and margin (i.e. $\overline{P_s}$ = 1.2). The denominator terms in the equation equal 1.00 (as they represent the average risk and rating factors over the whole population). The allowable rating factor (ARF) is based upon age and we calculated the average factors by applying the age and gender based values published by HHS[11] to the research data. For **Issuer A** and the nontraditional variable of family income category level, the transfer equation simplifies to the following (the numbers in the equations come from Table 1.3.3):

$$T_i = \left[\frac{PLRS_i \times \cancel{IDF_i \times GCF_i}}{\sum_i (s_i \times PLRS_i \times \cancel{IDF_i \times GCF_i})} - \frac{\cancel{AV_i} \times ARF_i \times \cancel{IDF_i \times GCF_i}}{\sum_i (s_i \times \cancel{AV_i} \times ARF_i \times \cancel{IDF_i \times GCF_i})}\right] \times \overline{P_s}$$

$$T_{Issuer\ A} = \left[\frac{0.937}{1.00} - \frac{ARF_{Issuer\ A} = 0.949}{1.00}\right] \times 1.2 = -0.014$$

$$T_{Issuer\ B} = \left[\frac{1.063}{1.00} - \frac{ARF_{Issuer\ A} = 1.051}{1.00}\right] \times 1.2 = +0.014$$

Once the transfer has been calculated, it is simple to compute the eventual revenue for Issuer A for the benefit year. The premium without risk selection for Issuer A is the state average premium times the allowable rating factor (i.e. 1.2 x 0.949[12] = 1.138). The eventual premium for Issuer A is premium without risk transfer plus the risk transfer (i.e. 1.138 + (-0.014) = 1.12). The expenditure for Issuer A is 0.918[13] and therefore has a loss ratio of about 82% (i.e. 0.918/1.12). Issuer B has exactly the opposite risk transfer (i.e. receives a payment of 0.014 from Issuer A) and has an expenditure of 1.082. The loss ratio for Issuer B is about 85%. The advantage in terms of the loss ratio for Issuer A; developed via segmenting the population based on income and selectively enrolling – is 85% less 82%, or about **3%**.

[11] Web source (1.30.2013): http://cciio.cms.gov/resources/files/market-rules-nprm-technical-summary-11-20-2012.pdf.

[12] From Table 1.3.3, Section C, line 5. The value represents the average demographic score, using factors published by HHS, and weighted by the member months of the members selecting to enroll with Issuer A or B.

[13] From Table 1.3.3, Section C, line 4.

This is the loss ratio advantage metric or LRA, and forms the most important piece of the conceptual framework presented in this report. At an LRA of 3.2%, this variable has a *moderate* business impact (note that this does not mean that income *generally* has a moderate business impact, please see Section 2.4.2). LRA ranges from 0-10% for most of the nontraditional variables. We qualitatively classify the impact of a variable as follows:

1. **Low**: LRA of less than 3.3%
2. **Medium**: Higher than 3.3 but less than 6%
3. **High**: Higher than 6%

The risk score has been calculated using a pharmacy-only model from the Wakely Risk Assessment (WRA) tool. Pharmacy models use National Drug Codes (NDCs) and these codes are fully specified in MEPS data, whereas ICD-9 diagnoses codes are only specified to three digits in this data. Pharmacy-only models have been shown to be very close in performance to diagnosis-only models, and therefore we applied such a model[14] on this data to calculate a member-level risk score. The model performs at a similar goodness-of-fit measure as the HCC model (at over 30%[15]). Additional details on this model are included in Section 3.4. This score is also adjusted such that it normalizes to 1.0 over the sample.

Question 5: How do we adjust a risk adjustment methodology to remove the incentive to select based on income level?

We now know (at least with respect to the MEPS data and methods presented in this research) that income can be an important characteristic of those seeking healthcare coverage. It appears that issuers have an incentive to enroll individuals having a certain income (see Sections 2.4.2 and 2.4.3), and that this incentive still persists even in a risk-adjusted environment which compensates for the fact that the higher income cohort is, on average, older.

Fortunately, risk adjustment methodologies may be adjusted periodically to better address the policy goals of risk adjustment. There is no one right way to construct an actuarially and clinically sound

[14] Specifically the Wakely Risk Assessment (WRA) Model (www.wramodel.com)

[15] The measure is calculated over proxy expenditures in this report, described in Section 3.2.1 – and on real expenditure the performance may be lower, but in the opinion of the author not low enough to significantly alter the conclusions of this work.

risk assessment model. Indeed, several commercial models (Winkelman & Mehmud, 2007) exist, with varying strengths and weaknesses. In this example, the risk adjustment model may simply be adjusted to include income category as a nontraditional variable.

Equation 1 below is a good representation of most risk assessment modeling approaches, which are based on linear regression. In the equation below, *Y* represents total healthcare cost (i.e. the dependent variable). The alpha represents the intercept term in the linear regression. There are twenty-four age/gender categories (twelve each for males and females) and they are represented by the first summation term in the equation. The beta-terms are the coefficients whereas the D_i term is a binary indicator for whether an individual belongs to the *i*-th demographic (i.e. age/gender) category. An individual may be indicated for up to sixty pharmacy-claim based categories in the WRA risk assessment model, and these are represented by the second summation term in the equation below.

Equation 1: Traditional Risk Adjustment Model

$$Y = \alpha + \sum_{i=1}^{24} \beta_i \times D_i + \sum_{j=1}^{60} \gamma_j \times C_j + \varepsilon$$

Equation 2 below represents a model in which the residual term (i.e. the difference of actual and risk score prediction based on traditional variables such as age/gender and clinical information) has been regressed on income categories. In this model there are *k* categories of income level (see Table 1.3.3), with coefficients represented by θ_k and categories of the nontraditional variable represented by N_k. In this manner, we are trying to adjust the model errors to be unbiased (i.e. correct where average error is different than zero) by income level. In practical terms, this removes the incentive to selectively enroll individuals based on income by recognizing and adequately compensating issuers for the income-related differences in utilization of healthcare services.

Equation 2: Potential Nontraditional Risk Adjustment Model

$$Y - \left(\alpha + \sum_{i=1}^{24} \beta_i \times D_i + \sum_{j=1}^{60} \gamma_j \times C_j \right) = \sum_{k} \theta_k N_k + \varepsilon$$

We spent a lot of time carefully thinking through the modeling construct presented in Equation 2. We concluded that this construct does *not work* because, by regressing only on the residual, we potentially introduce a worse bias by age/gender. The correct way to adjust the model is to include the nontraditional variable as an additional variable in the overall regression that includes age/gender and clinical markers and therefore *simultaneously* removes any bias from both traditional and nontraditional groupings. Equation 3 presents that correct model.

Equation 3: Recommended Nontraditional Risk Adjustment Model

$$Y = \alpha + \sum_{i=1}^{24} \beta_i \times D_i + \sum_{j=1}^{60} \gamma_j \times C_j + \sum_{k} \theta_k N_k + \varepsilon$$

If the risk adjustment model is adjusted in the manner described in equation 3, potentially all of the incentive for selection due to income level is mitigated. In reality however, not all of the risk may be mitigated because the model may not be calibrated[16] to exactly the same population that the model is being applied to. In order to help adjust for this, the model may be calibrated to a nationally representative data sample (for example similar to the HHS model), or if a state pursues an alternative model, to historic experience in that state.

1.3.1 Understanding the Results

We now turn our attention to the standard result layout that is used throughout this report. Please review Table 1.3.3 below. We developed this table to allow for a systematic and consistent description of results and to allow for easy comparison across variables. This table represents all of the results from the tables discussed above. The table includes four sections (**A to D**), and these are described in detail following the table.

Table 1.3.3, **Section A**: This section summarizes the key values from the data. The proportions of members that have been nationally weighted to represent the commercial and uninsured populations are presented in line 1. For example, 33.9% of individuals studied in this research belonged to Category

[16] Generally speaking, calibration is a process of adjusting the coefficients in a risk assessment model, where the parameters or independent variables are age/gender and clinical condition indicators. The process involves using a certain modeling technique (e.g. linear regression) in order to develop such coefficients. A calibration may be needed if the performance of the model is poor on a population that is not representative of the sample used to develop the model in the first place. Performance in this context primarily concerns accuracy and bias.

4 (i.e. **Catg4**), and these are Middle Income individuals (as can be seen from the category descriptions following Table 1.3.3).

Table 1.3.3 – Results for 'Family Income as % of Poverty Level'

Variable Name *POVCAT* **Class:** *Income* **Desc:** *family income as % of Poverty line*

***Section A*: Summarizing by non-traditional variable categories**

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	6.8%	2.7%	11.1%	33.9%	45.5%					
2 Total Expenditures	1.0000	0.8038	0.6756	0.7789	0.9340	1.1523					
3 Proxy Expenditures	1.0000	0.8989	0.8557	0.8494	0.9468	1.1003					
4 Traditional Risk Score	1.0000	0.8823	0.8767	0.8997	0.9580	1.0809					
5 Risk Score + *N*	1.0000	0.8989	0.8557	0.8494	0.9468	1.1003					
6 Risk Score + $\sum N'_{prop}$	1.0000	0.8775	0.8546	0.8727	0.9561	1.0910					
7 Allowable Rating Factor	1.0000	0.9479	0.9360	0.9345	0.9544	1.0617					
8 Proxy Exp Adjusted	1.0000	1.0165	0.9790	0.9497	0.9888	1.0194					

***Section B*: Issuer Selection Assumptions**

		Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5
1		**LRA Rank**	**4**	**2**	**1**	**3**	**5**
2	Issuer A	50.0%	2.3%	2.7%	11.1%	33.9%	
3	Issuer B	50.0%	4.5%	0.0%	0.0%	0.0%	45.5%

***Section C*: Market Scenario**

		Traditional Risk Score			Risk Score + *N*			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	0.22%									
2 Maximum {Pr > |*t*|}	0.0000	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.918	1.082	1.000						
5 Allowable Rating Factor		0.949	1.051	1.000						
6 Risk Score		0.937	1.063	1.000	0.918	1.082	1.000	0.928	1.072	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.138	1.262	1.200						
9 Premium with Risk Selection		1.125	1.275	1.200	1.102	1.298	1.200	1.114	1.286	1.200
10 Risk Selection Transfer		(0.014)	0.014	-	(0.037)	0.037	-	(0.024)	0.024	-
11 Loss Ratio		81.6%	84.8%	83.2%	83.3%	83.3%	83.3%	82.4%	84.1%	83.3%
12 Loss Ratio subject to risk corridor		81.6%	84.8%	83.2%	83.3%	83.3%	83.3%	82.4%	84.1%	83.3%
13 **Loss Ratio Advantage (LRA)**		**3.2%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**1.7%**	Model R^2:	34.4%

***Section D*: Statistical Significance Testing**

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5
1 *t*-statistic		(1.25)	0.94	2.56	1.01	(2.29)
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	No	No	Yes	No	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Poor/Negative
2. Near Poor
3. Low Income
4. Middle Income
5. High Income

The total expenditure or paid cost per year per member, expressed in a normalized manner (i.e. 1.0 is the average cost per member) is presented on line 2. The *proxy expenditures* correct (to a certain extent) for limitations of the paid data, and are presented on line 3. The limitations include for example, underreporting of healthcare cost for the uninsured segment of the population. The process of developing proxy expenditures is described in Section 3.2.3.

The *traditional* risk score is presented on line 4 – and this score is defined as traditional since it uses the typical age/gender and clinical information. We can see that this score is biased with respect to income level (i.e. is not the same as the normalized expenditure in line 3). Line 5 presents the risk score as modeled by traditional variables and includes the variable under discussion, i.e. income level. We can see that this score is unbiased with respect to expenditure. It is important to note that this may not be true for every variable. For a few variables with many ordinal splits, we modeled an aggregation of those splits keeping in mind the very important principle of model parsimony and avoiding 'over fitting' the model.

Line 6 presents a model that we refer throughout this report as **Model 3**. As part of this research, we investigated three models:

Model 1: Traditional risk score (calibrated to MEPS data). This is also reflected in the first of the three tables in Section C.

Model 2: Traditional risk score *and* the nontraditional variable under study. The results corresponding to this model are presented in the middle table in Section C (i.e. Risk Score + *N*).

Model 3: Traditional risk score *and* three selected nontraditional variables (i.e. Region, Wage, and Insurance Coverage). Results corresponding to this model are presented in the last table in Section C (i.e. Risk Score + $\sum N'_{prop}$). The subscript of 'prop' indicates that this is a proposed model, and the summation is over the three nontraditional variables (see Equation 3 in Section 1.3).

After an extensive review of variables as described in this report, we developed a model that used three of the key nontraditional variables. This is the author's recommendation of a model that should be considered in terms of adjusting the ACA risk adjustment models to reflect the important *and actionable* nontraditional variables. A nontraditional variable may be important because it has a high LRA, but may not be actionable since it may be practically infeasible to collect that information on those seeking coverage (e.g. a nontraditional variable indicating that pain hinders an individual's daily activities).

The seventh line in Section A presents the average **allowable rating factor**. Each individual in MEPS is assigned a demographic factor based on a age rating curve published by HHS[17]. Issuers will be able to rate based on age in the benefit year 2014 and beyond, and the risk adjustment transfer formula recognizes age adjustment since the objective is to calculate payments or charges based on factors that an issuer is unable to rate for.

Line 8 presents a key calculation, and that is ***risk adjusted proxy expenditures***. These are calculated as (Proxy Expenditures – Traditional Risk Score + 1), or Section A, line 3 minus line 4 plus 1. If risk scores estimate expenditures in an unbiased manner for each category of a nontraditional variable – then each value on this line will be a 1.00. A value greater than 1 indicates that the risk score may not fully recognize the expenditure level for a category of a nontraditional variable and a value less than 1 indicates that the risk score may be an overstated estimate of expenditure.

Table 1.3.3, Section B: Line 1 presents the ***LRA Rank***, which ranks the risk-adjusted average expenditure by nontraditional variable category from lowest to highest. Lines 2 and 3 present the enrollment pattern for Issuer A and B. As stated earlier, we assume that Issuer A is able to select based on the nontraditional variable, and Issuer B enrolls the remaining members. Issuer A prefers to enroll those individuals whose risk-adjusted expenditure is *lower than 1.00*. This means that the risk score is potentially biased upwards with respect to expenditure – and as a result the issuer may realize more in revenue than is paid out in claims.

Table 1.3.3, Section C: This section presents the calculation for the ultimate revenue calculated considering the HHS risk adjustment methodology for both Issuers A and B as described earlier in this section. In addition, the results are shown for all three versions of risk score, the versions being (1) traditional risk score using a typical commercial model such as WRA or HHS' ACA model, (2) risk score including the traditional variable under consideration, and (3) risk score including three selected nontraditional variables, and these are (i) total wage income, (ii) coverage type (i.e. uninsured or commercial insurance), and (iii) region.

Line 1 in Section C presents the stand-alone R^2 statistic. This represents the accuracy of a model that *only* includes the nontraditional variable under study (in this case, family income as a % of poverty

[17] As available on the web on 3-4-2013: http://cciio.cms.gov/resources/files/market-rules-nprm-technical-summary-11-20-2012.pdf

level). Line 2 indicates whether *all* of the coefficients of the stand-alone regression are statistically significant (i.e. a more restrictive condition on the model as a whole being statistically significant). A value of less than 0.05 indicates that the coefficients are significant.

Line 3 shows the market share by issuer, and by design each issuer has half of the market share. The average proxy expenditures (weighted by enrollment pattern from Section B) are presented on line 4. The average allowable rating factor is presented on line 5. In the case of this variable the results show that Issuer B generally enrolls an older cohort (and therefore the average allowable rating factor is over 1.00). Lines 3-5 do not vary across the columns for Models 1-3, and therefore these are only presented once.

The average risk score is presented in line 6. The risk score varies for each of the three risk models. Line 7 presents the statewide average premium, which is assumed to be 20% over the average cost (the average, normalized cost is assumed to be 1.0).

The ACA risk adjustment transfer calculation (line 10) is the difference between the premium with risk selection (line 9) and the premium without risk selection (line 8).

Loss ratio (line 11) is defined as the ratio of healthcare expenditure (line 4) to the premium with risk selection (line 9). This loss ratio is constrained by the provisions of the ACA risk corridor program, and this version of the calculation is presented on line 12. The difference in the loss ratio between Issuer B (which passively enrolls the remaining population) and Issuer A (which is assumed to actively select members based on a nontraditional variable) is presented on line 13 as the **LRA** metric. One can see that Model 2 perfectly mitigates the potential for selection (as all variable categories are used in the re-calibrated risk adjuster). Hence Model 2 has an LRA of 0%, whereas Model 3 mitigates only some of that selection potential. That is, Model 3 mitigates about half of the 3.2% LRA resulting from traditional risk score approach relative to Model 2; whereas Model 2 mitigates the full 3.2% that remains in the traditional model, which does not use family income in the regression formula as does Model 2.

Line 13 also presents the R^2 statistic for each of the three models. The results show that there is an immaterial change in this statistic when poverty level is added to the risk assessment model formula (the statistic remains at 34%), whereas the accuracy improves by a small amount when the three variables in Model 3 are included.

Table 1.3.3, Section D: This section calculates whether the differences in expenditure and by nontraditional category are in fact significant. The columns represent each of the categories listed in order of their descriptions below the exhibit. The first line calculates the *t*-statistic which is based on the standard deviation of the risk adjusted proxy expenditure values in the data, weighted by the sampling weights provided in MEPS. Line 2 defines the null hypothesis (i.e. the hypothesis that we are testing), whereas line 3 defines the alternate hypothesis. Line 4 presents the results of the statistical significance test, essentially rejecting the null hypothesis if the likelihood that we got the observed results by chance is greater than 5%. The 'Yes*' value in Table 1.3.3 tests the null hypothesis that the lowest risk-adjusted expenditure is in fact lower than the highest risk-adjusted expenditure. Further details for the statistical significance calculations are described in Section 3.5.1.

The example and table above illustrate all of the key concepts that are developed and presented in this research. Initially, almost fifteen hundred variables were considered in this research. That list was systematically and rigorously winnowed down to two hundred. Of those, thirty-five variables were selected, tested in exactly the same manner, and their results presented in Section 2 in an identical fashion as those presented in the above example.

As a note, cost sharing subsidies in ACA legislation are tied to income levels and the HHS model adjusts risk scores for these cost-sharing reductions (CSRs). While the HHS model adjusts the risk scores based on additional demand that may be induced due to reduced cost sharing, the model does not consider that there may be fundamentally different (e.g. clinical) utilization of services by income level[18].

1.4 Literature Review

The focus of this report is to quantify how well nontraditional variables explain medical cost variation, especially after taking risk adjustment into account. Establishing whether a link exists between such variables and health (and by extension healthcare cost) is important to a causal understanding of such a relationship. We have selected a few studies and papers that explore such links. Please note that the following does *not* represent an exhaustive review of published literature.

Over the progression of the twentieth century, a decrease has been observed in mortality rates throughout the developed world, and average life span of the population has increased dramatically.

[18] Income level is not incorporated into the risk assessment model itself, similar to *model 3* described above

Although all sections of the population have participated in this improvement in health status and life expectancy, in most countries individuals of lower socioeconomic status have faced higher mortality rates (Feinstein, 1993). The last 20 years have seen an extensive growth in literature that studies the relationships between socioeconomic status and health, comparing the mortality and morbidity experiences of different socioeconomic groups in each country, recording the degree of disparities, and discovering possible descriptions of differential health consequences.

Logue and Jarjoura (1990) investigated the relationship between social class and heart disease mortality in 1,200 surveyed areas located in eight Ohio counties (Logue & Jarjoura, 1990). They noticed that lower-middle-class territories have a higher mortality rate than upper-middle-class cohorts, and working poor have a higher mortality than that of the upper-middle-class.

Haan, Kaplan, and Camacho (1987) studied mortality outcomes over 1965-1974 among residents of Oakland. In a multivariate regression in which the "dependent variable measures mortality and that includes as independent variables a set of controls (age, sex, race, baseline physical health status, smoking, weight, and social support), education, income and dummy variable for residence in Oakland's poverty area, they find that neither income nor education is statistically significant, but that the poverty area dummy (variable) is significant" (Haan, Kaplan, & Camacho, 1987).

A few additional studies were reviewed and associated notes are presented in the appendix.

2. Results

This section presents the key results for each of the thirty-three selected variables, along with brief notes on interpretation and (limited) references from published literature. An in-depth discussion of the variables is outside the scope of this report. For limitations of the results please review section 4.

2.1 Traditional Variables

In the view of this author, the best way to crystallize the value of a nontraditional variable in a risk adjustment formula is to somehow compare it to a traditional one. Age and gender are firmly established variables in virtually every risk adjustment application. Fortunately there is a simple way to demonstrate the importance of these variables, and we do it by calculating the LRA measure for these traditional variables.

We can generate results for these traditional variables by first re-calculating the regression formula by *ignoring* age/gender categories. The risk assessment formula (from Section 1.3) becomes:

$$Y = \alpha + \cancel{\sum_{i=1}^{24} \beta_i \times D_i} + \sum_{j=1}^{60} \gamma_j \times C_j + \varepsilon$$

We then can then use this risk score, developed using only clinical information based on member diagnoses, in order to calculate the LRA measure. Next, we calculate the LRA measure separately for age and for gender. These results are discussed below.

2.1.1 Gender

Before going into the details, it is helpful to describe the idea behind Tables 2.1.1(1) and 2.1.1(2) at a high level. For Table 2.1.1(1), all of the three risk models include gender as an independent variable, and therefore no advantage is created for Issuer A who wishes to use gender as a "nontraditional" variable to selectively enroll. The simple reason is that one cannot increase the information content of a model by using a variable twice. The LRA measure is therefore 0%.

For Table 2.1.1(2), we assume that the 'standard' or 'traditional risk score' model does not include gender. Another way to think about this is to imagine what would happen if the ACA risk adjustment model did not include gender as an independent variable. Here the enhanced, or "Risk Score + *N*") model includes gender as an additional variable above and beyond the standard or traditional model. The high LRA in this illustration serves to demonstrate the importance of gender in the risk assessment model, even though its contribution to the accuracy of the model is marginal at best. Let us now review the details.

Table 2.1.1(1) shows the standard results by gender category. The 'standard' or 'traditional' results utilize a risk score model that ***includes*** age/gender markers in the regression formula. The LRA is zero for all three models (i.e. traditional risk score using age, gender, and diagnoses; risk score with the gender variable only (i.e. Risk Score + *N*); and the proposed risk score that includes geography, income and uninsured indication (i.e. Risk Score + ∑*N*)). We do not observe any bias by gender since it is an independent variable in all three models. The LRA rank indicates that issuer A selectively enrolls the female gender, however this is based on risk adjusted costs, and those are slightly different between males and females (somewhere beyond the fourth decimal point). The statistical significance testing (Section 4 in Figure 2.1.1(1)) confirms that the LRA results are *not* significant.

Table 2.1.1(2) presents more interesting results. This time we develop a risk adjuster that **excludes** gender from the regression formula. The results show a staggering **7.3%** LRA for model 1 (i.e. traditional risk score without the traditional demographic (i.e. age/gender) variable). It is clear that gender is an important risk adjustment variable. Models 2 and 3 show zero LRA since these models include gender. Statistical significance testing confirms the results to be significant.

Section 3 line 1 shows that the R^2 produced by gender alone is a mere 1%[19]. This is an excellent example how statistical performance is <u>not</u> the right lens with which to view the importance of a variable in risk adjustment. Statistical performance is enhanced only 1%, but profit margins are enhanced 7.3%. Furthermore, dropping age/gender from the risk adjustment variables decreased statistical performance a mere 0.5% (see Table 2.1.1(2) from 34% to 33.5%). This further underscores the importance of the conceptual framework developed in Section 1.3 for the study of nontraditional variables.

What happens when a model includes the age/gender variable, but is not specifically calibrated to the data that it is being applied to? As an example, the WRA model was developed using a commercial database. Table 2.1.1(3) shows some *very* interesting results when *offered weights* (i.e. original weights that are not calibrated to the data on hand) are applied to MEPS data that includes commercial and uninsured populations.

[19] Section 3 line 2 shows that the results of regression produce coefficients that are statistically significant

Table 2.1.1(1) – Results for Gender (using a calibrated[20] risk score that includes gender)

Variable Name *SEX* **Class:** *Demographic* **Desc:** *Gender*

Section A*: *Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	50.8%	49.2%								
2 Total Expenditures	1.0000	0.8505	1.1542								
3 Proxy Expenditures	1.0000	0.7862	1.2205								
4 Traditional Risk Score	1.0000	0.7862	1.2205								
5 Risk Score + N	1.0000	0.7862	1.2205								
6 Risk Score + $\sum N'_{prop}$	1.0000	0.7862	1.2205								
7 Allowable Rating Factor	1.0000	0.9904	1.0099								
8 Proxy Exp Adjusted	1.0000	1.0000	1.0000								

Section B*: *Issuer Selection Assumptions

1	**LRA Rank**	**2**	**1**
2 Issuer A	50.0%	0.8%	49.2%
3 Issuer B	50.0%	50.0%	0.0%

Section C*: *Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	1.09%									
2 Maximum {Pr > |t|}	-	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		1.214	0.786	1.000						
5 Allowable Rating Factor		1.010	0.990	1.000						
6 Risk Score		1.214	0.786	1.000	1.214	0.786	1.000	1.214	0.786	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.212	1.188	1.200						
9 Premium with Risk Selection		1.457	0.943	1.200	1.457	0.943	1.200	1.457	0.943	1.200
10 Risk Selection Transfer		0.245	(0.245)	-	0.245	(0.245)	-	0.245	(0.245)	-
11 Loss Ratio		83.3%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%
12 Loss Ratio subject to risk corridor		83.3%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%
13 **Loss Ratio Advantage (LRA)**		**0.0%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

1 t-statistic		(0.00)	0.00
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	No*	No	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Male 2. Female

[20] The word 'calibrated' here means that the risk adjustment model was re-fitted to the data using linear regression and includes the gender variable (which is being treated as a nontraditional variable in the current section)

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Table 2.1.1(2) - Results for Gender (using a calibrated risk score that <u>ex</u>cludes gender)

Variable Name *SEX* **Class:** *Demographic* **Desc:** *Gender*

Section 1 : Summarizing by non-traditional variable categories

	Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	Category %	100%	50.8%	49.2%								
2	Total Expenditures	1.0000	0.8505	1.1542								
3	Proxy Expenditures	1.0000	0.7862	1.2205								
4	Traditional Risk Score	1.0000	0.8418	1.1631								
5	Risk Score + *N*	1.0000	0.7862	1.2205								
6	Risk Score + $\sum N'_{prop}$	1.0000	0.7862	1.2205								
7	Allowable Rating Factor	1.0000	0.9904	1.0099								
8	Proxy Exp Adjusted	1.0000	0.9443	1.0574								

Section 2 : Issuer Selection Assumptions

1		**LRA Rank**	**1**	**2**
2	Issuer A	50.0%	50.0%	
3	Issuer B	50.0%	0.8%	49.2%

Section 3 : Market Scenario

			Traditional Risk Score			Risk Score + *N*			Risk Score + $\sum N'_{prop}$		
1	Stand-Alone R^2	1.09%									
2	Maximum {Pr > |*t*|}	-	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3	Market Share		50%	50%	100%						
4	Proxy Expenditures		0.786	1.214	1.000						
5	Allowable Rating Factor		0.990	1.010	1.000						
6	Risk Score		0.842	1.158	1.000	0.786	1.214	1.000	0.786	1.214	1.000
7	Statewide Average Premium				1.200						
8	Premium without Risk Selection		1.188	1.212	1.200						
9	Premium with Risk Selection		1.010	1.390	1.200	0.943	1.457	1.200	0.943	1.457	1.200
10	Risk Selection Transfer		(0.178)	0.178	-	(0.245)	0.245	-	(0.245)	0.245	-
11	Loss Ratio		77.8%	87.3%	82.6%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%
12	Loss Ratio subject to risk corridor		80.0%	87.3%	83.7%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%
13	**Loss Ratio Advantage (LRA)**		**7.3%**	Model R^2:	33.5%	**0.0%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.4%

Section 4 : Statistical Significance Testing

1	*t*-statistic		9.42	(7.65)
2	H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$
3	H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$
4	H_0 rejected (at α=5%)	Yes*	Yes	Yes

Table 2.1.1(3) shows a medium-high LRA of almost **6%** for this example of a risk model that uses offered weights (i.e. weights that are developed on some standard database) and not weights that have been recalibrated for the application at hand. While the LRA is lower than in the case of ignoring demographics (i.e. age/gender) altogether – *it is not that much lower*. The non-calibrated model's statistical performance is also low at about 23% R^2. As a note, the statistical performance of a concurrent risk adjuster is likely to suffer more from calibration issues than a prospective risk adjuster (the reason being that a concurrent adjuster places more weight on medical conditions).

Table 2.1.1(3) makes a crucial point – it is important to test calibration bias by analyzing demographic (i.e. age/gender) categories to ensure that further calibration is not needed. This may be vital to preserve the policy goals of risk adjustment, and important to do so when ACA takes effect in 2014. Most states will be using the HHS risk adjustment model in 2014 which is calibrated to a standard commercial dataset. It will be important for the HHS (and for states) to review statewide and market-wide data for evidence of any bias in demographic categories, and make appropriate adjustments as needed. Not to belabor the point– but think about this: If lack of calibration can produce bias in such a fundamental two-state category as gender, how much more could it affect results in terms of age, which has a wider cost variance and multiple band splits?

Table 2.1.1(3) - Results for Gender (using a non-calibrated risk score that includes demographics)

Variable Name *SEX* **Class:** *Demographic* **Desc:** *Gender*

Section 1 : Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	50.8%	49.2%								
2 Total Expenditures	1.0000	0.8505	1.1542								
3 Proxy Expenditures	1.0000	0.7862	1.2205								
4 Traditional Risk Score	1.0000	0.8220	1.1836								
5 Risk Score + *N*	1.0000	0.7862	1.2205								
6 Risk Score + $\sum N'_{prop}$	1.0000	0.7862	1.2205								
7 Allowable Rating Factor	1.0000	0.9904	1.0099								
8 Proxy Exp Adjusted	1.0000	0.9642	1.0369								

Section 2 : Issuer Selection Assumptions

1		**LRA Rank**	**1**	**2**
2	Issuer A	50.0%	50.0%	
3	Issuer B	50.0%	0.8%	49.2%

Section 3 : Market Scenario

		Traditional Risk Score			Risk Score + *N*			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	1.09%									
2 Maximum {Pr > |*t*|}	-	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.786	1.214	1.000						
5 Allowable Rating Factor		0.990	1.010	1.000						
6 Risk Score		0.822	1.178	1.000	0.786	1.214	1.000	0.786	1.214	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.188	1.212	1.200						
9 Premium with Risk Selection		0.986	1.414	1.200	0.943	1.457	1.200	0.943	1.457	1.200
10 Risk Selection Transfer		(0.202)	0.202	-	(0.245)	0.245	-	(0.245)	0.245	-
11 Loss Ratio		79.7%	85.9%	82.8%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%
12 Loss Ratio subject to risk corridor		80.0%	85.9%	82.9%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%
13 **Loss Ratio Advantage (LRA)**		**5.9%**	Model R^2:	22.6%	**0.0%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.4%

Section 4 : Statistical Significance Testing

1 *t*-statistic		5.53	(4.61)
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes

2.1.2 Age

In a similar manner Table 2.1.2(1) presents the results when we consider age to be a variable outside of the risk adjustment model. Age has a high LRA of almost 7% (similar to gender). You will notice that the LRA is not exactly zero for Model 2 (which includes age as the nontraditional variable) and Model 3 (including region, wage and insurance coverage along with age). We would have expected the LRA for both to be zero because they both isolate age as a nontraditional variable. However, the age categories presented in Tables 2.1.2 are different than the age categories used in the regression formulas. This discrepancy produces the small LRAs. Despite those slight differences, the LRA is not meaningful for any selection activity for these models. The stand-alone statistical performance of the age variable (as measured by the coefficient of determination) is around 3%[21]; this is better than gender, which has an R Squared of about 1%.

The term 'staggering' was used to describe the LRA for gender in the scenario where we used a *non-calibrated* concurrent risk adjustment model. We might need to come up with a stronger superlative to describe what happens when we look at the potential bias by age categories, and in terms of risk adjusted cost. At an LRA of over **16%**, little doubt is left as to what might happen in a market where a risk adjuster produces biased predictive ratios for age/gender categories. This is the highest LRA recorded in this research – and a nontraditional variable is not involved.

Obviously, age and gender are important to include in a risk adjustment formula. However, the results of this research suggest that other variables (e.g., geography and income at 8.6% and 5.5% LRA, respectively) are also important, and should be seriously considered for inclusion in the risk adjustment program, or at least their impact monitored as experience becomes available post-2014.

[21] Please see Section 3.5.3 for more detail

Table 2.1.2(1) – Results for Age (using a calibrated risk score that excludes age)

Variable Name *AGEX_C* **Class:** *Demographic* **Desc:** *Age of individual*

Section 1 ***: Summarizing by non-traditional variable categories***

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	0.4%	1.8%	10.0%	16.0%	6.0%	8.2%	8.3%	8.8%	18.6%	21.9%
2 Total Expenditures	1.0000	3.7529	1.0517	0.3873	0.5687	0.4823	0.6522	0.7999	0.8618	1.0848	1.8749
3 Proxy Expenditures	1.0000	2.8184	1.0265	0.5154	0.6008	0.6013	0.7908	0.9070	0.9312	1.0554	1.6829
4 Traditional Risk Score	1.0000	1.2769	0.5948	0.5570	0.6038	0.6844	0.8100	0.8951	0.9647	1.1094	1.6379
5 Risk Score + *N*	1.0000	1.8943	1.2173	0.5154	0.6042	0.5922	0.7908	0.9070	0.9312	1.0554	1.6829
6 Risk Score + $\sum N'_{prop}$	1.0000	2.8135	1.0275	0.5154	0.6133	0.5681	0.7908	0.9070	0.9312	1.0554	1.6829
7 Allowable Rating Factor	1.0000	0.7039	0.7039	0.7039	0.7039	0.7039	0.7442	0.8288	0.8728	1.0201	1.6556
8 Proxy Exp Adjusted	1.0000	2.5415	1.4317	0.9583	0.9970	0.9169	0.9808	1.0119	0.9665	0.9460	1.0450

Section 2 ***: Issuer Selection Assumptions***

		Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	**LRA Rank**	**10**	**9**	**3**	**6**	**1**	**5**	**7**	**4**	**2**	**8**
2 Issuer A	50.0%			10.0%		6.0%	6.6%		8.8%	18.6%	
3 Issuer B	50.0%	0.4%	1.8%	0.0%	16.0%	0.0%	1.6%	8.3%	0.0%	0.0%	21.9%

Section 3 ***: Market Scenario***

		Traditional Risk Score			**Risk Score + *N***			**Risk Score + $\sum N'_{prop}$**		
1 Stand-Alone R^2	3.14%									
2 Maximum {Pr > |*t*|}	0.0000	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.836	1.164	1.000						
5 Allowable Rating Factor		0.856	1.144	1.000						
6 Risk Score		0.883	1.117	1.000	0.835	1.165	1.000	0.832	1.168	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.028	1.372	1.200						
9 Premium with Risk Selection		1.059	1.341	1.200	1.002	1.398	1.200	0.998	1.402	1.200
10 Risk Selection Transfer		0.032	(0.032)	-	(0.026)	0.026	-	(0.029)	0.029	-
11 Loss Ratio		78.9%	86.8%	82.9%	83.4%	83.3%	83.3%	83.7%	83.0%	83.4%
12 Loss Ratio subject to risk corridor		80.0%	86.8%	83.4%	83.4%	83.3%	83.3%	83.7%	83.0%	83.4%
13 **Loss Ratio Advantage (LRA)**		**6.8%**	Model R^2:	33.5%	**-0.2%**	Model R^2:	34.0%	**-0.7%**	Model R^2:	34.4%

Section 4 ***: Statistical Significance Testing***

		Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 *t*-statistic		(8.86)	(6.71)	1.43	0.24	5.56	1.01	(0.68)	2.02	3.71	(3.34)
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	No	No	Yes	No	No	Yes	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Age 0 – 1
2. Age 2 – 9
3. Age 10 – 20
4. Age 21 – 24
5. Age 25 – 29
6. Age 30 – 34
7. Age 35 – 39
8. Age 40 – 49
9. Age 50+
10. Inapplicable

Table 2.1.1(2) - Results for Age (using a non-calibrated risk score that includes demographics)

Variable Name *AGEX_C* **Class:** *Demographic* **Desc:** *Age of individual*

Section 1 : Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	0.4%	1.8%	10.0%	16.0%	6.0%	8.2%	8.3%	8.8%	18.6%	21.9%
2 Total Expenditures	1.0000	3.7529	1.0517	0.3873	0.5687	0.4823	0.6522	0.7999	0.8618	1.0848	1.8749
3 Proxy Expenditures	1.0000	2.8184	1.0265	0.5154	0.6008	0.6013	0.7908	0.9070	0.9312	1.0554	1.6829
4 Traditional Risk Score	1.0000	1.9942	0.6965	0.4348	0.4719	0.5726	0.7506	0.8479	0.9414	1.1045	1.8539
5 Risk Score + *N*	1.0000	1.8943	1.2173	0.5154	0.6042	0.5922	0.7908	0.9070	0.9312	1.0554	1.6829
6 Risk Score + $\sum N'_{prop}$	1.0000	2.8135	1.0275	0.5154	0.6133	0.5681	0.7908	0.9070	0.9312	1.0554	1.6829
7 Allowable Rating Factor	1.0000	0.7039	0.7039	0.7039	0.7039	0.7039	0.7442	0.8288	0.8728	1.0201	1.6556
8 Proxy Exp Adjusted	1.0000	1.8242	1.3300	1.0806	1.1289	1.0286	1.0402	1.0591	0.9897	0.9510	0.8290

Section 2 : Issuer Selection Assumptions

		Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	**LRA Rank**	**10**	**9**	**7**	**8**	**4**	**5**	**6**	**3**	**2**	**1**
2 Issuer A	50.0%					0.7%			8.8%	18.6%	21.9%
3 Issuer B	50.0%	0.4%	1.8%	10.0%	16.0%	5.4%	8.2%	8.3%	0.0%	0.0%	0.0%

Section 3 : Market Scenario

		Traditional Risk Score			**Risk Score + *N***			**Risk Score + $\sum N'_{prop}$**		
1 Stand-Alone R^2	3.14%									
2 Maximum {Pr > |*t*|}	0.0000	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		1.303	0.697	1.000						
5 Allowable Rating Factor		1.269	0.731	1.000						
6 Risk Score		1.397	0.603	1.000	1.303	0.697	1.000	1.302	0.698	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.523	0.877	1.200						
9 Premium with Risk Selection		1.677	0.723	1.200	1.563	0.837	1.200	1.563	0.837	1.200
10 Risk Selection Transfer		0.154	(0.154)	-	0.041	(0.041)	-	0.040	(0.040)	-
11 Loss Ratio		77.7%	96.4%	87.1%	83.3%	83.3%	83.3%	83.4%	83.3%	83.3%
12 Loss Ratio subject to risk corridor		80.0%	96.4%	88.2%	83.3%	83.3%	83.3%	83.4%	83.3%	83.3%
13 **Loss Ratio Advantage (LRA)**		**16.4%**	Model R^2:	22.6%	**0.0%**	Model R^2:	34.0%	**-0.1%**	Model R^2:	34.4%

Section 4 : Statistical Significance Testing

	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 *t*-statistic		(5.27)	(4.86)	(2.57)	(9.49)	(1.83)	(2.00)	(3.21)	0.58	3.10	11.48
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Age 0 – 1
2. Age 2 – 9
3. Age 10 – 20
4. Age 21 – 24
5. Age 25 – 29
6. Age 30 – 34
7. Age 35 – 39
8. Age 40 – 49
9. Age 50+
10. Inapplicable

2.2 Nontraditional Variables

Research results for each of the nontraditional variables are presented below. The detailed results for all variables are calculated in exactly the same manner, promoting consistent comparisons amongst them. As mentioned before, the variables are categorized using judgment for the purposes of organizing results and evaluating the importance of broader characteristics of individuals.

In the process of producing the results, each nontraditional variable had to be categorized or grouped. For example if total wages are reflected in dollar terms – they need to be grouped together in some meaningful manner. We invested time in creating groupings for each of the nontraditional variables selected for in-depth study, and two versions of the groupings were created for each variable. In the first version the variables were grouped in up to ten categories. The number of categories was limited in order to maintain credibly-sized categories so that the results of statistical significance testing are meaningful. In the second version, the number of categories was restricted to only five and this version was used to develop the risk adjustment model that includes the nontraditional variables with age/gender and clinical markers. The number of categories was limited to five in order to develop regression coefficients that were for the most part statistically significant. The two different versions result in LRAs that may not be zero (for model 2), but will be close to zero.

While the discussion in the paragraph above involves a nuance, it is an important one. A non-zero LRA for Model 2 makes the important point that even if a nontraditional variable is included as a model variable, there is no guarantee of eliminating all bias. Different categorizations of that nontraditional variable may introduce slight bias. While the bias should be low, it requires testing to determine that the categorization is appropriate.

Please note that the sections below briefly describe each of the variables and provide high level commentary on the results. For details on MEPS data and how the survey data is collected and edited, please see Section 3.

2.3 Demographic Variables

Results for the nine selected demographic nontraditional variables are included below.

2.3.1 Years of Education

Description: This variable represents the number of years of education that an individual has completed. Children under the age of 5 were coded as 'inapplicable' regardless of whether they attended school (see Table 2.3.1(1)). The categories were created as follows:

i. Not ascertained/didn't know/refused/inapplicable

ii. Years of education between 0 – 3

iii. Years of education between 4 – 6 (early elementary school)

iv. Years of education between 7 – 8 (late elementary school)

v. Years of education between 9 – 11 (high school)

vi. Years of education 12 (completed high school)

vii. Years of education 13 (first year of college)

viii. Years of education between 14 – 15 (some college)

ix. Years of education 16 (4 years of college)

x. Years of education 17+ (more than 4 years of college)

For version two (see Section 2.2), we re-categorized MEPS variables in order to restrict them to five, and did so in order to avoid insignificant modeling results and to strengthen credibility in regression estimates. For presentation, Table 2.3.1(1) shows up to ten categories for this variable. The categories are described along with the table.

Results: The results indicate that if Insurer A selects those with less education (including children), the LRA measure is *medium* at 5.3%. Interestingly, Issuer A does not select the highly educated individuals (i.e. those with more than 16 years of education). The healthcare costs for these individuals are high and a traditional risk score does not fully account for their high cost. The cohort of individuals with nine to eleven years of education was the most preferred by Issuer A.

Including fewer groupings of the education variable (i.e. five instead of ten) results in mitigating some of the potential for selection. Generally, these results do not support the argument that an increase in education is coupled with a decrease in medical costs. This may have something to do with the fact that those with higher education seek more care (see later in this subsection), or that we are using a sample population (i.e. commercially insured and the uninsured) instead of the full population.

In other reports comparing education level to health care costs, the lifetime savings in government health expenditures for an expected high school graduate were analyzed. It was observed that people with higher education attainment have more insurance coverage, have better health outcomes, and lead healthier lives in general. These individuals also had an average increased lifespan with decreased rates of dying from cancer, lung disease, and cardiovascular disease. (The Alliance for Excellent Education, 2006).

Table 2.3.1(1) Results for 'Years of Education'

Variable Name *EDUCYEAR_C* **Class:** *Demographic* **Desc:** *Years of education when first entered MEPS*

***Section A**: Summarizing by non-traditional variable categories*

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	7.4%	7.7%	5.5%	4.1%	10.3%	23.0%	5.6%	13.3%	14.2%	8.8%
2 Total Expenditures	1.0000	0.5674	0.4344	0.5721	0.7548	0.7638	1.1448	1.1973	1.1393	1.2147	1.4537
3 Proxy Expenditures	1.0000	0.6629	0.5293	0.5793	0.7932	0.8160	1.1179	1.1885	1.1370	1.1811	1.3406
4 Traditional Risk Score	1.0000	0.7016	0.5587	0.6012	0.7639	0.8746	1.1306	1.1814	1.1552	1.1293	1.2408
5 Risk Score + *N*	1.0000	0.6629	0.5560	0.5421	0.7619	0.8284	1.1216	1.1733	1.1749	1.1454	1.3406
6 Risk Score + $\sum N'_{prop}$	1.0000	0.6591	0.5640	0.6090	0.7637	0.8476	1.1332	1.1950	1.1623	1.1422	1.2519
7 Allowable Rating Factor	1.0000	0.7273	0.7442	0.7914	0.8310	0.9114	1.1050	1.0546	1.0777	1.0874	1.1972
8 Proxy Exp Adjusted	1.0000	0.9613	0.9706	0.9780	1.0293	0.9414	0.9872	1.0071	0.9818	1.0518	1.0999

***Section B**: Issuer Selection Assumptions*

1	LRA Rank	2	3	4	8	1	6	7	5	9	10
2 Issuer A	50.0%	7.4%	7.7%	5.5%		10.3%	5.7%		13.3%		
3 Issuer B	50.0%	0.0%	0.0%	0.0%	4.1%	0.0%	17.3%	5.6%	0.0%	14.2%	8.8%

***Section C**: Market Scenario*

		Traditional Risk Score			Risk Score + *N*			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2 / 2 Maximum {Pr > |*t*|}	1.44% / 0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.844	1.156	1.000						
5 Allowable Rating Factor		0.912	1.088	1.000						
6 Risk Score		0.875	1.125	1.000	0.857	1.143	1.000	0.867	1.133	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.094	1.306	1.200						
9 Premium with Risk Selection		1.050	1.350	1.200	1.028	1.372	1.200	1.040	1.360	1.200
10 Risk Selection Transfer		(0.045)	0.045	-	(0.066)	0.066	-	(0.054)	0.054	-
11 Loss Ratio		80.4%	85.6%	83.0%	82.1%	84.3%	83.2%	81.1%	85.0%	83.1%
12 Loss Ratio subject to risk corridor		80.4%	85.6%	83.0%	82.1%	84.3%	83.2%	81.1%	85.0%	83.1%
13 Loss Ratio Advantage (LRA)		5.3%	Model R^2:	34.0%	2.2%	Model R^2:	34.0%	3.9%	Model R^2:	34.4%

***Section D**: Statistical Significance Testing*

		Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 *t*-statistic		3.58	1.91	1.52	(1.55)	3.11	0.96	(0.38)	0.94	(3.48)	(5.34)
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu >= 1$	$\mu <= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu < 1$	$\mu > 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	No	No	Yes	No	No	No	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Refused/Inapplicable
2. 0 – 3 Years of Education
3. 4 – 6 Years of Education
4. 7 – 8 Years of Education
5. 9 – 11 Years of Education
6. 12 Years of Education
7. 13 Years of Education
8. 14 – 15 Years of Education
9. 16 Years of Education
10. 17+ Years of Education

There is another analysis however, which suggests that an individual with a lower education level may have lower total health care costs, partly because those with higher education are more likely to seek care, and less educated individuals are more likely to have shorter lives which reduces future healthcare costs. If we take these factors into account, the lifetime savings in health care costs per an average graduate may actually be lower (Henry Levin, 2006).

2.3.2 Worked for Pay

Description: Respondents in the MEPS survey were asked if they had ever worked for pay in their life. This question was asked of everyone who indicated that they were not working at the time of the interview.

Table 2.3.2(1) – Results for 'Ever worked for pay'

Variable Name *EVRWRK* **Class:** *Demographic* **Desc:** *Ever worked for pay in life*

Section A : Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	88.8%	5.9%	5.2%							
2 Total Expenditures	1.0000	0.9148	2.4795	0.7688							
3 Proxy Expenditures	1.0000	0.9265	2.2337	0.8496							
4 Traditional Risk Score	1.0000	0.9431	1.9781	0.8576							
5 Risk Score + N	1.0000	0.9265	2.2337	0.8496							
6 Risk Score + $\sum N'_{prop}$	1.0000	0.9286	2.1312	0.9296							
7 Allowable Rating Factor	1.0000	0.9826	1.3823	0.8611							
8 Proxy Exp Adjusted	1.0000	0.9834	1.2557	0.9920							

Section B : Issuer Selection Assumptions

			Catg1	Catg2	Catg3
1		LRA Rank	1	3	2
2	Issuer A	50.0%	50.0%		
3	Issuer B	50.0%	38.8%	5.9%	5.2%

Section C : Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	2.22%									
2 Maximum {Pr > |t|}	0.0001	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.926	1.074	1.000						
5 Allowable Rating Factor		0.983	1.017	1.000						
6 Risk Score		0.943	1.057	1.000	0.926	1.074	1.000	0.929	1.071	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.179	1.221	1.200						
9 Premium with Risk Selection		1.132	1.268	1.200	1.112	1.288	1.200	1.114	1.286	1.200
10 Risk Selection Transfer		(0.048)	0.048	-	(0.067)	0.067	-	(0.065)	0.065	-
11 Loss Ratio		81.9%	84.6%	83.3%	83.3%	83.3%	83.3%	83.1%	83.5%	83.3%
12 Loss Ratio subject to risk corridor		81.9%	84.6%	83.3%	83.3%	83.3%	83.3%	83.1%	83.5%	83.3%
13 Loss Ratio Advantage (LRA)		2.8%	Model R^2:	34.0%	0.0%	Model R^2:	34.0%	0.4%	Model R^2:	34.4%

Section D : Statistical Significance Testing

		Catg1	Catg2	Catg3
1 t-statistic		3.29	(9.51)	0.41
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Refused/Inapplicable 2. Yes
3. No

Results: The results show a pattern that individuals that are either currently working (Category 1), or have worked in their life (Category 2) have a lower risk adjusted cost. Having an LRA of about

2.8%, we classify this variable as having a low impact. Detailed results are presented in Table 2.3.3(1). Issuer A prefers individuals that are currently working (i.e. Category 1). Due to the *skip pattern* of the MEPS survey, this question was only asked of individuals that had indicated that they were not working at the time of the survey (i.e. Categories 2 and 3).

For an individual who is unemployed, studies have shown that unemployment has an adverse effect on health (see Section 1.4). While controlling for other variables, those who are unemployed generally have higher rates of mortality, poorer mental health, a higher chance of disease (including cardiovascular disease and high blood pressure), lower perceived health, increased healthcare utilization (mainly hospital admissions, doctor visits, and outpatient visits), and decreased health for close family members. Although there are many factors that can influence and complicate this relation, there is evidence that unemployed adults generally have worse health than employed adults (Mathers & Schofield, 1998).

2.3.3 Family Size

Description: This variable indicates the number of persons associated with a single family unit after students are linked to their associated parent for analytical purposes (AHRQ, 2012).

Results: Detailed results are presented in Table 2.3.4(1). Issuer A selects two-person families first, and then larger families. At an LRA of about 4%, this variable has a *medium* impact. The results are statistically significant overall, and the risk adjusted differences are significant for a few categories. The results indicate that risk adjusted expenditures are lower for families compared to individuals (Category 2). To clarify, 'family' in MEPS refers to two or more persons living together in the same household who are related by blood, marriage, or adoption (AHRQ, 2012).

Table 2.3.3(1) – Results for 'Family Size'

Variable Name *FAMS1231_C* **Class:** *Demographic* **Desc:** *Family size of responding family*

Section A*: *Summarizing by non-traditional variable categories

	Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	Category %	100%	2.6%	12.8%	22.5%	43.0%	19.2%					
2	Total Expenditures	1.0000	1.6488	1.1605	1.4220	0.8638	0.6154					
3	Proxy Expenditures	1.0000	1.2963	1.1711	1.3211	0.9104	0.6704					
4	Traditional Risk Score	1.0000	1.0589	1.1370	1.3608	0.9063	0.6881					
5	Risk Score + N	1.0000	1.2963	1.1711	1.3211	0.9104	0.6704					
6	Risk Score + $\sum N'_{prop}$	1.0000	1.1778	1.1137	1.3554	0.9080	0.6898					
7	Allowable Rating Factor	1.0000	0.9559	1.0930	1.2567	0.9159	0.8318					
8	Proxy Exp Adjusted	1.0000	1.2373	1.0341	0.9603	1.0041	0.9822					

Section B*: *Issuer Selection Assumptions

			Catg1	Catg2	Catg3	Catg4	Catg5
1		**LRA Rank**	5	4	1	3	2
2	Issuer A	50.0%			22.5%	8.3%	19.2%
3	Issuer B	50.0%	2.6%	12.8%	0.0%	34.6%	0.0%

Section C*: *Market Scenario

			Traditional Risk Score			**Risk Score + N**			**Risk Score + $\sum N'_{prop}$**		
1	Stand-Alone R^2	1.24%									
2	Maximum {Pr > |t|}	0.0000	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3	Market Share		50%	50%	100%						
4	Proxy Expenditures		1.003	0.997	1.000						
5	Allowable Rating Factor		1.037	0.963	1.000						
6	Risk Score		1.027	0.973	1.000	1.003	0.997	1.000	1.025	0.975	1.000
7	Statewide Average Premium				1.200						
8	Premium without Risk Selection		1.244	1.156	1.200						
9	Premium with Risk Selection		1.232	1.168	1.200	1.203	1.197	1.200	1.230	1.170	1.200
10	Risk Selection Transfer		(0.012)	0.012	-	(0.041)	0.041	-	(0.014)	0.014	-
11	Loss Ratio		81.4%	85.4%	83.4%	83.3%	83.3%	83.3%	81.5%	85.3%	83.4%
12	Loss Ratio subject to risk corridor		81.4%	85.4%	83.4%	83.3%	83.3%	83.3%	81.5%	85.3%	83.4%
13	**Loss Ratio Advantage (LRA)**		**4.0%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**3.8%**	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

			Catg1	Catg2	Catg3	Catg4	Catg5
1	t-statistic		(6.64)	(1.37)	2.71	(0.43)	2.27
2	H_0: Null Hypothesis		$\mu <= 1$	$\mu <= 1$	$\mu >= 1$	$\mu <= 1$	$\mu >= 1$
3	H_1: Alternate Hypothesis		$\mu > 1$	$\mu > 1$	$\mu < 1$	$\mu > 1$	$\mu < 1$
4	H_0 rejected (at α=5%)	Yes*	Yes	No	Yes	No	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Inapplicable
2. Family Size: 1
3. Family Size: 2
4. Family Size: 3 – 4
5. Family Size: 5+

2.3.4 Occupation Group

Description: Occupation codes have long been in use in underwriting. It is a relevant question to ask whether risk adjustment fully accounts for the relative healthcare utilization across occupations. Up to ten categories were created for the presentation of results, as follows:

i. Not Ascertained/Inapplicable
ii. Management, business, and financial operations
iii. Professional and related occupations
iv. Service occupations
v. Sales and related occupations
vi. Office and administrative support
vii. Farming, fishing, and forestry
viii. Construction, extraction, and maintenance
ix. Production, transportation, and material moving
x. Military occupations, unclassifiable

For purposes of regression modeling several of these categories were combined to limit the independent variables to five.

Results: Detailed results are presented in Table 2.3.5(1). At an LRA of less than 3%, this variable has a low business impact. Issuer A selects service occupations, production/transportation, management/business/financial operations, and professional related occupations – while avoiding office/administrative, sales related and construction/maintenance workers. The results are statistically significant overall, but are not significant for several of the individual occupation categories (i.e. we cannot reliably tell whether the risk-adjusted costs are higher or lower than average for these categories).

The LRA for Model 2 is about 2%, suggesting that aggregating ten categories into five for building a risk assessment model only modestly captures the variation across occupation groups.

Table 2.3.4(1) – Results for 'Occupation Group'

Variable Name *OCCCAT31_C* **Class:** *Demographic* **Desc:** *Occupation group*

***Section A**: Summarizing by non-traditional variable categories*

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	49.4%	4.6%	6.0%	6.6%	3.9%	3.5%	5.6%	11.2%	4.0%	5.2%
2 Total Expenditures	1.0000	0.9281	0.6826	1.0576	0.9839	1.1783	1.1281	0.9854	1.3105	0.7201	1.2528
3 Proxy Expenditures	1.0000	0.9391	0.6906	1.0061	0.9749	1.0812	1.1600	0.9518	1.3594	0.7772	1.1507
4 Traditional Risk Score	1.0000	0.9278	0.7459	1.0395	1.0078	1.0559	1.0919	0.9779	1.3451	0.8333	1.1538
5 Risk Score + N	1.0000	0.9381	0.7175	1.0112	0.9970	1.0389	1.0963	0.9796	1.3426	0.8319	1.1420
6 Risk Score + $\sum N'_{prop}$	1.0000	0.9533	0.6980	1.0352	0.9827	1.0350	1.0786	0.9510	1.3262	0.7829	1.1243
7 Allowable Rating Factor	1.0000	0.9111	1.0618	1.1227	1.0461	1.1218	1.0924	1.0760	1.1247	0.9449	1.1264
8 Proxy Exp Adjusted	1.0000	1.0113	0.9447	0.9666	0.9672	1.0253	1.0681	0.9739	1.0144	0.9438	0.9969

***Section B**: Issuer Selection Assumptions*

1	LRA Rank		7	2	3	4	9	10	5	8	1	6
2	Issuer A	50.0%	18.0%	4.6%	6.0%	6.6%			5.6%		4.0%	5.2%
3	Issuer B	50.0%	31.3%	0.0%	0.0%	0.0%	3.9%	3.5%	0.0%	11.2%	0.0%	0.0%

***Section C**: Market Scenario*

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	0.27%									
2 Maximum {Pr > |t|}	0.0002	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.940	1.060	1.000						
5 Allowable Rating Factor		1.012	0.988	1.000						
6 Risk Score		0.957	1.043	1.000	0.952	1.048	1.000	0.948	1.052	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.214	1.186	1.200						
9 Premium with Risk Selection		1.148	1.252	1.200	1.142	1.258	1.200	1.137	1.263	1.200
10 Risk Selection Transfer		(0.066)	0.066	-	(0.072)	0.072	-	(0.077)	0.077	-
11 Loss Ratio		81.8%	84.7%	83.3%	82.3%	84.3%	83.3%	82.6%	84.0%	83.3%
12 Loss Ratio subject to risk corridor		81.8%	84.7%	83.3%	82.3%	84.3%	83.3%	82.6%	84.0%	83.3%
13 Loss Ratio Advantage (LRA)		2.8%	Model R^2:	34.0%	2.0%	Model R^2:	34.0%	1.3%	Model R^2:	34.4%

***Section D**: Statistical Significance Testing*

		Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 t-statistic		(1.80)	4.16	1.53	1.64	(1.06)	(2.28)	1.04	(0.72)	3.03	0.12
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu >= 1$	$\mu <= 1$	$\mu >= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu < 1$	$\mu > 1$	$\mu < 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	No	No	No	Yes	No	No	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. Management/Business/Financial Operations
3. Professional/Related Occupations
4. Service Occupations
5. Sales/Related Occupations
6. Office/Administrative Support
7. Farming/Fishing/Forestry
8. Construction/Extraction/Maintenance
9. Production/Transportation/Material Moving
10. Military/Unclassifiable

2.3.5 Census Region

Description: While MEPS has region indicators, the publicly available data does not have more detailed indicators such as state, county, or zip code. We tested the influence of a broader region variable having the following values: (i) inapplicable, (ii) Northeast, (iii) Midwest, (iv) South, (v) West.

Results: Detailed results are presented in Table 2.3.4(1). At an LRA of over 8%, this is a *high* impact variable. The power of geography as a nontraditional variable is important, even though regional differences may be mitigated in ACA risk adjustment because risk transfers occur within a state. Section 2.8 presents an illustrative argument as to why geography might be important to consider within a state as well as when defining rating areas for risk adjustment. Since all region categories are input to the regression in Models 2 and 3, the potential for selection on the basis of region is fully neutralized (i.e. LRA equals zero).

Table 2.3.5(1) – Results for 'Region'

Variable Name *REGION10* **Class:** *Demographic* **Desc:** *Census Region*

Section A : Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	0.4%	18.3%	22.9%	35.5%	22.9%					
2 Total Expenditures	1.0000	3.7426	1.0146	1.1273	0.9277	0.9289					
3 Proxy Expenditures	1.0000	2.8104	1.0494	1.1033	0.9736	0.8691					
4 Traditional Risk Score	1.0000	1.8943	0.9709	1.0423	1.0592	0.8747					
5 Risk Score + *N*	1.0000	2.8104	1.0494	1.1033	0.9736	0.8691					
6 Risk Score + $\sum N'_{prop}$	1.0000	2.8104	1.0494	1.1033	0.9736	0.8691					
7 Allowable Rating Factor	1.0000	0.7041	1.0126	1.0019	1.0037	0.9871					
8 Proxy Exp Adjusted	1.0000	1.9161	1.0784	1.0610	0.9144	0.9944					

Section B : Issuer Selection Assumptions

		Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5
1		**LRA Rank**	5	4	3	1	2
2	Issuer A	50.0%				35.5%	14.5%
3	Issuer B	50.0%	0.4%	18.3%	22.9%	0.0%	8.5%

Section C : Market Scenario

		Traditional Risk Score			Risk Score + *N*			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	0.44%									
2 Maximum {Pr > |*t*|}	-	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.943	1.057	1.000						
5 Allowable Rating Factor		0.999	1.001	1.000						
6 Risk Score		1.006	0.994	1.000	0.943	1.057	1.000	0.943	1.057	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.199	1.201	1.200						
9 Premium with Risk Selection		1.207	1.193	1.200	1.132	1.268	1.200	1.132	1.268	1.200
10 Risk Selection Transfer		0.008	(0.008)	-	(0.067)	0.067	-	(0.067)	0.067	-
11 Loss Ratio		78.2%	88.6%	83.4%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%
12 Loss Ratio subject to risk corridor		80.0%	88.6%	84.3%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%
13 **Loss Ratio Advantage (LRA)**		**8.6%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.4%

Section D : Statistical Significance Testing

		Catg1	Catg2	Catg3	Catg4	Catg5
1 *t*-statistic		(5.42)	(1.37)	(4.91)	8.79	0.65
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu >= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu < 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	No	Yes	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Inapplicable
2. Northeast
3. Midwest
4. South
5. West

2.3.6 Marriage Status

Description: This variable indicates the marital status of the survey respondent.

Results: Detailed results are presented in Table 2.3.7(1). At an LRA of about 3.7%, this is a *medium* impact variable. Issuer A prefers individuals that are never married, under 16 (children), and to a somewhat lesser extent those that are married. The results by category are not statistically significant for all of the categories, however the results overall are significant (i.e. between the lowest and highest risk adjusted cost categories). The risk adjusted costs of widowed and separated respondents are higher.

The table shows that married individuals cost more, even on a risk adjusted basis compared to individuals that have never been married. On the surface the results seem to contradict conventional wisdom that married individuals live healthier lives (see discussion later in this subsection). However there is the confounding variable of demographics in the results. For example the average age of those that are married is 44 in the table, whereas the average of those that have never been married is 27.

Table 2.3.6(1) – Results for Marital Status

Variable Name *MARRYX*		Class: *Demographic*			Desc: *Marital Status*						
***Section A**: Summarizing by non-traditional variable categories*											
Description	**Total/Agg**	**Catg1**	**Catg2**	**Catg3**	**Catg4**	**Catg5**	**Catg6**	**Catg7**	**Catg8**	**Catg9**	**Catg10**
1 Category %	100%	44.7%	1.2%	8.4%	1.3%	24.2%	20.1%				
2 Total Expenditures	1.0000	1.3013	1.8553	1.3527	1.1414	0.6665	0.5225				
3 Proxy Expenditures	1.0000	1.2530	1.8654	1.3394	1.2600	0.6977	0.5894				
4 Traditional Risk Score	1.0000	1.2367	1.7418	1.3206	1.1858	0.7346	0.6015				
5 Risk Score + N	1.0000	1.2530	1.8654	1.3394	1.2600	0.6977	0.5893				
6 Risk Score + $\sum N'_{prop}$	1.0000	1.2505	1.7541	1.2898	1.1407	0.7258	0.5966				
7 Allowable Rating Factor	1.0000	1.1706	1.5742	1.2414	1.0968	0.8125	0.7039				
8 Proxy Exp Adjusted	1.0000	1.0163	1.1236	1.0188	1.0742	0.9631	0.9879				
***Section B**: Issuer Selection Assumptions*											
1	**LRA Rank**	3	6	4	5	1	2				
2 Issuer A	50.0%	5.7%				24.2%	20.1%				
3 Issuer B	50.0%	39.0%	1.2%	8.4%	1.3%	0.0%	0.0%				

***Section C**: Market Scenario*

		Traditional Risk Score			**Risk Score + N**			**Risk Score + $\sum N'_{prop}$**		
1 Stand-Alone R^2	2.41%									
2 Maximum {Pr > |t|}	0.0000	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.717	1.283	1.000						
5 Allowable Rating Factor		0.809	1.191	1.000						
6 Risk Score		0.738	1.262	1.000	0.717	1.283	1.000	0.733	1.267	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		0.971	1.429	1.200						
9 Premium with Risk Selection		0.886	1.514	1.200	0.861	1.539	1.200	0.880	1.520	1.200
10 Risk Selection Transfer		(0.086)	0.086	-	(0.111)	0.111	-	(0.091)	0.091	-
11 Loss Ratio		81.0%	84.7%	82.8%	83.3%	83.3%	83.3%	81.5%	84.4%	82.9%
12 Loss Ratio subject to risk corridor		81.0%	84.7%	82.8%	83.3%	83.3%	83.3%	81.5%	84.4%	82.9%
13 **Loss Ratio Advantage (LRA)**		**3.7%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**2.9%**	Model R^2:	34.4%

***Section D**: Statistical Significance Testing*

		Catg1	Catg2	Catg3	Catg4	Catg5	Catg6
1 t-statistic		(2.35)	(2.22)	(0.53)	(1.91)	1.30	1.35
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu >= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu < 1$	$\mu < 1$
4 H_0 rejected (at α =5%)	Yes*	Yes	Yes	No	Yes	No	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Married
2. Widowed
3. Divorced
4. Separated
5. Never Married
6. Under 16 (inapplicable)

It is a well-published theory that married individuals live healthier lives than unmarried individuals. It has been reported that married adults have lower rates of acute conditions, of chronic conditions that hamper social activity, of morbidity, and of disability due to health problems (Mrela, Bender, & Torres, 2008). A couple of models may be used to further study the link between healthcare and marriage. They are called the *marital resource model* and the *stress model* (Liu & Umberson, 2011). In the marital resource model, marriage gives social, psychological, and economic benefits and resources which cause married individuals to have better physical health and increased life expectancy. In the event of marital dissolution, the stress model says that the individuals involved comparably have much more strain and stress, which in turn leads to a larger gap in the health between the two groups (Liu & Umberson, 2011).

2.3.7 Insurance Coverage

Description: This variable is not available in MEPS, and was developed by studying the period of enrollment of an individual in either a private commercial plan, or whether the person was uninsured. A person was assigned to one of these two categories if they had more than seven months in that category:

i. Any private coverage
ii. Uninsured

Results: At an LRA of over 4.5%, the influence of this variable is *medium*. The results indicate that an issuer would have an economic preference for individuals that were uninsured, followed by those in commercial private insurance. These results are greatly limited by two important factors. One is that the healthcare utilization of uninsured in MEPS is likely to be underreported, and another is that the uninsured may incur additional costs due to induced utilization once they are covered. Note that the cost for uninsured was re-calculated using average commercial unit costs using the process described in Section 3.2.3. Detailed results are presented in Table 2.3.8(1).

In other research, a unique study was done in 2008 by the state Oregon where the state drew names for a lottery that provided medical insurance for low-income, uninsured adults. On average the annual health care expenditures and utilization increased significantly for the newly insured (Finkelstein, 2011).

Table 2.3.7(1) – Results for 'Insurance Coverage'

Variable Name *COVG_TYPE*		Class: *Demographic*			Desc: *Coverage Type*						
***Section A* : Summarizing by non-traditional variable categories**											
Description	**Total/Agg**	**Catg1**	**Catg2**	**Catg3**	**Catg4**	**Catg5**	**Catg6**	**Catg7**	**Catg8**	**Catg9**	**Catg10**
1 Category %	100%	82.0%	18.0%								
2 Total Expenditures	1.0000	1.1308	0.4057								
3 Proxy Expenditures	1.0000	1.0976	0.5567								
4 Traditional Risk Score	1.0000	1.0698	0.6827								
5 Risk Score + N	1.0000	1.0976	0.5567								
6 Risk Score + $\sum N'_{prop}$	1.0000	1.0976	0.5567								
7 Allowable Rating Factor	1.0000	1.0100	0.9544								
8 Proxy Exp Adjusted	1.0000	1.0277	0.8740								

***Section B* : Issuer Selection Assumptions**			
1	**LRA Rank**	**2**	**1**
2 Issuer A	50.0%	32.0%	18.0%
3 Issuer B	50.0%	50.0%	0.0%

***Section C* : Market Scenario**		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	1.00%									
2 Maximum {Pr > |t|}	-	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.902	1.098	1.000						
5 Allowable Rating Factor		0.990	1.010	1.000						
6 Risk Score		0.930	1.070	1.000	0.902	1.098	1.000	0.902	1.098	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.188	1.212	1.200						
9 Premium with Risk Selection		1.116	1.284	1.200	1.083	1.317	1.200	1.083	1.317	1.200
10 Risk Selection Transfer		(0.072)	0.072	-	(0.105)	0.105	-	(0.105)	0.105	-
11 Loss Ratio		80.8%	85.5%	83.2%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%
12 Loss Ratio subject to risk corridor		80.8%	85.5%	83.2%	83.3%	83.3%	83.3%	83.3%	83.3%	83.3%
13 **Loss Ratio Advantage (LRA)**		**4.6%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.4%

***Section D* : Statistical Significance Testing**			
1 t-statistic		(4.95)	17.97
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Any Private Coverage
2. Uninsured

2.3.8 Hispanic Ethnicity

Description: This variable represents whether the person's ethnicity was Hispanic (Category 1) or not (Category 2).

Results: At an LRA of a under 3%, this is a *low*-impact variable. The results are statistically significant, and Issuer A selects respondents identifying themselves as Hispanic.

Table 2.3.8(1) – Results for 'Hispanic Ethnicity'

Variable Name *HISPANX* **Class:** *Demographic* **Desc:** *Hispanic Ethnicity*

Section A : *Summarizing by non-traditional variable categories*

	Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	Category %	100%	13.6%	86.4%								
2	Total Expenditures	1.0000	0.5175	1.0762								
3	Proxy Expenditures	1.0000	0.5837	1.0657								
4	Traditional Risk Score	1.0000	0.6865	1.0495								
5	Risk Score + N	1.0000	0.5837	1.0657								
6	Risk Score + $\sum N'_{prop}$	1.0000	0.6446	1.0561								
7	Allowable Rating Factor	1.0000	0.9080	1.0145								
8	Proxy Exp Adjusted	1.0000	0.8972	1.0162								

Section B : *Issuer Selection Assumptions*

1		**LRA Rank**	**1**	**2**
2	Issuer A	50.0%	13.6%	36.4%
3	Issuer B	50.0%	0.0%	50.0%

Section C : *Market Scenario*

			Traditional Risk Score			**Risk Score + N**			**Risk Score + $\sum N'_{prop}$**		
1	Stand-Alone R^2	0.63%									
2	Maximum {Pr > |t|}	0.0000	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3	Market Share		50%	50%	100%						
4	Proxy Expenditures		0.934	1.066	1.000						
5	Allowable Rating Factor		0.985	1.015	1.000						
6	Risk Score		0.951	1.049	1.000	0.934	1.066	1.000	0.944	1.056	1.000
7	Statewide Average Premium				1.200						
8	Premium without Risk Selection		1.183	1.217	1.200						
9	Premium with Risk Selection		1.141	1.259	1.200	1.121	1.279	1.200	1.133	1.267	1.200
10	Risk Selection Transfer		(0.042)	0.042	-	(0.061)	0.061	-	(0.050)	0.050	-
11	Loss Ratio		81.9%	84.6%	83.3%	83.3%	83.3%	83.3%	82.5%	84.1%	83.3%
12	Loss Ratio subject to risk corridor		81.9%	84.6%	83.3%	83.3%	83.3%	83.3%	82.5%	84.1%	83.3%
13	**Loss Ratio Advantage (LRA)**		**2.7%** Model R^2:		34.0%	**0.0%** Model R^2:		34.0%	**1.6%** Model R^2:		34.4%

Section D : *Statistical Significance Testing*

1	t-statistic		16.07	(1.94)
2	H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$
3	H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$
4	H_0 rejected (at α =5%)	Yes*	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Hispanic
2. Not Hispanic

Although controversial, the ethnicity of an individual can be a factor in health care costs. In a research study of immigrants and US-born individuals, Hispanics tended to have lower health care costs as compared to other races/ethnicities based upon data from a 1998 survey (Mohanty MD, 2005). While this disparity was more pronounced in US-born individuals, immigrant Hispanics had lower per capita health care costs as well. Another study determined that while Hispanics represented about 16% of the population, they also represented 24.5% of the individuals at the bottom 50% of health care spending (Yu, 2012).

Readers should be aware that use of any such (i.e. race or ethnicity) factor for underwriting or rating purposes may be prohibited by applicable regulations and other considerations.

2.4 Economic Variables

2.4.1 Employment Status

Description: This variable indicates the employment status of the respondent. The following categories were used in the tabulation of results in Table 2.4.1(1). The categories correspond to the following:

i. Unknown/didn't know/refused to answer/inapplicable
ii. Employed (if the person had a job at the time of the MEPS survey)
iii. Has a job to return to (if the person did not work during the reference period for the survey but had a job to return to as of the interview date)
iv. Employed during the reference period (if the person had no job at the interview date but did work during the time for which other information on the individual was collected)
v. Not employed with no job to return to (if the person did not have a job at the interview date, did not work during the reference period, and did not have a job to which he or she could return)

Results: At an LRA of over 5 percent, the influence of this variable is *medium*. The results indicate that an issuer would have an economic preference for individuals that were employed. Furthermore, the risk-adjusted costs are statistically significantly different than average (i.e. 1.0) by each category as well as overall.

Table 2.4.1(1) – Results for 'Employment Status'

Variable Name *EMPST31* **Class:** *Income* **Desc:** *Employment status* x

Section A: Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	21.8%	61.3%	0.3%	1.2%	15.3%					
2 Total Expenditures	1.0000	0.5378	1.0298	1.2215	1.0295	1.5315					
3 Proxy Expenditures	1.0000	0.5955	1.0200	1.2957	1.1971	1.4741					
4 Traditional Risk Score	1.0000	0.6075	1.0504	1.0869	1.0454	1.3515					
5 Risk Score + N	1.0000	0.5955	1.0200	1.2957	1.1971	1.4741					
6 Risk Score + $\sum N'_{prop}$	1.0000	0.6035	1.0274	1.0765	1.0349	1.4505					
7 Allowable Rating Factor	1.0000	0.7094	1.0797	0.9921	0.9747	1.0969					
8 Proxy Exp Adjusted	1.0000	0.9880	0.9696	1.2088	1.1518	1.1226					

Section B: Issuer Selection Assumptions

1	LRA Rank	2	1	5	4	3
2 Issuer A	50.0%		50.0%			
3 Issuer B	50.0%	21.8%	11.3%	0.3%	1.2%	15.3%

Section C: Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	1.64%									
2 Maximum {Pr > |t|}	0.0225	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		1.020	0.980	1.000						
5 Allowable Rating Factor		1.080	0.920	1.000						
6 Risk Score		1.050	0.950	1.000	1.020	0.980	1.000	1.027	0.973	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.296	1.104	1.200						
9 Premium with Risk Selection		1.261	1.139	1.200	1.224	1.176	1.200	1.233	1.167	1.200
10 Risk Selection Transfer		(0.035)	0.035	-	(0.072)	0.072	-	(0.063)	0.063	-
11 Loss Ratio		80.9%	86.0%	83.5%	83.3%	83.3%	83.3%	82.7%	84.0%	83.3%
12 Loss Ratio subject to risk corridor		80.9%	86.0%	83.5%	83.3%	83.3%	83.3%	82.7%	84.0%	83.3%
13 **Loss Ratio Advantage (LRA)**		**5.1%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**1.2%**	Model R^2:	34.4%

Section D: Statistical Significance Testing

		Catg1	Catg2	Catg3	Catg4	Catg5
1 t-statistic		1.98	3.47	(2.54)	(1.99)	(3.46)
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	Yes	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Refused/Inapplicable
2. Employed
3. Job to Return to
4. Employed during Reference Period
5. Not Employed

2.4.2 Person's Wage Income

Description: This variable indicates the person's wage income.

Results: At an LRA of over 5% this is a medium impact nontraditional variable. A significant proportion of individuals reported no wage income based on not being employed at the time of the survey, and issuer A prefers not to enroll these members. There is a clear trend of rising average age by average income however there is not a clear trend in terms of risk-adjusted income. The conclusion is materially the same as in Section 2.4.1 (i.e. Issuer A preferring individuals that are employed vs. those that are not).

Table 2.4.2(1) – Results for 'Person's Wage Income'

Variable Name *WAGEPX_C* **Class:** *Income* **Desc:** *Person's wage income*

Section A : Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	32.6%	12.6%	14.9%	19.4%	20.6%					
2 Total Expenditures	1.0000	0.9632	0.8464	0.9036	1.0648	1.1611					
3 Proxy Expenditures	1.0000	0.9665	0.8867	0.9521	1.0541	1.1061					
4 Traditional Risk Score	1.0000	0.9147	0.8948	1.0045	1.0930	1.1086					
5 Risk Score + N	1.0000	0.9665	0.8867	0.9710	1.0643	1.0828					
6 Risk Score + $\sum N'_{prop}$	1.0000	0.9665	0.8867	0.9406	1.0685	1.1009					
7 Allowable Rating Factor	1.0000	0.8611	0.9335	1.0406	1.0832	1.1529					
8 Proxy Exp Adjusted	1.0000	1.0518	0.9918	0.9477	0.9612	0.9975					

Section B : Issuer Selection Assumptions

		Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5
1		LRA Rank	5	3	1	2	4
2	Issuer A	50.0%		12.6%	14.9%	19.4%	3.1%
3	Issuer B	50.0%	32.6%	0.0%	0.0%	0.0%	17.4%

Section C : Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	0.07%									
2 Maximum {Pr > |t|}	0.6504	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.985	1.015	1.000						
5 Allowable Rating Factor		1.037	0.963	1.000						
6 Risk Score		1.018	0.982	1.000	0.993	1.007	1.000	0.987	1.013	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.245	1.155	1.200						
9 Premium with Risk Selection		1.221	1.179	1.200	1.192	1.208	1.200	1.184	1.216	1.200
10 Risk Selection Transfer		(0.023)	0.023	-	(0.053)	0.053	-	(0.061)	0.061	-
11 Loss Ratio		80.6%	86.1%	83.4%	82.7%	84.0%	83.3%	83.2%	83.5%	83.3%
12 Loss Ratio subject to risk corridor		80.6%	86.1%	83.4%	82.7%	84.0%	83.3%	83.2%	83.5%	83.3%
13 Loss Ratio Advantage (LRA)		5.5%	Model R^2:	34.0%	1.4%	Model R^2:	34.0%	0.3%	Model R^2:	34.4%

Section D : Statistical Significance Testing

	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5
1 t-statistic		(6.98)	0.72	4.07	3.20	0.21
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	No	Yes	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. $0
2. $9 – $12,500
3. $12,501 – $24,960
4. $24,961 – $43,655
5. $43,656+

Statistically, research on income has been shown to be highly correlated with overall health. In one particular study comparing adults with below-average incomes to adults with above-average incomes, the lower-income adults were more likely to wait more days for an appointment with a doctor and to go without care because of high costs. Lower-income adults also had a higher likelihood of going to an emergency room for care as compared to higher-income adults (Huynh, Schoen, Osborn, & Holmgren, 2006).

2.4.3 Income Level

The results for this variable are discussed in detail in Section 1.3. The results are reproduced from that section below.

Table 2.4.3(1) – Results for 'Family Income as % of Poverty Level'

Variable Name *POVCAT* **Class:** *Income* **Desc:** *family income as % of Poverty line*

***Section A** : Summarizing by non-traditional variable categories*

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	6.8%	2.7%	11.1%	33.9%	45.5%					
2 Total Expenditures	1.0000	0.8038	0.6756	0.7789	0.9340	1.1523					
3 Proxy Expenditures	1.0000	0.8989	0.8557	0.8494	0.9468	1.1003					
4 Traditional Risk Score	1.0000	0.8823	0.8767	0.8997	0.9580	1.0809					
5 Risk Score + N	1.0000	0.8989	0.8557	0.8494	0.9468	1.1003					
6 Risk Score + $\sum N'_{prop}$	1.0000	0.8775	0.8546	0.8727	0.9561	1.0910					
7 Allowable Rating Factor	1.0000	0.9479	0.9360	0.9345	0.9544	1.0617					
8 Proxy Exp Adjusted	1.0000	1.0165	0.9790	0.9497	0.9888	1.0194					

***Section B** : Issuer Selection Assumptions*

1	LRA Rank	4	2	1	3	5
2 Issuer A	50.0%	2.3%	2.7%	11.1%	33.9%	
3 Issuer B	50.0%	4.5%	0.0%	0.0%	0.0%	45.5%

***Section C** : Market Scenario*

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	0.22%									
2 Maximum {Pr > |t|}	0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.918	1.082	1.000						
5 Allowable Rating Factor		0.949	1.051	1.000						
6 Risk Score		0.937	1.063	1.000	0.918	1.082	1.000	0.928	1.072	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.138	1.262	1.200						
9 Premium with Risk Selection		1.125	1.275	1.200	1.102	1.298	1.200	1.114	1.286	1.200
10 Risk Selection Transfer		(0.014)	0.014	-	(0.037)	0.037	-	(0.024)	0.024	-
11 Loss Ratio		81.6%	84.8%	83.2%	83.3%	83.3%	83.3%	82.4%	84.1%	83.3%
12 Loss Ratio subject to risk corridor		81.6%	84.8%	83.2%	83.3%	83.3%	83.3%	82.4%	84.1%	83.3%
13 Loss Ratio Advantage (LRA)		**3.2%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**1.7%**	Model R^2:	34.4%

***Section D** : Statistical Significance Testing*

1 t-statistic		(1.25)	0.94	2.56	1.01	(2.29)
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	No	No	Yes	No	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Poor/Negative
2. Near Poor
3. Low Income
4. Middle Income
5. High Income

2.5 Lifestyle Variables

Lifestyle can have a significant effect on the health outcomes for a person. We appreciate this intuitively and based on the numerous news stories and advertising directed at improving our diets and bodies. The following sections explore the value (from a business perspective) of nontraditional lifestyle variables.

2.5.1 Restricting High Fat / Cholesterol

Description: This variable indicates whether a doctor or other health professional had advised an individual to eat fewer high fat or high cholesterol foods. This variable by itself *moderately* predicts claim cost variation (with a coefficient of determination or R^2 of about 1.2%)[22], and in the presence of risk adjustment has a negligible incremental impact on the R^2 statistic (see Table 2.5.1(1), Section C line 1). In MEPS, a series of questions relating to preventive care and /or screening examinations are asked of each person[23]. Questions varied in terms of their applicability by age and gender[24]. One of the questions related to food intake, specifically whether a doctor has ever advised the person to restrict high fat or high cholesterol foods. This survey question has a 'Yes' or 'No' response.

Results: The results show much higher costs (over 50%) than average for individuals that have been advised by a doctor or other healthcare professional to eat fewer high fat or high cholesterol foods (see Section 1, line 3). It is likely that part of this higher cost is due to a positive bias in utilization, since a 'Yes' response indicates a visit with a doctor or a healthcare professional. At an LRA of 4.1% this is a medium impact variable, with Issuer A preferring to enroll members that have *not* been advised by a physician to eat fewer high fat/cholesterol foods.

Although there is a dearth of published research articles quantifying the detrimental effects of high fat or high cholesterol food on either risk adjustment factors or expected medical cost, directional effects of these types of food on health status has been noticed for a long time. High fat or high

[22] See section 3.5.3 for further detail
[23] Excluding for deceased persons
[24] For example, children were excluded from questions regarding time since last blood pressure check

cholesterol significantly increases the risk of heart disease, while foods high in trans fats can cause cardiovascular disease (Jakobsen, et al., 2009).

Table 2.5.1(1) – Results for 'Restricting High Fat / High Cholesterol'

Variable Name *NOFAT53*	**Class:** *Lifestyle*	**Desc:** *restrict hgh fat/choles food (>17)*

Section A: Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	37.3%	19.0%	43.7%							
2 Total Expenditures	1.0000	0.6782	1.8228	0.9172							
3 Proxy Expenditures	1.0000	0.7087	1.7241	0.9340							
4 Traditional Risk Score	1.0000	0.7424	1.6750	0.9266							
5 Risk Score + N	1.0000	0.7112	1.7295	0.9295							
6 Risk Score + $\sum N'_{prop}$	1.0000	0.7470	1.6757	0.9224							
7 Allowable Rating Factor	1.0000	0.8317	1.2772	1.0232							
8 Proxy Exp Adjusted	1.0000	0.9663	1.0491	1.0074							

Section B: Issuer Selection Assumptions

1 LRA Rank		1	3	2
2 Issuer A	50.0%	37.3%		12.7%
3 Issuer B	50.0%	0.0%	19.0%	31.0%

Section C: Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	1.23%									
2 Maximum {Pr > |t|}	0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.766	1.234	1.000						
5 Allowable Rating Factor		0.880	1.120	1.000						
6 Risk Score		0.789	1.211	1.000	0.767	1.233	1.000	0.792	1.208	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.056	1.344	1.200						
9 Premium with Risk Selection		0.947	1.453	1.200	0.920	1.480	1.200	0.950	1.450	1.200
10 Risk Selection Transfer		(0.109)	0.109	-	(0.136)	0.136	-	(0.107)	0.107	-
11 Loss Ratio		80.9%	84.9%	82.9%	83.3%	83.4%	83.3%	80.6%	85.1%	82.9%
12 Loss Ratio subject to risk corridor		80.9%	84.9%	82.9%	83.3%	83.4%	83.3%	80.6%	85.1%	82.9%
13 Loss Ratio Advantage (LRA)		**4.1%**	Model R^2:	34.0%	**0.1%**	Model R^2:	34.0%	**4.5%**	Model R^2:	34.4%

Section D: Statistical Significance Testing

1 t-statistic		5.61	(3.97)	(0.75)
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Refused/Inapplicable 2. Yes
3. No

2.5.2 Smoking

Description: This variable indicates whether an individual is a smoker, with responses marked as 'Yes' or 'No'.

Table 2.5.2(1) – Results for 'Smoking'

Variable Name *ADSMOK42*	**Class:** *Lifestyle*	**Desc:** *saq: currently smoke*

***Section A*: Summarizing by non-traditional variable categories**

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	30.4%	14.6%	54.9%							
2 Total Expenditures	1.0000	0.6210	1.0220	1.2041							
3 Proxy Expenditures	1.0000	0.6590	1.0466	1.1765							
4 Traditional Risk Score	1.0000	0.6723	1.1140	1.1512							
5 Risk Score + *N*	1.0000	0.6590	1.0466	1.1765							
6 Risk Score + $\sum N'_{prop}$	1.0000	0.6757	1.0969	1.1539							
7 Allowable Rating Factor	1.0000	0.7805	1.0750	1.1016							
8 Proxy Exp Adjusted	1.0000	0.9867	0.9327	1.0253							

***Section B*: Issuer Selection Assumptions**

1		LRA Rank	2	1	3
2	Issuer A	50.0%	30.4%	14.6%	4.9%
3	Issuer B	50.0%	0.0%	0.0%	50.0%

***Section C*: Market Scenario**

		Traditional Risk Score			Risk Score + *N*			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	1.22%									
2 Maximum {Pr > |*t*|}	-	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.824	1.176	1.000						
5 Allowable Rating Factor		0.898	1.102	1.000						
6 Risk Score		0.849	1.151	1.000	0.824	1.176	1.000	0.846	1.154	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.078	1.322	1.200						
9 Premium with Risk Selection		1.019	1.381	1.200	0.988	1.412	1.200	1.015	1.385	1.200
10 Risk Selection Transfer		(0.059)	0.059	-	(0.090)	0.090	-	(0.063)	0.063	-
11 Loss Ratio		80.9%	85.2%	83.0%	83.3%	83.3%	83.3%	81.1%	85.0%	83.0%
12 Loss Ratio subject to risk corridor		80.9%	85.2%	83.0%	83.3%	83.3%	83.3%	81.1%	85.0%	83.0%
13 **Loss Ratio Advantage (LRA)**		**4.3%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**3.9%**	Model R^2:	34.4%

***Section D*: Statistical Significance Testing**

1 *t*-statistic		2.14	5.64	(2.31)
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu >= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu < 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. Yes
3. No

Results: With an LRA of 4.3%, this is a medium-impact variable. A surprising result from Table 2.5.2(1) is that Issuer A prefers to enroll individuals that smoke. The costs as well as risk-adjusted costs for these members are lower relative to nonsmokers. The author contacted the Agency for Healthcare

Research and Quality (who maintain MEPS data) to inquire whether the results were reasonable, with staff at AHRQ recommending looking at other variables (e.g. race or gender, etc.) that may be influencing the comparisons. The costs for smokers are lower even after we adjust for demographic (i.e. age/gender) factors and therefore demographic differences alone do not explain the observed difference. On further investigation one finds that coverage type is a discriminant factor as far as rates of smoking are concerned. The rate of smoking amongst the uninsured is significantly higher than in commercially insured cohorts. We discussed in Section 2.3.8 that the uninsured utilization and costs may be underreported in MEPS data, and that may partially explain why smokers exhibit lower costs. While we have not dug deeper into this counter-intuitive result, it certainly merits further study. Table 2.5.2(1) suggests that the results are statistically significant.

According to a study by the CDC, smoking attributes to 443,000 premature deaths annually as well as $96B per year in smoking-attributable health care expenditures, averaged from 2001-2004 (Adhikari, Kahende, Malarcher, Pechacek, & Tong, 2008). In a similar actuarial report, smokers were estimated to have health care costs average 34% more than non-smokers and that smoking-attributable expenditures represent 7% of the total cost of health care (Leif Associates, 2012). While smokers generally have more disease than non-smokers, their life expectancies are much shorter which offset these costs because of the additional costs incurred later in life.

2.5.3 Advised to Exercise More

Description: This variable indicates whether a doctor has ever advised the person to exercise more, with responses marked as a 'Yes' or 'No'.

Results: With an LRA of 3.9% this is a *medium*-impact variable. The stand-alone accuracy (as measured by the R^2) of this variable is high for a nontraditional variable at almost 2% (similar to that of gender), and the resulting coefficients are all statistically significant. Issuer A prefers members that have *not* been advised to exercise more.

Research has shown that individuals who are physically inactive tend to have a higher risk of developing diabetes and cardiovascular diseases. Those who are more physically active also have lower health care expenditures and lower health care utilization. One study has suggested that annual healthcare costs decrease with increased physical activity, independent of BMI and other variables (Wang, McDonald, Reffitt, & Edington, 2005).

Table 2.5.3(1) – Results for 'Advised to Exercise More'

Variable Name *EXRCIS53* **Class:** *Lifestyle* **Desc:** *advised to exercise more (>17)*

Section A*: *Summarizing by non-traditional variable categories

	Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	Category %	100%	37.2%	22.1%	40.7%							
2	Total Expenditures	1.0000	0.6775	1.7531	0.8851							
3	Proxy Expenditures	1.0000	0.7088	1.6800	0.8962							
4	Traditional Risk Score	1.0000	0.7420	1.6417	0.8867							
5	Risk Score + N	1.0000	0.7109	1.6894	0.8892							
6	Risk Score + $\sum N'_{prop}$	1.0000	0.7466	1.6413	0.8827							
7	Allowable Rating Factor	1.0000	0.8309	1.2399	1.0240							
8	Proxy Exp Adjusted	1.0000	0.9668	1.0383	1.0095							

Section B*: *Issuer Selection Assumptions

			Catg1	Catg2	Catg3
1		LRA Rank	1	3	2
2	Issuer A	50.0%	37.2%		12.8%
3	Issuer B	50.0%	0.0%	22.1%	27.9%

Section C*: *Market Scenario

			Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1	Stand-Alone R^2	1.98%									
2	Maximum {Pr > |t|}	0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3	Market Share		50%	50%	100%						
4	Proxy Expenditures		0.757	1.243	1.000						
5	Allowable Rating Factor		0.880	1.120	1.000						
6	Risk Score		0.779	1.221	1.000	0.757	1.243	1.000	0.782	1.218	1.000
7	Statewide Average Premium				1.200						
8	Premium without Risk Selection		1.056	1.344	1.200						
9	Premium with Risk Selection		0.935	1.465	1.200	0.908	1.492	1.200	0.938	1.462	1.200
10	Risk Selection Transfer		(0.122)	0.122	-	(0.149)	0.149	-	(0.119)	0.119	-
11	Loss Ratio		81.0%	84.9%	82.9%	83.4%	83.3%	83.3%	80.7%	85.0%	82.9%
12	Loss Ratio subject to risk corridor		81.0%	84.9%	82.9%	83.4%	83.3%	83.3%	80.7%	85.0%	82.9%
13	Loss Ratio Advantage (LRA)		3.9%	Model R^2:	34.0%	0.0%	Model R^2:	34.0%	4.3%	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

			Catg1	Catg2	Catg3
1	t-statistic		5.52	(3.33)	(1.01)
2	H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu <= 1$
3	H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu > 1$
4	H_0 rejected (at α=5%)	Yes*	Yes	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Refused/Inapplicable 2. Yes
3. No

Another study provided employees with a small financial incentive to exercise regularly In order to study its effect on claim costs. For employees who participated in the program and worked out 8 times per month, their monthly medical costs were significantly lower than that of the control group (Medica, 2007).

2.5.4 Problems with Health & Social Activities

Description: This variable indicates if physical health or emotional problems interfered with social activities during the past four weeks.

Results: At an LRA of over 8%, this is a *high*-impact variable. Issuer A has a strong preference for members reporting that problems with health impeded their social activities 'none of the time'. Despite that Issuer A's overall risk is below average and cuts a sizeable check to Issuer B, Issuer A comes out far ahead of Issuer B in terms of financial performance. The stand-alone power (i.e. R^2 metric) of this variable to explain variation in healthcare costs is also high at over 5%.

Table 2.5.4(1) – Results for 'Problems with Health & Social Activities'

Variable Name *ADSOCA42* **Class:** *Lifestyle* **Desc:** *Health stopped social activities*

***Section A**: Summarizing by non-traditional variable categories*

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	30.5%	1.0%	2.1%	7.0%	11.5%	47.9%				
2 Total Expenditures	1.0000	0.6276	3.5792	3.3027	1.8815	1.3688	0.8640				
3 Proxy Expenditures	1.0000	0.6617	2.9439	2.9023	1.8526	1.3315	0.8864				
4 Traditional Risk Score	1.0000	0.6713	2.2490	2.2362	1.6963	1.3175	0.9503				
5 Risk Score + N	1.0000	0.6617	2.9439	2.9023	1.8526	1.3315	0.8864				
6 Risk Score + $\sum N'_{prop}$	1.0000	0.6743	2.2391	2.2319	1.6870	1.3126	0.9513				
7 Allowable Rating Factor	1.0000	0.7802	1.1638	1.1608	1.1298	1.0879	1.0892				
8 Proxy Exp Adjusted	1.0000	0.9904	1.6949	1.6661	1.1563	1.0140	0.9360				

***Section B**: Issuer Selection Assumptions*

		Catg1	Catg2	Catg3	Catg4	Catg5	Catg6
1	LRA Rank	2	6	5	4	3	1
2 Issuer A	50.0%	2.1%					47.9%
3 Issuer B	50.0%	28.4%	1.0%	2.1%	7.0%	11.5%	0.0%

***Section C**: Market Scenario*

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	5.05%									
2 Maximum {Pr > |t|}	0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.877	1.123	1.000						
5 Allowable Rating Factor		1.076	0.924	1.000						
6 Risk Score		0.939	1.061	1.000	0.877	1.123	1.000	0.940	1.060	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.291	1.109	1.200						
9 Premium with Risk Selection		1.126	1.274	1.200	1.052	1.348	1.200	1.128	1.272	1.200
10 Risk Selection Transfer		(0.165)	0.165	-	(0.239)	0.239	-	(0.164)	0.164	-
11 Loss Ratio		77.9%	88.2%	83.0%	83.3%	83.3%	83.3%	77.8%	88.3%	83.0%
12 Loss Ratio subject to risk corridor		80.0%	88.2%	84.1%	83.3%	83.3%	83.3%	80.0%	88.3%	84.1%
13 Loss Ratio Advantage (LRA)		**8.2%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**8.3%**	Model R^2:	34.4%

***Section D**: Statistical Significance Testing*

		Catg1	Catg2	Catg3	Catg4	Catg5	Catg6
1 t-statistic		1.54	(8.58)	(10.22)	(5.11)	(0.79)	5.55
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	Yes*	No	Yes	Yes	Yes	No	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Inapplicable
2. All of the Time
3. Most of the Time
4. Some of the Time
5. Little of the Time
6. None of the Time

2.5.5 Attitude towards Healthcare Utilization

Description: This variable describes an attitude towards using healthcare services. Individuals were asked to what extent they agreed with the statement that they 'can overcome ills without medical help'.

Table 2.5.5(1) – Results for 'Attitude towards Healthcare Utilization'

Variable Name *ADOVER42* **Class:** *Lifestyle* **Desc:** *Person can overcome illness without medical help*

***Section A*: Summarizing by non-traditional variable categories**

	Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	Category %	100%	30.9%	26.3%	16.9%	8.0%	15.2%	2.7%				
2	Total Expenditures	1.0000	0.6318	1.6761	1.0510	0.7702	0.7086	0.6334				
3	Proxy Expenditures	1.0000	0.6617	1.5613	1.0976	0.8212	0.7724	0.6079				
4	Traditional Risk Score	1.0000	0.6765	1.4731	1.1307	0.8729	0.8186	0.6768				
5	Risk Score + N	1.0000	0.6617	1.5613	1.0976	0.8212	0.7724	0.6079				
6	Risk Score + $\sum N'_{prop}$	1.0000	0.6799	1.4737	1.1305	0.8668	0.8182	0.6534				
7	Allowable Rating Factor	1.0000	0.7855	1.1939	1.0707	1.0074	1.0179	0.9991				
8	Proxy Exp Adjusted	1.0000	0.9852	1.0881	0.9669	0.9483	0.9538	0.9311				

***Section B*: Issuer Selection Assumptions**

			Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1		LRA Rank	5	6	4	2	3	1				
2	Issuer A	50.0%	7.2%		16.9%	8.0%	15.2%	2.7%				
3	Issuer B	50.0%	23.7%	26.3%	0.0%	0.0%	0.0%	0.0%				

***Section C*: Market Scenario**

			Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1	Stand-Alone R^2	3.10%									
2	Maximum {Pr > |t|}	0.0503	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3	Market Share		50%	50%	100%						
4	Proxy Expenditures		0.865	1.135	1.000						
5	Allowable Rating Factor		1.000	1.000	1.000						
6	Risk Score		0.904	1.096	1.000	0.865	1.135	1.000	0.902	1.098	1.000
7	Statewide Average Premium				1.200						
8	Premium without Risk Selection		1.200	1.200	1.200						
9	Premium with Risk Selection		1.085	1.315	1.200	1.038	1.362	1.200	1.083	1.317	1.200
10	Risk Selection Transfer		(0.114)	0.114	-	(0.162)	0.162	-	(0.117)	0.117	-
11	Loss Ratio		79.7%	86.3%	83.0%	83.3%	83.3%	83.3%	79.9%	86.2%	83.0%
12	Loss Ratio subject to risk corridor		80.0%	86.3%	83.2%	83.3%	83.3%	83.3%	80.0%	86.2%	83.1%
13	**Loss Ratio Advantage (LRA)**		**6.3%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**6.2%**	Model R^2:	34.4%

***Section D*: Statistical Significance Testing**

			Catg1	Catg2	Catg3	Catg4	Catg5	Catg6
1	t-statistic		2.39	(7.84)	3.00	3.75	3.10	3.63
2	H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$
3	H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$
4	H_0 rejected (at α=5%)	Yes*	Yes	Yes	Yes	Yes	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. Disagree Strongly
3. Disagree Somewhat
4. Uncertain
5. Agree Somewhat
6. Agree Strongly

Results: This is a rather interesting variable, one that with an LRA of over 6% has a *high*-impact. Issuer A prefers members that generally agree with the statement that they can overcome health ailments without medical help. Consequently their measured risk score is higher than their cost – resulting in risk adjusted costs that are much lower than average. The presumed explanation is that despite predicting higher than expected medical costs, these individuals are actually able to overcome those diagnoses or ills without utilizing as many medical resources as expected. Perhaps these individuals are less inclined to over-utilize medical care and more likely to take a wait-and-see approach in certain cases, rather than rush to obtain medical care (this is of course speculative).

2.5.6 Energy

Description: This variable indicates whether an individual had a lot of energy during the past four weeks.

Results: The stand-alone statistical accuracy (i.e. the R^2) of this variable is high at almost 5%. Even though its stand-alone predictive accuracy is high, this variable has a negligible marginal contribution to overall accuracy of a traditional risk adjustment model (this is a theme for all nontraditional variables). As stated through this report, we focus on the financial incentives rather than statistical performance – and at an LRA of over 6% – this is a high impact variable. Issuer A prefers enrolling individuals that had energy 'most of the time' or 'all of the time'. The differences in risk-adjusted cost are statistically significant each category level of this nontraditional variable.

Table 2.5.6(1) – Results for 'Energy'

Variable Name *ADNRGY42*		Class: *Lifestyle*			Desc: *Had a lot of energy*						
***Section A*: Summarizing by non-traditional variable categories**											
Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	48.3%	6.4%	25.4%	13.9%	4.3%	1.7%				
2 Total Expenditures	1.0000	0.7628	0.4781	0.9281	1.4512	2.4461	3.4378				
3 Proxy Expenditures	1.0000	0.7806	0.5302	0.9382	1.4364	2.3512	2.9409				
4 Traditional Risk Score	1.0000	0.8140	0.6252	0.9751	1.3813	2.0257	2.3546				
5 Risk Score + N	1.0000	0.7806	0.5302	0.9382	1.4364	2.3512	2.9409				
6 Risk Score + $\sum N'_{prop}$	1.0000	0.8184	0.6060	0.9756	1.3772	2.0191	2.3452				
7 Allowable Rating Factor	1.0000	0.8874	1.0192	1.1095	1.1107	1.1494	1.2072				
8 Proxy Exp Adjusted	1.0000	0.9666	0.9051	0.9630	1.0550	1.3255	1.5863				

***Section B*: Issuer Selection Assumptions**

1	LRA Rank		3	1	2	4	5	6
2	Issuer A	50.0%	18.2%	6.4%	25.4%			
3	Issuer B	50.0%	30.1%	0.0%	0.0%	13.9%	4.3%	1.7%

***Section C*: Market Scenario**

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	4.86%									
2 Maximum {Pr > |t|}	0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.829	1.171	1.000						
5 Allowable Rating Factor		1.017	0.983	1.000						
6 Risk Score		0.872	1.128	1.000	0.829	1.171	1.000	0.871	1.129	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.221	1.179	1.200						
9 Premium with Risk Selection		1.046	1.354	1.200	0.995	1.405	1.200	1.045	1.355	1.200
10 Risk Selection Transfer		(0.174)	0.174	-	(0.226)	0.226	-	(0.175)	0.175	-
11 Loss Ratio		79.2%	86.5%	82.9%	83.3%	83.3%	83.3%	79.3%	86.5%	82.9%
12 Loss Ratio subject to risk corridor		80.0%	86.5%	83.3%	83.3%	83.3%	83.3%	80.0%	86.5%	83.2%
13 Loss Ratio Advantage (LRA)		**6.5%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**6.5%**	Model R^2:	34.4%

***Section D*: Statistical Significance Testing**

1 t-statistic		5.89	9.40	2.56	(3.97)	(9.52)	(9.08)
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	Yes	Yes	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. All of the Time
3. Most of the Time
4. Some of the Time
5. Little of the Time
6. None of the Time

2.5.7 Socially Limited

Description: This variable indicates whether health limited social activities and whether the person indicated use of assistive technology, with responses marked as a 'Yes' or 'No'.

Results: The results of the stand-alone regression performance are similar to those presented for the 'having energy' indicator (Section 2.5.6). At an LRA of over 4% this is a medium impact variable. Issuer A prefers members that have indicated that they do not use any assistive technologies.

Table 2.5.7(1) – Results for 'Socially Limited'

Variable Name *SOCLIM31* **Class:** *Lifestyle* **Desc:** *social limitations*

Section A*: *Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	0.7%	2.0%	97.3%							
2 Total Expenditures	1.0000	1.3296	5.3089	0.9101							
3 Proxy Expenditures	1.0000	1.0294	4.3480	0.9318							
4 Traditional Risk Score	1.0000	0.9227	3.0455	0.9591							
5 Risk Score + *N*	1.0000	1.0294	4.3480	0.9318							
6 Risk Score + $\sum N'_{prop}$	1.0000	0.7989	3.1065	0.9587							
7 Allowable Rating Factor	1.0000	0.7580	1.2559	0.9966							
8 Proxy Exp Adjusted	1.0000	1.1067	2.3024	0.9728							

Section B*: *Issuer Selection Assumptions

		Total/Agg	Catg1	Catg2	Catg3
1	**LRA Rank**		2	3	1
2	Issuer A	50.0%			50.0%
3	Issuer B	50.0%	0.7%	2.0%	47.3%

Section C*: *Market Scenario

		Traditional Risk Score			Risk Score + *N*			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	5.22%									
2 Maximum {Pr > |*t*|}	0.0539	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.932	1.068	1.000						
5 Allowable Rating Factor		0.997	1.003	1.000						
6 Risk Score		0.959	1.041	1.000	0.932	1.068	1.000	0.959	1.041	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.196	1.204	1.200						
9 Premium with Risk Selection		1.151	1.249	1.200	1.118	1.282	1.200	1.150	1.250	1.200
10 Risk Selection Transfer		(0.045)	0.045	-	(0.078)	0.078	-	(0.045)	0.045	-
11 Loss Ratio		81.0%	85.5%	83.2%	83.3%	83.3%	83.3%	81.0%	85.5%	83.2%
12 Loss Ratio subject to risk corridor		81.0%	85.5%	83.2%	83.3%	83.3%	83.3%	81.0%	85.5%	83.2%
13 **Loss Ratio Advantage (LRA)**		**4.5%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**4.5%**	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

		Issuer A	Issuer B	Market
1 *t*-statistic		(2.12)	(14.11)	1.02
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu <= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu > 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Refused/Inapplicable 2. Yes
3. No

2.5.8 Physical Activity

Description: This variable indicates whether the person currently spends a half hour or more in moderate to vigorous physical activity at least three times a week. This was only asked of individuals aged 18 and older, with responses marked as a 'Yes' or 'No'.

Results: Issuer A prefers members that indicate that they currently engage in some physical activity through the week – however at an LRA of 2.3% this is a *low* impact variable. The magnitude of the impact is lower than the author would have suspected – one reason is that the risk score of those that indicated that they did not exercise regularly corresponds closely with their costs.

Table 2.5.8(1) – Results for 'Physical Activity'

Variable Name *PHYACT53* **Class:** *Lifestyle* **Desc:** *Physical activity more than three times per week*

Section A*: *Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	24.1%	46.1%	29.8%							
2 Total Expenditures	1.0000	0.6139	0.9711	1.3561							
3 Proxy Expenditures	1.0000	0.6494	0.9868	1.3032							
4 Traditional Risk Score	1.0000	0.6361	1.0026	1.2895							
5 Risk Score + N	1.0000	0.6374	0.9930	1.3032							
6 Risk Score + $\sum N'_{prop}$	1.0000	0.6417	1.0036	1.2834							
7 Allowable Rating Factor	1.0000	0.7142	1.0765	1.1123							
8 Proxy Exp Adjusted	1.0000	1.0133	0.9842	1.0137							

Section B*: *Issuer Selection Assumptions

1		**LRA Rank**	**2**	**1**	**3**
2	Issuer A	50.0%	3.9%	46.1%	
3	Issuer B	50.0%	20.2%	0.0%	29.8%

Section C*: *Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	1.53%									
2 Maximum {Pr > |t|}	0.0050	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.961	1.039	1.000						
5 Allowable Rating Factor		1.048	0.952	1.000						
6 Risk Score		0.974	1.026	1.000	0.965	1.035	1.000	0.976	1.024	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.258	1.142	1.200						
9 Premium with Risk Selection		1.169	1.231	1.200	1.159	1.241	1.200	1.171	1.229	1.200
10 Risk Selection Transfer		(0.089)	0.089	-	(0.099)	0.099	-	(0.087)	0.087	-
11 Loss Ratio		82.2%	84.4%	83.3%	82.9%	83.7%	83.3%	82.1%	84.5%	83.3%
12 Loss Ratio subject to risk corridor		82.2%	84.4%	83.3%	82.9%	83.7%	83.3%	82.1%	84.5%	83.3%
13 **Loss Ratio Advantage (LRA)**		**2.3%**	Model R^2:	34.0%	**0.8%**	Model R^2:	34.0%	**2.5%**	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

1 t-statistic		(1.92)	1.81	(1.44)
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu >= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu < 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Refused/Inapplicable 2. Yes
3. No

2.5.9 Risk Aversion

Description: This variable indicates whether the respondent was more likely to take risks than the average person.

Table 2.5.9(1) – Results for 'Risk Aversion'

Variable Name *ADRISK42* **Class:** *Lifestyle* **Desc:** *saq: more likely to take risks*

Section A: Summarizing by non-traditional variable categories

	Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	Category %	100%	31.0%	25.7%	17.0%	10.1%	12.7%	3.4%				
2	Total Expenditures	1.0000	0.6318	1.4518	1.1130	0.9870	0.8869	0.8314				
3	Proxy Expenditures	1.0000	0.6621	1.4121	1.1214	0.9987	0.8694	0.8452				
4	Traditional Risk Score	1.0000	0.6778	1.3755	1.1135	1.0052	0.9081	0.8541				
5	Risk Score + N	1.0000	0.6621	1.4121	1.1214	0.9987	0.8694	0.8452				
6	Risk Score + $\sum N'_{prop}$	1.0000	0.6810	1.3806	1.1153	0.9990	0.8991	0.8304				
7	Allowable Rating Factor	1.0000	0.7867	1.1754	1.0718	1.0354	1.0363	1.0150				
8	Proxy Exp Adjusted	1.0000	0.9843	1.0366	1.0079	0.9936	0.9612	0.9911				

Section B: Issuer Selection Assumptions

1	LRA Rank		2	6	5	4	1	3
2	Issuer A	50.0%	31.0%			2.8%	12.7%	3.4%
3	Issuer B	50.0%	0.0%	25.7%	17.0%	7.2%	0.0%	0.0%

Section C: Market Scenario

			Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1	Stand-Alone R^2	1.95%									
2	Maximum {Pr > |t|}	0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3	Market Share		50%	50%	100%						
4	Proxy Expenditures		0.747	1.253	1.000						
5	Allowable Rating Factor		0.880	1.120	1.000						
6	Risk Score		0.767	1.233	1.000	0.747	1.253	1.000	0.765	1.235	1.000
7	Statewide Average Premium				1.200						
8	Premium without Risk Selection		1.056	1.344	1.200						
9	Premium with Risk Selection		0.921	1.479	1.200	0.896	1.504	1.200	0.918	1.482	1.200
10	Risk Selection Transfer		(0.135)	0.135	-	(0.160)	0.160	-	(0.138)	0.138	-
11	Loss Ratio		81.1%	84.7%	82.9%	83.3%	83.3%	83.3%	81.3%	84.6%	83.0%
12	Loss Ratio subject to risk corridor		81.1%	84.7%	82.9%	83.3%	83.3%	83.3%	81.3%	84.6%	83.0%
13	Loss Ratio Advantage (LRA)		3.6%	Model R^2:	34.0%	0.0%	Model R^2:	34.0%	3.2%	Model R^2:	34.4%

Section D: Statistical Significance Testing

1	t-statistic		2.54	(3.40)	(0.66)	0.45	2.70	0.44
2	H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$
3	H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$
4	H_0 rejected (at α=5%)	Yes*	Yes	Yes	No	No	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. Disagree Strongly
3. Disagree Somewhat
4. Uncertain
5. Agree Somewhat
6. Agree Strongly

Results: A little counter-intuitive, Issuer A prefers members that either did not respond to this question or those that take more risks than the average person. The term 'risk' is not fully defined in the

MEPS survey questionnaire and so it is possible, for example, that individuals that are athletic and go rock climbing would pencil in ‘agree strongly’ as a response. At an LRA of over 3.3% this is a *medium* impact variable.

2.5.10 Attitude towards Healthcare Insurance

Description: This variable describes an attitude towards purchasing health insurance. Individuals were asked whether they agree or disagree with the statement that they ‘do not need health insurance’.

Table 2.5.10(1) – Results for ‘Attitude towards Healthcare Insurance’

Variable Name *ADINSA42* **Class:** *Lifestyle* **Desc:** *Do not need health insurance (attitude towards i*

***Section A*: Summarizing by non-traditional variable categories**

	Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	Category %	100%	30.8%	45.3%	11.0%	4.8%	6.1%	2.0%				
2	Total Expenditures	1.0000	0.6310	1.4840	0.6702	0.5027	0.4119	0.5337				
3	Proxy Expenditures	1.0000	0.6605	1.4295	0.7487	0.5920	0.4651	0.5037				
4	Traditional Risk Score	1.0000	0.6754	1.3747	0.8241	0.6603	0.5770	0.5923				
5	Risk Score + N	1.0000	0.6605	1.4295	0.7487	0.5920	0.4651	0.5037				
6	Risk Score + $\sum N'_{prop}$	1.0000	0.6788	1.3806	0.8158	0.6407	0.5606	0.5482				
7	Allowable Rating Factor	1.0000	0.7843	1.1562	1.0010	0.9607	0.9617	0.9891				
8	Proxy Exp Adjusted	1.0000	0.9851	1.0548	0.9245	0.9317	0.8881	0.9114				

***Section B*: Issuer Selection Assumptions**

			Catg1	Catg2	Catg3	Catg4	Catg5	Catg6
1		LRA Rank	5	6	3	4	1	2
2	Issuer A	50.0%	26.0%		11.0%	4.8%	6.1%	2.0%
3	Issuer B	50.0%	4.7%	45.3%	0.0%	0.0%	0.0%	0.0%

***Section C*: Market Scenario**

			Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1	Stand-Alone R^2	3.61%									
2	Maximum {Pr > |t|}	0.2778	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3	Market Share		50%	50%	100%						
4	Proxy Expenditures		0.643	1.357	1.000						
5	Allowable Rating Factor		0.879	1.121	1.000						
6	Risk Score		0.691	1.309	1.000	0.643	1.357	1.000	0.686	1.314	1.000
7	Statewide Average Premium				1.200						
8	Premium without Risk Selection		1.055	1.345	1.200						
9	Premium with Risk Selection		0.830	1.570	1.200	0.772	1.628	1.200	0.823	1.577	1.200
10	Risk Selection Transfer		(0.225)	0.225	-	(0.283)	0.283	-	(0.232)	0.232	-
11	Loss Ratio		77.5%	86.4%	82.0%	83.3%	83.3%	83.3%	78.2%	86.0%	82.1%
12	Loss Ratio subject to risk corridor		80.0%	86.4%	83.2%	83.3%	83.3%	83.3%	80.0%	86.0%	83.0%
13	Loss Ratio Advantage (LRA)		6.4%	Model R^2:	34.0%	0.0%	Model R^2:	34.0%	6.0%	Model R^2:	34.4%

***Section D*: Statistical Significance Testing**

			Catg1	Catg2	Catg3	Catg4	Catg5	Catg6
1	t-statistic		2.40	(5.93)	7.46	4.35	6.43	3.93
2	H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$
3	H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$
4	H_0 rejected (at α=5%)	Yes*	Yes	Yes	Yes	Yes	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. Disagree Strongly
3. Disagree Somewhat
4. Uncertain
5. Agree Somewhat
6. Agree Strongly

Results: This is an interesting variable – and at an LRA of over 6% is also *high* impact. Issuer A prefers members that feel like they do *not* need health insurance. (We assume issuer A can actually enroll these individuals!). This is consistent with the results for the insurance coverage variable (section 2.3.8). The results in 2.5.10(1) suggest that the risk adjusted average costs for all of the categories for this variable are significantly different than the population average (i.e. 1.00).

2.5.11 Problems with Getting involved in Sports or Hobbies

Description: This variable indicates whether a child has behavioral problems with getting involved in activities like sports or hobbies. The MEPS study only includes children ages 5 – 17 and answers are based on the Columbia Impairment Scale. Respondents were asked to respond on a scale from 0 to 4, where a '0' indicated 'No Problem' and a '4' indicated 'A Very Big Problem'.

Results: At an LRA of little over 1% this is a *low* impact variable. The question was asked only of children, which covers a smaller proportion of the tested population. This illustrates the importance of the proportion of the population for which information can be collected. If information is available on only a small segment of the population that is demographically homogenous or homogenous in traditional average risk score, then that variable is less likely to produce a high impact. In the case of this variable, not only does it involve responses for a small section of the population, that demographic cohort is already adjusted in the traditional risk adjustment formula. However if a nontraditional variable yields information on a small subset of the population and that subset has very high or very low risk adjusted cost – then the variable may have a higher impact.

Table 2.5.11(1) – Results for 'Getting Involved in Sports or Hobbies'

Variable Name *SPRPRO42* **Class:** *Lifestyle* **Desc:** *problem w/sports/hobbies (5-17)*

Section A*: *Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	82.1%	13.8%	2.0%	1.2%	0.4%	0.3%	0.0%			
2 Total Expenditures	1.0000	1.1038	0.4624	0.5545	0.8609	0.7839	1.2565	0.4579			
3 Proxy Expenditures	1.0000	1.0931	0.5145	0.6158	0.8599	0.8958	1.2151	0.6698			
4 Traditional Risk Score	1.0000	1.0935	0.5361	0.6023	0.7106	0.8093	0.9607	0.5670			
5 Risk Score + N	1.0000	1.0931	0.5145	0.6158	0.8599	0.8958	1.2151	0.5583			
6 Risk Score + $\sum N'_{prop}$	1.0000	1.0922	0.5413	0.6148	0.7217	0.8070	0.9575	0.5316			
7 Allowable Rating Factor	1.0000	1.0644	0.7039	0.7039	0.7039	0.7039	0.7039	0.7039			
8 Proxy Exp Adjusted	1.0000	0.9995	0.9784	1.0135	1.1493	1.0865	1.2545	1.1028			

Section B*: *Issuer Selection Assumptions

			Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7
1		LRA Rank	2	1	3	6	4	7	5
2	Issuer A	50.0%	36.2%	13.8%					
3	Issuer B	50.0%	46.0%	0.0%	2.0%	1.2%	0.4%	0.3%	0.0%

Section C*: *Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	1.00%									
2 Maximum {Pr > |t|}	0.1052	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.933	1.067	1.000						
5 Allowable Rating Factor		0.965	1.035	1.000						
6 Risk Score		0.939	1.061	1.000	0.933	1.067	1.000	0.940	1.060	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.158	1.242	1.200						
9 Premium with Risk Selection		1.127	1.273	1.200	1.119	1.281	1.200	1.128	1.272	1.200
10 Risk Selection Transfer		(0.030)	0.030	-	(0.038)	0.038	-	(0.030)	0.030	-
11 Loss Ratio		82.8%	83.8%	83.3%	83.3%	83.3%	83.3%	82.7%	83.9%	83.3%
12 Loss Ratio subject to risk corridor		82.8%	83.8%	83.3%	83.3%	83.3%	83.3%	82.7%	83.9%	83.3%
13 Loss Ratio Advantage (LRA)		1.1%	Model R^2:	34.0%	0.0%	Model R^2:	34.0%	1.1%	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7
1 t-statistic		0.09	3.60	(0.79)	(3.30)	(1.40)	(2.22)	(0.77)
2 H_0: Null Hypothesis		μ >= 1	μ >= 1	μ <= 1	μ <= 1	μ <= 1	μ <= 1	μ <= 1
3 H_1: Alternate Hypothesis		μ < 1	μ < 1	μ > 1	μ > 1	μ > 1	μ > 1	μ > 1
4 H_0 rejected (at α =5%)	Yes*	No	Yes	No	Yes	No	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Refused/Inapplicable
2. 0 (scale of 0 – 4)
3. 1 (scale of 0 – 4)
4. 2 (scale of 0 – 4)
5. 3 (scale of 0 – 4)
6. 4 (scale of 0 – 4)
7. Asked, But Inapplicable

2.5.12 Body Mass Index (BMI)

Description: This variable is a mix of the adult Body Mass Index (ages 18 and older) and the child's Body Mass Index. The adult BMI is solely based on the individual's reported height and weight while the child's BMI also takes into account age.

Results: At an LRA of less than 2% this is a *low* impact variable. Interestingly, issuer A selects individuals that either did not respond to the question, or had a *normal-high* BMI while avoiding members with a low BMI. One reason is that while the costs for the obese individuals are high, their risk score slightly over-predicts their costs. Therefore the issuer has a slight incentive to choose these members.

Table 2.5.12(1) – Results for 'Body Mass Index'

Variable Name *BMINDX53_C* **Class:** *Lifestyle* **Desc:** *adult body mass index (>17)*

Section A*: *Summarizing by non-traditional variable categories

	Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	Category %	100%	31.8%	1.2%	25.1%	24.1%	17.9%					
2	Total Expenditures	1.0000	0.6894	0.9891	0.9842	1.0657	1.4861					
3	Proxy Expenditures	1.0000	0.7178	1.0298	0.9703	1.0497	1.4738					
4	Traditional Risk Score	1.0000	0.7356	0.9606	0.9517	1.0493	1.4735					
5	Risk Score + *N*	1.0000	0.7205	0.9316	0.9707	1.0504	1.4741					
6	Risk Score + $\sum N'_{prop}$	1.0000	0.7404	0.9658	0.9548	1.0467	1.4637					
7	Allowable Rating Factor	1.0000	0.8013	0.9264	1.0258	1.1249	1.1534					
8	Proxy Exp Adjusted	1.0000	0.9822	1.0692	1.0186	1.0004	1.0003					

Section B*: *Issuer Selection Assumptions

			Catg1	Catg2	Catg3	Catg4	Catg5
1	LRA Rank		1	5	4	3	2
2	Issuer A	50.0%	31.8%			0.4%	17.9%
3	Issuer B	50.0%	0.0%	1.2%	25.1%	23.7%	0.0%

Section C*: *Market Scenario

			Traditional Risk Score			Risk Score + *N*			Risk Score + $\sum N'_{prop}$		
1	Stand-Alone R^2	1.32%									
2	Maximum {Pr > |*t*|}	-	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3	Market Share		50%	50%	100%						
4	Proxy Expenditures		0.991	1.009	1.000						
5	Allowable Rating Factor		0.930	1.070	1.000						
6	Risk Score		1.002	0.998	1.000	0.992	1.008	1.000	1.001	0.999	1.000
7	Statewide Average Premium				1.200						
8	Premium without Risk Selection		1.116	1.284	1.200						
9	Premium with Risk Selection		1.202	1.198	1.200	1.191	1.209	1.200	1.202	1.198	1.200
10	Risk Selection Transfer		0.087	(0.087)	-	0.075	(0.075)	-	0.086	(0.086)	-
11	Loss Ratio		82.4%	84.3%	83.3%	83.2%	83.5%	83.3%	82.4%	84.2%	83.3%
12	Loss Ratio subject to risk corridor		82.4%	84.3%	83.3%	83.2%	83.5%	83.3%	82.4%	84.2%	83.3%
13	**Loss Ratio Advantage (LRA)**		**1.9%**	Model R^2:	34.0%	**0.3%**	Model R^2:	34.0%	**1.8%**	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

			Catg1	Catg2	Catg3	Catg4	Catg5
1	*t*-statistic		2.76	(1.62)	(0.55)	(0.04)	(0.03)
2	H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$
3	H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$
4	H_0 rejected (at α =5%)	Yes*	Yes	No	No	No	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. 1 – 18.5
3. 18.6 – 24.9
4. 25 – 29.9
5. 30+

2.6 Psychological Self-Assessment Variables

This section presents the results for the nontraditional variables that were categorized as relating to mental or behavioral well-being as assessed by the respondents in the MEPS survey.

2.6.1 Problems Having Fun

Description: This variable indicates whether a child has behavioral problems ‘having fun’. This question was only asked of children aged 5 – 17 and answers are based on the Columbia Impairment Scale. Respondents were asked to respond on a scale from 0 to 4, where a ‘0’ indicated ‘No Problem’ and a ‘4’ indicated ‘A Very Big Problem’.

Table 2.6.1(1) – Results for ‘Problems Having Fun’

Variable Name *HAVFUN42* **Class:** *Psychological Statu* **Desc:** *problem having fun (5-17)*

Section A*: *Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	82.1%	15.8%	1.4%	0.6%	0.1%	0.1%	0.0%			
2 Total Expenditures	1.0000	1.1039	0.4861	0.6852	1.0031	1.2469	0.8262	0.5711			
3 Proxy Expenditures	1.0000	1.0932	0.5306	0.7499	1.0838	1.5056	1.1145	0.3462			
4 Traditional Risk Score	1.0000	1.0937	0.5494	0.6631	0.8214	0.9377	0.8871	0.4737			
5 Risk Score + *N*	1.0000	1.0932	0.5306	0.7499	1.0838	1.5056	1.1145	0.4601			
6 Risk Score + $\sum N'_{prop}$	1.0000	1.0924	0.5544	0.6791	0.8376	0.9415	0.8539	0.4077			
7 Allowable Rating Factor	1.0000	1.0645	0.7039	0.7039	0.7039	0.7039	0.7039	0.7039			
8 Proxy Exp Adjusted	1.0000	0.9995	0.9812	1.0868	1.2625	1.5678	1.2274	0.8726			

Section B*: *Issuer Selection Assumptions

		Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1		LRA Rank	3	2	4	6	7	5	1			
2	Issuer A	50.0%	34.2%	15.8%					0.0%			
3	Issuer B	50.0%	47.9%	0.0%	1.4%	0.6%	0.1%	0.1%	0.0%			

Section C*: *Market Scenario

		Traditional Risk Score			Risk Score + *N*			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	1.00%									
2 Maximum {Pr > |*t*|}	0.8997	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.915	1.085	1.000						
5 Allowable Rating Factor		0.951	1.049	1.000						
6 Risk Score		0.922	1.078	1.000	0.915	1.085	1.000	0.922	1.078	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.141	1.259	1.200						
9 Premium with Risk Selection		1.106	1.294	1.200	1.099	1.301	1.200	1.107	1.293	1.200
10 Risk Selection Transfer		(0.035)	0.035	-	(0.042)	0.042	-	(0.034)	0.034	-
11 Loss Ratio		82.8%	83.8%	83.3%	83.3%	83.3%	83.3%	82.7%	83.9%	83.3%
12 Loss Ratio subject to risk corridor		82.8%	83.8%	83.3%	83.3%	83.3%	83.3%	82.7%	83.9%	83.3%
13 Loss Ratio Advantage (LRA)		**1.1%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**1.2%**	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7
1 *t*-statistic		0.09	3.07	(3.68)	(3.68)	(2.05)	(1.16)	0.64
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu < 1$
4 H_0 rejected (at α =5%)	Yes*	No	Yes	Yes	Yes	Yes	No	No

Category Description (e.g. (1) corresponds with Catg1 in table 2.6.1 above)

1. Not Ascertained/Didn't Know/Refused/Inapplicable
2. 0 (scale of 0 – 4)
3. 1 (scale of 0 – 4)
4. 2 (scale of 0 – 4)
5. 3 (scale of 0 – 4)
6. 4 (scale of 0 – 4)
7. Asked, But Inapplicable

Results: This variable has the same issues as the variable 'Problems with Getting involved in Sports or Hobbies' (Section 2.5.11), and the same discussion applies. Result details are presented in Table 2.6.1(1).

2.6.2 Mental Health

Description: This variable indicates the respondent's perception of his or her mental well-being.

Table 2.6.2(1) – Results for 'Mental Health'

Variable Name *MNHLTH31*		Class: *Psychological Statu*			Desc: *perceived mental health status*						
Section A: Summarizing by non-traditional variable categories											
Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	0.7%	48.0%	29.1%	18.6%	3.1%	0.6%				
2 Total Expenditures	1.0000	1.2774	0.7875	0.9621	1.3069	2.2801	3.4756				
3 Proxy Expenditures	1.0000	0.9711	0.8051	0.9680	1.2676	2.2627	3.4491				
4 Traditional Risk Score	1.0000	0.9011	0.8314	0.9876	1.2457	1.9708	2.6307				
5 Risk Score + N	1.0000	0.9711	0.8051	0.9680	1.2676	2.2627	3.4491				
6 Risk Score + $\sum N'_{prop}$	1.0000	0.7720	0.8336	0.9884	1.2405	1.9817	2.6698				
7 Allowable Rating Factor	1.0000	0.7670	0.9542	1.0191	1.0739	1.1131	1.1295				
8 Proxy Exp Adjusted	1.0000	1.0700	0.9737	0.9804	1.0219	1.2919	1.8184				
Section B: Issuer Selection Assumptions											
1 LRA Rank		4	1	2	3	5	6				
2 Issuer A	50.0%		48.0%	2.0%							
3 Issuer B	50.0%	0.7%	0.0%	27.0%	18.6%	3.1%	0.6%				

Section C: Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	2.67%									
2 Maximum {Pr > |t|}	0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.812	1.188	1.000						
5 Allowable Rating Factor		0.957	1.043	1.000						
6 Risk Score		0.838	1.162	1.000	0.812	1.188	1.000	0.840	1.160	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.148	1.252	1.200						
9 Premium with Risk Selection		1.005	1.395	1.200	0.974	1.426	1.200	1.008	1.392	1.200
10 Risk Selection Transfer		(0.143)	0.143	-	(0.174)	0.174	-	(0.140)	0.140	-
11 Loss Ratio		80.7%	85.2%	83.0%	83.3%	83.3%	83.3%	80.5%	85.4%	82.9%
12 Loss Ratio subject to risk corridor		80.7%	85.2%	83.0%	83.3%	83.3%	83.3%	80.5%	85.4%	82.9%
13 Loss Ratio Advantage (LRA)		**4.5%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**4.8%**	Model R^2:	34.4%

Section D: Statistical Significance Testing

1 t-statistic		(1.40)	0.62	2.40	(1.89)	(7.69)	(6.37)
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$
4 H_0 rejected (at α=5%)	Yes*	No	No	Yes	Yes	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Refused/Inapplicable	2. Excellent
3. Very Good	4. Good
5. Fair	6. Poor

Results: At an LRA of over 4% this is a *medium* impact variable. Issuer A selects members that assess themselves as having 'excellent' or 'very good' mental health. The responses provide a clear correlation of mental well-being (self-assessed) with costs and risk adjusted costs, both of which are lower than the average. Table 2.6.2(1) indicates that the results are statistically significant.

Studies have shown that patients with mental health problems pose a difficult problem for health care costs because mental illnesses are challenging to categorize, often misdiagnosed, and vary widely from person to person. From 1997 to 2002, the number of individuals with mental disorders increased from 20.1 million to 31.2 million, partly from changes in how mental health disorders are categorized. Medical expenditures for mental disorders also increased $11.3B during this period (Olin & Rhoades, 2005). Mental health disorders can also be more costly if left untreated. For those left untreated, mental disorders may lead to increased unemployment, hospital and emergency room use, suicide, early deaths due to chronic illness, and loss of productivity.

2.6.3 Cognitive Limitations

Description: This variable indicates any cognitive limitation such as (1) experienced confusion or memory loss, (2) had problems making decisions, or (3) required supervision for their own safety. If the individual selected 'Yes' for any one of these categories, then they were coded as 'Yes' for the MEPS survey. Responses are marked with either a 'Yes' or 'No'

Results: This is a *low* impact nontraditional variable. Issuer A selects those individuals that did not respond to the question or responded that they did not have cognitive limitations.

Table 2.6.3(1) – Results for ‘Cognitive Limitations’

Variable Name *COGLIM31*		**Class:** *Psychological Statu*		**Desc:** *cognitive limitations*							
Section A*: *Summarizing by non-traditional variable categories											
Description	**Total/Agg**	**Catg1**	**Catg2**	**Catg3**	**Catg4**	**Catg5**	**Catg6**	**Catg7**	**Catg8**	**Catg9**	**Catg10**
1 Category %	100%	24.8%	1.3%	73.9%							
2 Total Expenditures	1.0000	0.5414	4.2737	1.0946							
3 Proxy Expenditures	1.0000	0.6037	4.0004	1.0787							
4 Traditional Risk Score	1.0000	0.6189	2.9804	1.0920							
5 Risk Score + *N*	1.0000	0.6037	4.0004	1.0787							
6 Risk Score + $\sum N'_{prop}$	1.0000	0.6093	3.0402	1.0941							
7 Allowable Rating Factor	1.0000	0.7072	1.2402	1.0938							
8 Proxy Exp Adjusted	1.0000	0.9847	2.0201	0.9867							

Section B*: *Issuer Selection Assumptions

1	**LRA Rank**	**1**	**3**	**2**
2 Issuer A	50.0%	24.8%		25.2%
3 Issuer B	50.0%	0.0%	1.3%	48.7%

Section C*: *Market Scenario

		Traditional Risk Score			**Risk Score + *N***			**Risk Score + $\sum N'_{prop}$**		
1 Stand-Alone R^2	3.78%									
2 Maximum {Pr > |*t*|}	-	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.843	1.157	1.000						
5 Allowable Rating Factor		0.902	1.098	1.000						
6 Risk Score		0.858	1.142	1.000	0.843	1.157	1.000	0.854	1.146	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.083	1.317	1.200						
9 Premium with Risk Selection		1.029	1.371	1.200	1.012	1.388	1.200	1.025	1.375	1.200
10 Risk Selection Transfer		(0.054)	0.054	-	(0.071)	0.071	-	(0.058)	0.058	-
11 Loss Ratio		81.9%	84.4%	83.2%	83.3%	83.3%	83.3%	82.3%	84.1%	83.2%
12 Loss Ratio subject to risk corridor		81.9%	84.4%	83.2%	83.3%	83.3%	83.3%	82.3%	84.1%	83.2%
13 **Loss Ratio Advantage (LRA)**		**2.4%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**1.8%**	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

1 *t*-statistic		2.56	(11.18)	0.43
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu < 1$
4 H_0 rejected (at α =5%)	Yes*	Yes	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Didn’t Know/Inapplicable
2. Yes
3. No

2.6.4 Feeling Calm and Peaceful

Description: This variable indicates if a person felt calm and peaceful during the last four weeks.

Results: At an LRA of over 6% this is a *high* impact variable – and Issuer A selects members that felt calm or peaceful (or did not respond to the survey question) all of the time. This question was asked of respondents as part of the Self-Administered Questionnaire (SAQ), a paper and pencil based survey of adults only. It is interesting to note that the only category preferred by Issuer A is where members felt calm and peaceful all of the time, with the secondary preference being children or where there was not a response to the survey question. One possible reason is that the costs (Section A.3 in Table 2.6.4(1)) rise significantly as the respondent feels calm and peaceful less often, and the risk score does not rise commensurate with this increase in costs (Section A.4 in table 2.6.4).

Table 2.6.4(1) – Results for 'Feeling Calm and Peaceful'

Variable Name *ADCAPE42* **Class:** *Psychological Statu.* **Desc:** *saq 4wks: felt calm/peaceful*

***Section A**: Summarizing by non-traditional variable categories*

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	48.3%	7.0%	26.6%	12.2%	4.3%	1.6%				
2 Total Expenditures	1.0000	0.7614	0.6852	1.1292	1.4589	1.9683	1.3693				
3 Proxy Expenditures	1.0000	0.7807	0.6932	1.1029	1.4385	1.9031	1.5174				
4 Traditional Risk Score	1.0000	0.8141	0.7751	1.0939	1.3645	1.7118	1.3702				
5 Risk Score + N	1.0000	0.7807	0.6932	1.1029	1.4385	1.9031	1.5174				
6 Risk Score + $\sum N'_{prop}$	1.0000	0.8185	0.7571	1.0945	1.3622	1.7040	1.3449				
7 Allowable Rating Factor	1.0000	0.8875	1.0726	1.1285	1.0848	1.0882	1.0593				
8 Proxy Exp Adjusted	1.0000	0.9666	0.9181	1.0090	1.0740	1.1913	1.1472				

***Section B**: Issuer Selection Assumptions*

1	**LRA Rank**	**2**	**1**	**3**	**4**	**6**	**5**				
2 Issuer A	50.0%	43.0%	7.0%								
3 Issuer B	50.0%	5.3%	0.0%	26.6%	12.2%	4.3%	1.6%				

***Section C**: Market Scenario*

1 Stand-Alone R^2	2.27%	Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
2 Maximum {Pr > |t|}	0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.768	1.232	1.000						
5 Allowable Rating Factor		0.914	1.086	1.000						
6 Risk Score		0.809	1.191	1.000	0.768	1.232	1.000	0.810	1.190	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.096	1.304	1.200						
9 Premium with Risk Selection		0.970	1.430	1.200	0.922	1.478	1.200	0.972	1.428	1.200
10 Risk Selection Transfer		(0.126)	0.126	-	(0.174)	0.174	-	(0.124)	0.124	-
11 Loss Ratio		79.2%	86.1%	82.7%	83.3%	83.3%	83.3%	79.1%	86.2%	82.7%
12 Loss Ratio subject to risk corridor		80.0%	86.1%	83.1%	83.3%	83.3%	83.3%	80.0%	86.2%	83.1%
13 **Loss Ratio Advantage (LRA)**		**6.1%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**6.2%**	Model R^2:	34.4%

***Section D**: Statistical Significance Testing*

1 t-statistic		5.90	7.56	(0.62)	(4.98)	(6.40)	(3.74)				
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$				
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$				
4 H_0 rejected (at α =5%)	Yes*	Yes	Yes	No	Yes	Yes	Yes				

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. All of the Time
3. Most of the Time
4. Some of the Time
5. Little of the Time
6. None of the Time

2.6.5 Work Limited due to Mental Issues

Description: Adult respondents in MEPS were asked the question "During the past 4 weeks, how much of the time have you had any of the following problems with your work or other regular daily activities *as a result of any emotional problems* (such as feeling depressed or anxious)?" The follow up multiple choice question was if the respondent "did work or other activities *less carefully* than usual".

Table 2.6.5(1) – Results for 'Work Limited due to Mental Issues'

Variable Name *ADMWLM42* **Class:** *Psychological Statu* **Desc:** *limited in work in past 4 weeks, due to mental healt*

Section A: Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	48.5%	0.5%	1.0%	4.0%	8.8%	37.3%				
2 Total Expenditures	1.0000	0.7654	4.7423	3.2659	1.7978	1.4742	0.9958				
3 Proxy Expenditures	1.0000	0.7842	3.3744	3.0294	1.8264	1.4142	1.0079				
4 Traditional Risk Score	1.0000	0.8162	2.3833	2.3490	1.6915	1.3538	1.0269				
5 Risk Score + N	1.0000	0.8013	3.3744	3.0294	1.8264	1.4142	0.9858				
6 Risk Score + $\sum N'_{prop}$	1.0000	0.8205	2.3844	2.3464	1.6815	1.3471	1.0240				
7 Allowable Rating Factor	1.0000	0.8887	1.1957	1.2029	1.1461	1.1203	1.0927				
8 Proxy Exp Adjusted	1.0000	0.9681	1.9911	1.6804	1.1349	1.0603	0.9810				

Section B: Issuer Selection Assumptions

1	LRA Rank		1	6	5	4	3	2
2	Issuer A	50.0%	48.5%					1.5%
3	Issuer B	50.0%	0.0%	0.5%	1.0%	4.0%	8.8%	35.7%

Section C: Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	3.10%									
2 Maximum {Pr > |t|}	0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.791	1.209	1.000						
5 Allowable Rating Factor		0.895	1.105	1.000						
6 Risk Score		0.823	1.177	1.000	0.807	1.193	1.000	0.827	1.173	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.074	1.326	1.200						
9 Premium with Risk Selection		0.987	1.413	1.200	0.968	1.432	1.200	0.992	1.408	1.200
10 Risk Selection Transfer		(0.087)	0.087	-	(0.106)	0.106	-	(0.082)	0.082	-
11 Loss Ratio		80.1%	85.6%	82.9%	81.7%	84.4%	83.1%	79.7%	85.9%	82.8%
12 Loss Ratio subject to risk corridor		80.1%	85.6%	82.9%	81.7%	84.4%	83.1%	80.0%	85.9%	82.9%
13 **Loss Ratio Advantage (LRA)**		**5.4%**	Model R^2:	34.0%	**2.7%**	Model R^2:	34.0%	**5.9%**	Model R^2:	34.4%

Section D: Statistical Significance Testing

1 t-statistic		5.61	(8.00)	(7.22)	(3.15)	(2.69)	1.41
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	Yes*	Yes	Yes	Yes	Yes	Yes	No

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Inapplicable
2. All of the Time
3. Most of the Time
4. Some of the Time
5. Little of the Time
6. None of the Time

 WAKELY CONSULTING GROUP

Results: Issuer A selects members that either did not respond to the question – or mental health issues did not in any way limit work or other activities. This is a *medium* impact variable.

2.7 Physical Self-Assessment Variables

The physical self-assessment nontraditional variables are interesting in that they are most directly related to healthcare cost, and not surprisingly also rank highest in terms of LRA or any class of nontraditional variables. This section presents detailed results for four selected variables that reflect a person's physical well-being.

2.7.1 Limited in Moderate Activities

Description: This variable indicates whether any IADL (instrumental activities of daily living), functional, activity, or sensory limitations questions were checked as 'Yes' during the survey. If so, then this variable was coded as 'Yes'. Responses were marked with either a 'Yes' or a 'No'.

Results: This variable has one of the highest stand-alone model predictive accuracy, and is also a *high* impact variable with an LRA of 8%. Issuer A selects individuals that indicate that they were not limited in their activities by their health. The risk adjusted costs for individuals that indicated that they *were* limited is very high at 39% over the population average. This indicates that the traditional risk score is not able to reflect the full risk of these members, risk that is assumed by issuer B.

Table 2.7.1(1) – Results for 'Limited in Moderate Activities'

Variable Name *ANYLIM*		**Class:** *Physical Status*				**Desc:** *Any IADL, ADL, sensory, or activity limitation*					
Section A*: *Summarizing by non-traditional variable categories											
Description	**Total/Agg**	**Catg1**	**Catg2**	**Catg3**	**Catg4**	**Catg5**	**Catg6**	**Catg7**	**Catg8**	**Catg9**	**Catg10**
1 Category %	100%	1.9%	13.5%	84.6%							
2 Total Expenditures	1.0000	1.1399	2.7040	0.7245							
3 Proxy Expenditures	1.0000	0.9768	2.4039	0.7760							
4 Traditional Risk Score	1.0000	0.9358	2.0064	0.8405							
5 Risk Score + *N*	1.0000	0.9016	2.4039	0.7777							
6 Risk Score + $\sum N'_{prop}$	1.0000	0.9870	2.0141	0.8382							
7 Allowable Rating Factor	1.0000	0.8016	1.2684	0.9614							
8 Proxy Exp Adjusted	1.0000	1.0411	1.3975	0.9355							
Section B*: *Issuer Selection Assumptions											
1	**LRA Rank**	**2**	**3**	**1**							
2 Issuer A	50.0%			50.0%							
3 Issuer B	50.0%	1.9%	13.5%	34.6%							

Section C*: *Market Scenario

		Traditional Risk Score			**Risk Score + *N***			**Risk Score + $\sum N'_{prop}$**		
1 Stand-Alone R^2	7.28%									
2 Maximum {Pr > |*t*|}	0.0000	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**	**Issuer A**	**Issuer B**	**Market**
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.776	1.224	1.000						
5 Allowable Rating Factor		0.961	1.039	1.000						
6 Risk Score		0.840	1.160	1.000	0.778	1.222	1.000	0.838	1.162	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.154	1.246	1.200						
9 Premium with Risk Selection		1.009	1.391	1.200	0.933	1.467	1.200	1.006	1.394	1.200
10 Risk Selection Transfer		(0.145)	0.145	-	(0.220)	0.220	-	(0.148)	0.148	-
11 Loss Ratio		76.9%	88.0%	82.5%	83.2%	83.4%	83.3%	77.2%	87.8%	82.5%
12 Loss Ratio subject to risk corridor		80.0%	88.0%	84.0%	83.2%	83.4%	83.3%	80.0%	87.8%	83.9%
13 **Loss Ratio Advantage (LRA)**		**8.0%**	Model R^2:	34.0%	**0.3%**	Model R^2:	34.0%	**7.8%**	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

1 *t*-statistic		(1.37)	(12.68)	6.20
2 H_0: Null Hypothesis		$\mu <= 1$	$\mu <= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu > 1$	$\mu > 1$	$\mu < 1$
4 H_0 rejected (at α=5%)	Yes*	No	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. Yes
3. No

2.7.2 Pain Interfered with Normal Life

Description: This variable indicates if during the past 4 weeks, pain interfered with normal work outside the home and housework.

Results: This is a *high* impact variable – with Issuer A having a strong incentive to select members that indicated that pain does not interfere with their normal activities 'at all'. The risk adjusted cost for individuals that indicated pain 'extremely' interfered with their activities is over 200%! This implies that a traditional risk score may not do an adequate job of reflecting the underlying risk of these individuals.

Table 2.7.2(1) – Results for 'Pain Interfered with Normal Life'

Variable Name *ADPAIN42* **Class:** *Physical Status* **Desc:** *saq 4wks:pain limits normal work*

Section A*: *Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	30.0%	42.3%	17.1%	5.8%	3.5%	1.3%				
2 Total Expenditures	1.0000	0.6275	0.7266	1.2817	2.0639	3.0578	4.4847				
3 Proxy Expenditures	1.0000	0.6579	0.7640	1.2727	1.9150	2.8394	3.9366				
4 Traditional Risk Score	1.0000	0.6672	0.8500	1.2760	1.7483	2.3703	2.8913				
5 Risk Score + N	1.0000	0.6579	0.7640	1.2727	1.9150	2.8394	3.9366				
6 Risk Score + $\sum N'_{prop}$	1.0000	0.6708	0.8495	1.2723	1.7422	2.3695	2.9017				
7 Allowable Rating Factor	1.0000	0.7749	1.0366	1.1554	1.2196	1.2713	1.2457				
8 Proxy Exp Adjusted	1.0000	0.9908	0.9141	0.9968	1.1667	1.4690	2.0453				

Section B*: *Issuer Selection Assumptions

1		LRA Rank	2	1	3	4	5	6
2	Issuer A	50.0%	7.7%	42.3%				
3	Issuer B	50.0%	22.3%	0.0%	17.1%	5.8%	3.5%	1.3%

Section C*: *Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	8.08%									
2 Maximum {Pr > |t|}	-	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.748	1.252	1.000						
5 Allowable Rating Factor		0.996	1.004	1.000						
6 Risk Score		0.822	1.178	1.000	0.748	1.252	1.000	0.822	1.178	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.195	1.205	1.200						
9 Premium with Risk Selection		0.986	1.414	1.200	0.897	1.503	1.200	0.986	1.414	1.200
10 Risk Selection Transfer		(0.209)	0.209	-	(0.298)	0.298	-	(0.209)	0.209	-
11 Loss Ratio		75.8%	88.6%	82.2%	83.3%	83.3%	83.3%	75.8%	88.6%	82.2%
12 Loss Ratio subject to risk corridor		80.0%	88.6%	84.3%	83.3%	83.3%	83.3%	80.0%	88.6%	84.3%
13 **Loss Ratio Advantage (LRA)**		**8.6%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**8.6%**	Model R^2:	34.4%

Section D*: *Statistical Significance Testing

		Catg1	Catg2	Catg3	Catg4	Catg5	Catg6
1 t-statistic		1.47	11.14	0.29	(7.09)	(11.69)	(12.59)
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu <= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu > 1$
4 H_0 rejected (at α =5%)	Yes*	No	Yes	No	Yes	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Didn't Know/Inapplicable
2. Not at All
3. A Little Bit
4. Moderately
5. Quite a Bit
6. Extremely

2.7.3 Difficulty in Climbing Stairs

Description: This variable indicates if during the day, the person had limitations in climbing several flights of stairs.

Results: Also a *high* impact variable, Issuer A selects members that are not limited by their health in an activity such as climbing stairs. The risk adjusted cost for individuals that are 'limited a lot' is over 70% higher than average – indicating that a traditional risk score does not fully recognize their risk.

Table 2.7.3(1) – Results for 'Difficulty in Climbing Stairs'

Variable Name *ADCLIM42* **Class:** *Physical Status* **Desc:** *Health limits climbing stairs*

Section A* : *Summarizing by non-traditional variable categories

Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1 Category %	100%	30.1%	3.5%	10.9%	55.5%						
2 Total Expenditures	1.0000	0.6292	4.3102	1.8040	0.8341						
3 Proxy Expenditures	1.0000	0.6553	3.6120	1.7564	0.8734						
4 Traditional Risk Score	1.0000	0.6679	2.8572	1.6941	0.9266						
5 Risk Score + N	1.0000	0.6553	3.6120	1.7564	0.8734						
6 Risk Score + $\sum N'_{prop}$	1.0000	0.6715	2.8633	1.6838	0.9264						
7 Allowable Rating Factor	1.0000	0.7772	1.3613	1.2524	1.0487						
8 Proxy Exp Adjusted	1.0000	0.9874	1.7549	1.0623	0.9468						

Section B* : *Issuer Selection Assumptions

			Catg1	Catg2	Catg3	Catg4
1	LRA Rank		2	4	3	1
2	Issuer A	50.0%				50.0%
3	Issuer B	50.0%	30.1%	3.5%	10.9%	5.5%

Section C* : *Market Scenario

		Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1 Stand-Alone R^2	8.01%									
2 Maximum {Pr > |t|}	0.0000	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3 Market Share		50%	50%	100%						
4 Proxy Expenditures		0.873	1.127	1.000						
5 Allowable Rating Factor		1.049	0.951	1.000						
6 Risk Score		0.927	1.073	1.000	0.873	1.127	1.000	0.926	1.074	1.000
7 Statewide Average Premium				1.200						
8 Premium without Risk Selection		1.258	1.142	1.200						
9 Premium with Risk Selection		1.112	1.288	1.200	1.048	1.352	1.200	1.112	1.288	1.200
10 Risk Selection Transfer		(0.146)	0.146	-	(0.210)	0.210	-	(0.147)	0.147	-
11 Loss Ratio		78.5%	87.5%	83.0%	83.3%	83.3%	83.3%	78.6%	87.4%	83.0%
12 Loss Ratio subject to risk corridor		80.0%	87.5%	83.7%	83.3%	83.3%	83.3%	80.0%	87.4%	83.7%
13 Loss Ratio Advantage (LRA)		7.5%	Model R^2:	34.0%	0.0%	Model R^2:	34.0%	7.4%	Model R^2:	34.4%

Section D* : *Statistical Significance Testing

		Catg1	Catg2	Catg3	Catg4
1 t-statistic		2.02	(15.83)	(2.66)	4.65
2 H_0: Null Hypothesis		$\mu >= 1$	$\mu <= 1$	$\mu <= 1$	$\mu >= 1$
3 H_1: Alternate Hypothesis		$\mu < 1$	$\mu > 1$	$\mu > 1$	$\mu < 1$
4 H_0 rejected (at α =5%)	Yes*	Yes	Yes	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. Limited a Lot
3. Limited a Little
4. Not Limited

2.7.4 General Health Today

Description: This variable indicates what the general health status of the respondent was at the time of the survey.

Results: Issuer A selects members that are in ‘excellent’, ‘very good’ or ‘good’ health and has a *high* (6.1%) LRA value as a result.

Table 2.7.4(1) – Results for ‘General Health Today’

Variable Name *ADGENH42* **Class:** *Physical Status* **Desc:** *general health today*

Section A: Summarizing by non-traditional variable categories

	Description	Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6	Catg7	Catg8	Catg9	Catg10
1	Category %	100%	30.1%	15.2%	28.1%	20.4%	5.3%	1.0%				
2	Total Expenditures	1.0000	0.6212	0.6047	0.9078	1.3477	2.5862	5.7732				
3	Proxy Expenditures	1.0000	0.6593	0.6578	0.9383	1.3289	2.2983	4.8204				
4	Traditional Risk Score	1.0000	0.6686	0.6865	0.9817	1.3551	2.0901	3.3872				
5	Risk Score + N	1.0000	0.6593	0.6578	0.9383	1.3289	2.2983	4.8204				
6	Risk Score + $\sum N'_{prop}$	1.0000	0.6724	0.6915	0.9844	1.3454	2.0767	3.3916				
7	Allowable Rating Factor	1.0000	0.7759	1.0037	1.0754	1.1468	1.2410	1.3162				
8	Proxy Exp Adjusted	1.0000	0.9907	0.9713	0.9567	0.9738	1.2082	2.4332				

Section B: Issuer Selection Assumptions

		Total/Agg	Catg1	Catg2	Catg3	Catg4	Catg5	Catg6
1	LRA Rank		4	2	1	3	5	6
2	Issuer A	50.0%		15.2%	28.1%	6.6%		
3	Issuer B	50.0%	30.1%	0.0%	0.0%	13.7%	5.3%	1.0%

Section C: Market Scenario

			Traditional Risk Score			Risk Score + N			Risk Score + $\sum N'_{prop}$		
1	Stand-Alone R^2	7.03%									
2	Maximum {Pr > |t|}	-	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market	Issuer A	Issuer B	Market
3	Market Share		50%	50%	100%						
4	Proxy Expenditures		0.905	1.095	1.000						
5	Allowable Rating Factor		1.063	0.937	1.000						
6	Risk Score		0.941	1.059	1.000	0.905	1.095	1.000	0.943	1.057	1.000
7	Statewide Average Premium				1.200						
8	Premium without Risk Selection		1.276	1.124	1.200						
9	Premium with Risk Selection		1.129	1.271	1.200	1.085	1.315	1.200	1.132	1.268	1.200
10	Risk Selection Transfer		(0.146)	0.146	-	(0.190)	0.190	-	(0.144)	0.144	-
11	Loss Ratio		80.1%	86.2%	83.2%	83.3%	83.3%	83.3%	79.9%	86.4%	83.2%
12	Loss Ratio subject to risk corridor		80.1%	86.2%	83.2%	83.3%	83.3%	83.3%	80.0%	86.4%	83.2%
13	**Loss Ratio Advantage (LRA)**		**6.1%**	Model R^2:	34.0%	**0.0%**	Model R^2:	34.0%	**6.4%**	Model R^2:	34.4%

Section D: Statistical Significance Testing

			Catg1	Catg2	Catg3	Catg4	Catg5	Catg6
1	t-statistic		1.48	3.08	3.84	2.37	(7.70)	(12.59)
2	H_0: Null Hypothesis		$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu >= 1$	$\mu <= 1$	$\mu <= 1$
3	H_1: Alternate Hypothesis		$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu < 1$	$\mu > 1$	$\mu > 1$
4	H_0 rejected (at α=5%)	Yes*	No	Yes	Yes	Yes	Yes	Yes

Category Description (e.g. (1) corresponds with Catg1 above)

1. Not Ascertained/Inapplicable
2. Excellent
3. Very Good
4. Good
5. Fair
6. Poor

2.8 Geography

Geography represents an important class of *nontraditional* variables. Since we know that claim costs including treatment patterns vary geographically, it is a given that this variable can explain cost variation beyond risk adjustment. Geography is also an interesting variable as it is readily available and useful in terms of devising a selection strategy. The variable is typically available in enrollment data, and may be used in marketing efforts in order to attract a certain membership.

Throughout this report we have used MEPS data, but this database does not have a well-defined geography variable. The database includes four broad regions (Northeast, Midwest, South and West) with multiple states being grouped in each of the regions. The results of using this region-level variable are described in Section 2.3.6. We need more detail, perhaps county-level information in order to explore the full potential of geography as a nontraditional variable.

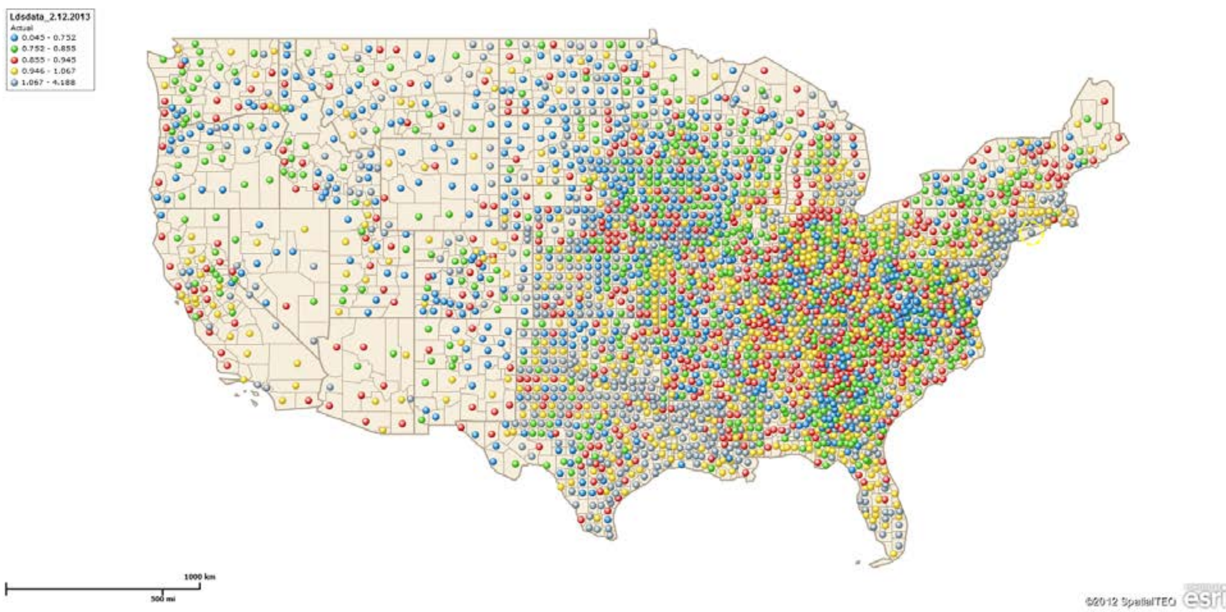
For purposes of this report we studied the geographic distribution of individuals that are sicker or healthier than their risk score would suggest. An issuer would be incented to target individuals that are healthier compared to their risk score, and so if there are any geographic patterns then they would be of great interest.

We used the Medicare 5% sample (year 2007-2008) and the CMS-HCC prospective risk adjustment model in order to test the theory that there are geographic patterns in *risk-adjusted cost*. The work we performed for this section is for illustrative purposes (using outdated data, so any conclusions may no longer apply). The changes to the approach that would make results more relevant include applying it to a commercial dataset and using the HHS ACA risk adjustment model.

Figure 2.8.1 shows the distribution of counties that represent a randomly sampled 5% of the Medicare population. The counties are color coded according to the **average cost** of Medicare beneficiaries in those counties. The grey circles indicate a higher than average cost, whereas the blue, green, and red circles indicate an increasing, but lower than average cost.

There appear to be patterns by average cost, and certain low or high average cost counties are clustered together. The map boundaries reflect state and county borders.

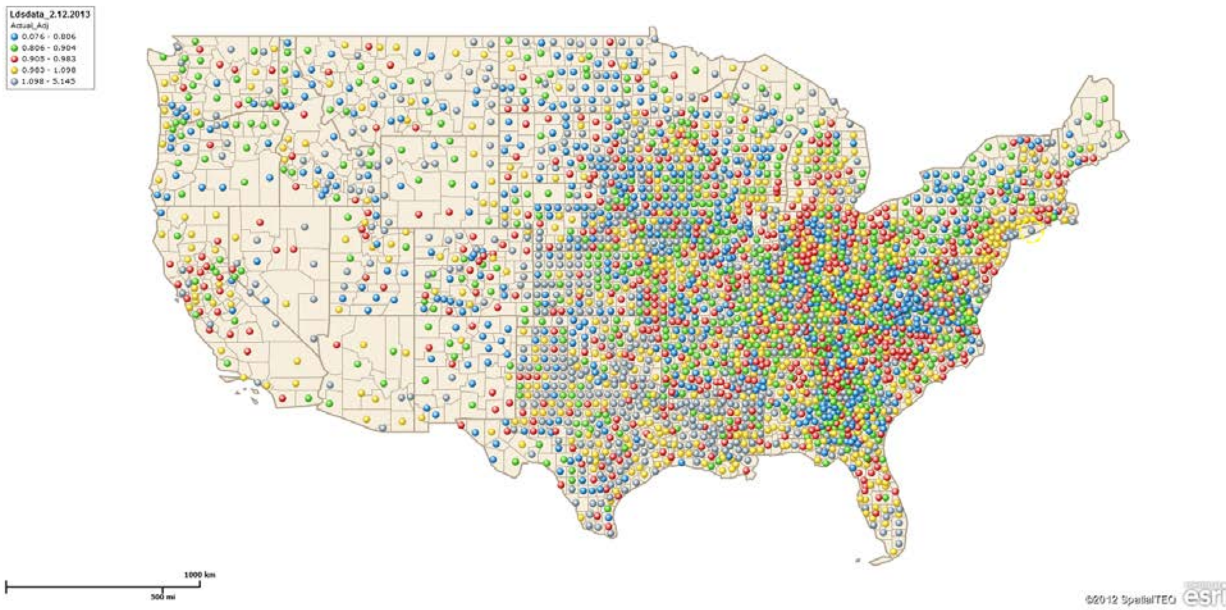
Figure 2.8.1 – Average Normalized Cost of Medicare Beneficiaries by County, 2007



Any patterns we find in absolute costs here would be misleading because Medicare Advantage is a risk adjusted program. From the perspective of these issuers, it is more interesting to look at *risk-adjusted costs*.

If risk-adjusted costs are higher than 1, this indicates that costs are higher relative to the risk measured by the HCC model, and conversely if risk-adjusted costs are lower than 1 this indicates that costs will be lower than that indicated by the risk score. A plan may have the incentive to increase enrollment in those counties where the risk-adjusted costs are lower than 1. Figure 2.8.2 shows the distribution of risk adjusted costs.

Figure 2.8.2 – Average Normalized *Risk Adjusted* Cost of Medicare Beneficiaries by County, 2007



While it is tedious to observe directly from the maps above, several counties go from being low cost on a total paid basis to high cost on the basis of risk-adjusted paid dollars (e.g. Okanogan County, WA), and vice versa (e.g. Atlantic County, NJ). Many counties remain consistently low or high cost on either measure. We can see that even on a risk-adjusted basis patterns persist in the map. We can visually observe clusters of counties where the risk adjusted costs are low (blue dots) or high (grey dots). The differences are certainly driven by region-level differences in cost of treatment, and that is not at issue since the ACA risk adjustment program is a state-level program. However we can observe clusters of high and low average risk-adjusted cost counties within a state as well. The ACA program does allow for the development of rating areas (both as an allowable rating variable and as a variable in the risk adjustment methodology). In order to avoid selection issues, the rating areas would need to be carefully developed, not only from geographical and network perspectives, but also from the perspective of differences in risk-adjusted costs.

3. Methodology

This section presents details regarding the data that was used in this research. Almost the entire research was performed using publicly available sources of data, and interested practitioners are encouraged to explore and extend this work.

3.1 Analysis Design

The analytical design is explained in three sub-sections, (1) preparation of data for analysis including selection of data, (2) a high-level algorithm explaining how the data is manipulated to answer targeted questions, and (3) an explanation of the process developed for this research that generates the result tables.

An important component of the analysis is risk score based on traditional variables. We used a publicly available risk assessment model that was specifically designed for a commercial population. Details on the Wakely Risk Assessment (WRA) model are presented in Section 3.4. We used a pharmacy-only model that utilizes NDC codes and age/gender information to assess health risk.

3.2 Data Preparation

We used Medical Expenditure Panel Survey (MEPS) data for years 2000-2010 in this analysis. This data is publicly available for download through the MEPS website[25]. This is a unique database that includes healthcare cost and utilization information as well as a broad array of socioeconomic and other nontraditional clinical information (e.g. whether a physician advised changes in diet during a visit) on a nationally representative non-institutionalized civilian population. Data is collected through a telephonic survey as well as limited reviews of insurer, pharmacy and physician records. An individual or household is followed for up to two years. Information on about 30-40k individuals is recorded every year, and the observations are statistically weighted to represent the nationwide mix across the US. For further details on this database, please review the MEPS database documentation (AHRQ, 2012).

We utilized two types of available data files. These are:

1. Full-year consolidated data files: Person-level variables are consolidated into one file, and it contains demographic information as well as cost and utilization variables, including the nontraditional variables studied in this report.

[25] http://meps.ahrq.gov/mepsweb/

2. Prescribed medicines files: this file contains fully specified National Drug Codes (NDCs), and is used for developing risk scores

The section below describes MEPS data in more detail.

3.2.1 Medical Expenditure Panel Survey

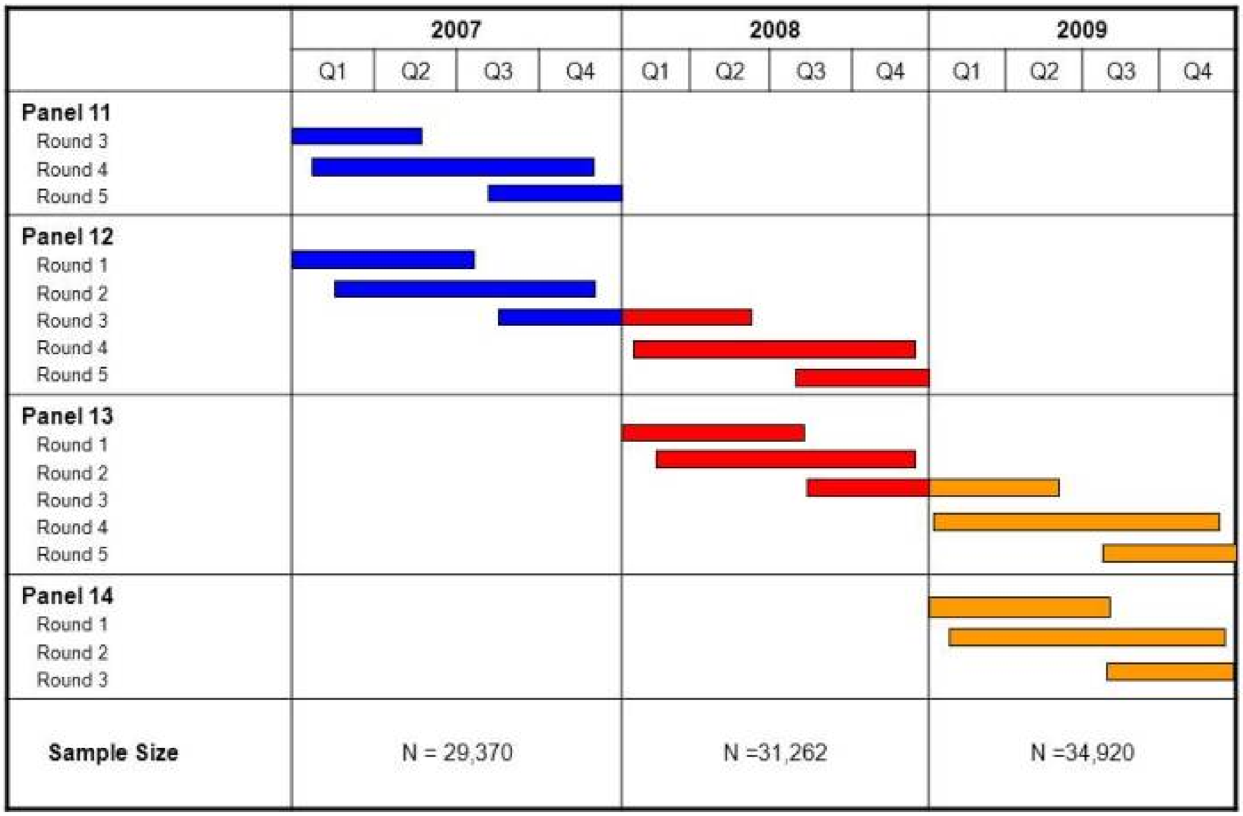
As described by AHRQ[26]: "The Household Component of the Medical Expenditure Panel Survey (MEPS-HC) is a nationally representative survey of the U.S. civilian non-institutionalized population. The sampling frame is drawn from respondents to the National Health Interview Survey, which is conducted by the National Center for Health Statistics.

"The MEPS-HC collects data from a nationally representative sample of households through an overlapping panel design. A new panel of sample households is selected each year, and data for each panel are collected for two calendar years. The two years of data for each panel are collected in five rounds of interviews that take place over a two and a half year period. This provides continuous and current estimates of health care expenditures at both the person and household level for two panels for each calendar year.

"The chart below illustrates the timing and relationship between panels, rounds, and calendar years. For example, looking at the data collection by panel, Panel 12 consists of five rounds of interviews; with Rounds 1–3 providing data for 2007 and Rounds 3–5 providing data for 2008. Looking at the data collection by year, data for the year 2008 consists of data collected from Rounds 3–5 of Panel 12 and Rounds 1–3 of Panel 13.

[26] Source: MEPS-HC Sample Design and Collection Process. Agency for Healthcare Research and Quality, Rockville, Md. http://www.meps.ahrq.gov/survey_comp/hc_data_collection.jsp

MEPS Panel Design: Data Reference Periods



"Each round of MEPS-HC interviews collects information pertaining to a specific time period called a reference period. Using Panel 12 again as an example, the reference period for the first interview of Panel 12 began on January 1, 2007, and ended on the date of each reporting unit's Round 1 interview, conducted from March through June 2007. The reference periods for Rounds 2, 3, and 4 varied from household to household and covered the time between interview dates of the previous round and the current round. The last reference period of Panel 12 (Round 5) ended on December 31, 2008. (December 31st of the second calendar year is always the end of the last reference period.)

"MEPS is a large-scale and comprehensive data collection effort that includes many types of survey questions, some of which only pertain to subsets of the diverse respondents participating in the survey. To accommodate the extensive array of questions covered, yet minimize the number of questions asked of each respondent, data are collected using an intricate system of skip patterns and questionnaire modules grouped into sections. Computer-assisted personal interviewing (CAPI) using a laptop computer makes it possible to field such a complex data collection instrument.

"Since data are collected using CAPI, rather than a hard copy questionnaire, the data collection instrument actually consists of sections that are composed of a series of computer screens containing questions, interviewing instructions, and skip pattern directions, as well as computer programming notes embedded along with each data item. The MEPS data collection in a given round consists of different sections. Some sections are included in every round of data collection. Other sections are only included in one or two rounds—this type of section is also referred to as a supplement.

"Any single question must be considered within the context of the skip patterns incorporated into the questionnaire. Some questions appear in several CAPI screens because of the variety of skip patterns that lead to the question. The question is only asked when the skip pattern determines that it should be asked of that respondent. Items asking the same question of various respondents typically map back to a single variable in the database."

3.2.2 Data Sampling

We used data for eleven MEPS survey years (i.e. 2000-2010) in this project. The nature of this research required that many observations be available in order to discern the relationship between healthcare cost and the large number of independent predictor variables that were considered for testing. MEPS data does not have sufficient observations in any given year in order to satisfy the scale requirements of building complicated multivariate models.

In order to develop concurrent risk models we simply appended the years of data into a single file, while trending the cost variables at the rate recommended by curators of the MEPS data[27]. The guideline is to use the Personal Health Care Expenditure (PHCE) Price Index, developed by the Office of the Actuary of the Centers for Medicare and Medicaid Services (CMS).

Each respondent in MEPS is tracked for up to two years, therefore we have *year 1* and *year 2* information on that individual. We appended all of the year 1's and year 2's in separate files. In this

[27] Source: http://meps.ahrq.gov/mepsweb/about_meps/Price_Index.shtml

manner we created the base year (i.e. year 1) and the prediction year (i.e. year 2) for a large number of individuals.

For building concurrent risk models we used predictor variable information from year *N* as independent variables, and healthcare expenditure information also from year *N* as the dependent variable. We used both years (1 & 2) in this analysis. For building prospective risk models we used predictor variable information from year *N* in order to explain the variation in healthcare costs from year *N*+1. As indicated in Section 1, results from concurrent and prospective analyses are similar. Due to this reason and the fact that ACA risk adjustment in 2014 will be on a concurrent basis, we present only the concurrent version of results in this report.

Since MEPS represents a sampling of the US population, each individual in this data has an associated *weight* variable. The sum of the weight variable reflects the total US population, and therefore this variable may be used to develop nationally representative estimates from within MEPS data. Since we are appending years of data together, this variable may still be used to appropriately weight each observation. However in total, it will be about ten times the current US population (and reflect growth in the population over time).

For purposes of this research we did not want to include individuals eligible for Medicare, and therefore we limited the data sample to respondents that were less than sixty-five years old at the time of the survey. We included Commercial, and Uninsured segments in the data. An implicit focus of this research is on Commercial population, since that is the segment that will be most relevant for ACA risk adjustment programs. We thought carefully about including Medicaid data in this research since it is important to discern the relationship between income and healthcare cost. There is concern that Medicaid-focused health plans may be likely to face uncompensated adverse selection in 2014 and beyond (Dreyfus & Davidson, 2012) if socio-economic variables are not considered in risk adjustment. However we concluded that including Medicaid data would lead to incorrect conclusions regarding several variables that are important to consider from the perspective of the ACA risk adjustment program. For example the income-related variable of poverty-level appears to be more than three times as influential if we include the Medicaid population. The ACA risk adjustment program is a focal point in this research, and since individuals enrolling in Medicaid will not be included in the ACA commercial risk adjustment pool we decided to exclude the Medicaid population from our analysis.

We included the uninsured segment since it will also play a key role as millions of uninsured individuals are expected to enroll in ACA commercial individual plans in 2014 and thus will become subject to risk adjustment. There are limitations with using healthcare utilization data on the uninsured, discussed in Section 2.3.8. About 10% of individuals were covered under other state programs including Tricare and hospital/physician programs. These individuals were also excluded from the analysis.

An individual may switch coverage during the course of a year. We assigned an individual to a coverage type based on whether an individual was enrolled in that coverage for more than six months in that year. In this manner, individuals were assigned to Commercial/Private, Medicaid, Uninsured, and Medicaid/SCHIP and Other Public Hospital/Physician Coverage. The cohorts identified as having commercial/private coverage and the uninsured are used in this research. Note that these cohorts are likely to be closest to small group and individual plans in terms of member characteristics, and these plans will be subject to risk adjustment under ACA. MEPS data does not include employer size as a variable and therefore the commercial block includes both small and large groups. In this research we do not make a distinction between individual, small group, and large group commercial data. Rather we explore the impact of nontraditional variables as they relate to commercial insurance as a whole. In Section 4 we discuss this and other data limitations.

3.2.3 Expenditure Variables

The MEPS Household Component (HC) collects data on use and expenditures for office and facility-based care in each round, including prescribed medicines, vision aids, dental care, and home health services. The HC file includes utilization and expenditure variables for several categories of services.

In general there is one utilization variable, thirteen expenditure variables, and one charge variable for each category of healthcare service. The utilization variable is typically a count of the number of medical events reported for the category. The thirteen expenditure variables consist of an aggregate total payment variable, ten main component sources of payment category variables, and two additional sources of payment category variables.

The two types of MEPS expenditures are billed and paid amounts. There are issues with using either of these variables for analytical purposes. Billed amounts are not *real* in the sense that these are not the amounts that get paid and there may be a huge variation in billed amounts across providers.

This variation can cloud the analytics such that it becomes very difficult to isolate the impact of a variable. The same is true for paid amounts, which can vary significantly due to contracting differences. In this research we want to use a standard unit cost measure such that we can control for differences other than those in the variables that we wish to quantify. Towards this goal we developed a *proxy expenditure* variable, similar to one described by Tia Sawhney (Sawhney, 2012). The calculation of proxy expenditure followed the following construct:

$$P_{y,i} = \sum_{l=1}^{6}\left(\left(\sum\nolimits_{l,j} v_{i,y}\right) \times {\sum_m\left(W_{m,i,y} \times C_{l,m,i,y}\right)}\Big/{\sum_m\left(W_{m,i,y} \times U_{l,m,i,y}\right)}\right)$$

where $P_{y,i}$ represents the proxy expenditure of person *i* and for year *y* in the data. The first summation on the left hand side of the equation is over six separate service categories, and these are (1) office-based visits, (2) hospital outpatient visits, (3) emergency visits, (4) inpatient hospital visits, (5) dental care visits, and (6) pharmacy utilization. The term $\sum_{l,j} v_{i,y}$sums a person's total visits in a year for the corresponding service category. The second term is a weighted (by sample weights *W*) average unit cost (costs are indicated by *C* and utilization by *U*) as calculated over just the commercially insured population (i.e. summation over *m*).

3.2.4 Variable Winnowing

MEPS databases contain about 1,500-2,000 variables (the exact number of variables differs depending upon year). The first task was to reduce the number of variables to a set that would be *relevant* to this research. Variables that did not sufficiently persist from year 2000 to 2010 were not considered. In determining whether a variable was of interest, we considered whether a variable could plausibly explain the variation in individual healthcare cost, and secondly whether it had any potential to be used by an issuer in order to select risks. There were many variables that were either intuitively not related to healthcare cost (e.g. whether an individual had difficulty getting along with their parents), or presented duplicative information (e.g. there are multiple flags for age at various points in a year), or are already reflected in traditional risk adjustment (e.g. whether an individual had been diagnosed with cancer). In this manner we further reduced the initial list of variables to about two hundred variables.

Two hundred variables are still too many to feasibly model and quantify their potential influence. Therefore, we developed a selection process based upon the *differentials* produced by these variables in relation to cost with and without adjustment.

Before developing and studying the LRA measure, we invested a significant amount of time developing a *stepwise regression* process to select top variables. This process selected the top variable (or variable split, see the section below) that maximized a certain statistical measure (e.g. R^2) of the goodness of fit of the model. The process then selected a second variable *given* the first one that was already selected, and so on. As we studied the results more closely (mentioned in Section 1) we found that maximizing metric accuracy was too far removed from the bottom line business impact to warrant further study. Therefore we changed course and focused on the LRA measure, and the voluminous results of the stepwise regression process are not included together with this report.

3.2.5 Variable Transformation

Once the variables have been selected, they need to be transformed into appropriate inputs for the regression modeling process. For example MEPS contains many ordinal variables. These need to be transformed into binary variables that would represent independent regression variables. Other continuous variables (e.g. total income) need to be appropriately bucketed (according to frequency of observations and relationship to cost) and then converted into binary variables for modeling. As stated earlier, we limited each variable to five categories and an additional unknown category. (This included instances where a response was not ascertained, was inapplicable in cases where the question was only asked of individuals who had responded 'yes' to another related question, or the interviewee refused to respond.

3.3 Risk Scoring

All individuals in the sampled data were risk scored using the WRA model[28]. For concurrent risk assessment, we used fully specified national drug codes (NDCs) from pharmacy data on individuals for year N in order to 'predict' healthcare costs for the same year.

The report also uses the 2011 Centers of Medicare & Medicaid Services Hierarchical Condition Category (CMS-HCC) model for Section 2.8 only. A different model was used to explore geography since

[28] Description and white paper available at wramodel.com

MEPS data does not include a county identifier. Medicare data was used to study risk adjusted costs by county, and therefore the Medicare risk assessment model was used for that purpose. The CMS-HCC model is based upon the Diagnostic Cost Groups (DCG) / HCC model. It is similar to the PIP-DCG that was developed with CMS funding by researchers at RTI International, Boston University, with clinical input from physicians at Harvard Medical School (Pope, 2004).

3.4 Statistical Metrics

This report presents a large number of results based on the underlying data. Data contains noise, however, and conclusions may be affected by that noise. As such, it is important to evaluate the accuracy and reliability of the estimates. In order to monitor reliability, the following statistical metrics were developed and presented together with the results for each nontraditional variable.

3.4.1 Statistical Significance

An important metric in this research is verifying whether the differences in mean *risk-adjusted cost* across nontraditional variable categorization are statistically significant. The importance lies in the fact that if these differences are not significant, then these may be an artifact of data sampling, and the calculated LRA measure may not be meaningful. The LRA measure is the key result for each nontraditional variable, and indicates how much an issuer might gain by selecting members based on that variable.

In order to test for statistical significance we specify the null (***H₀***) and alternate hypothesis (***H₁***) as follows:

H_0: The null hypothesis is that the average cost for a nontraditional variable category is in fact higher (or lower) than the average cost for the population (which is 1.0).

H_1: The alternate hypothesis is that the average cost by a nontraditional variable category is in fact lower (or higher) than the average cost for the population.

The test statistic is calculated as follows:

$$t = \frac{\bar{C}_{RA}^{1} - \bar{C}_{RA}^{2}}{\sqrt{{s_1^2}/{N_1} + {s_2^2}/{N_2}}}$$

Where $\bar{C}_{RA}^{1}$ is the mean risk-adjusted cost of cohort 1; s_1^2 is the sample variance of that cost, and N_1 is the number of observations in that sample. The risk adjusted cost and variance is weighted by the sampling weight in MEPS. For example, the sample variance is calculated using the following formula.

$$s_1^2 = \frac{\sum_{i=1}^{N_1} w_i \left(C_{RA,i}^{1} - \bar{C}_{RA}^{2} \right)^2}{(N_1 - 1) \sum_{i=1}^{N_1} w_i \Big/ N_1}$$

Once the *t*-statistic is calculated we look up critical values from the *t* distribution table in order to compare the probability for getting a value as extreme as the one observed. If the probability is less than 5% we conclude that the null hypothesis cannot be rejected at the 5% significance level.

3.4.2 Test of Coefficient Statistical Significance

The standard results template presented through Section 2 includes a metric: "Maximum {Pr > |t|}". If the value of this metric is greater than 0.05 then at least one of the calculated coefficients for the splits of a nontraditional variable may not be credible. This test is similar to the t-test described in Section 3.5.1, and is carried out for the fitted coefficient for each nontraditional variable category.

We do not present individual coefficients and *t*-test statistics for variable splits, as these are less useful. Each nontraditional model is fit together with over eighty clinical and age/gender categories, and as such one would need to view all of the coefficients together – and that does not present a readable perspective. Also, reviewing each individual *t*-statistic is tedious when most of the variable category splits are statistically significant. Finally the categories displayed in the results are not identical to the categories used in regression. As explained earlier, the nontraditional variable splits were further aggregated for regression in order to yield significant coefficient estimates and preserve the principle of model parsimony.

3.4.3 Coefficient of Determination

R-squared or the coefficient of determination may be defined as the percentage of the variation in medical claim cost explained by a risk adjuster model (Winkelman & Mehmud, 2007). The formula for R^2 is (where the summation is over the entire sample[29]):

$$R^2 = 1 - \frac{\sum(\text{Actual-Predicted})^2}{\sum(\text{Actual-Average of Actual})^2}$$

[29] It may be useful to note that this formula is a derived from the basic R^2 formula, and that the derivation holds true if the prediction is based on the least-squares algorithm and developed after fitting to the data.

4. Limitations & Recommendations

The research presented in this report required a lot of effort, time, and resources. The issue of nontraditional variables in risk adjustment is too broad, nuanced, and complex to be captured fully by arguably the first study of its kind. The findings of this report suggest that the influence of nontraditional variables in a risk-adjusted environment is important to study, monitor, and address as appropriate. Furthermore the issue is relevant and timely with respect to the implementation and policy goals of the ACA risk adjustment program. The author hopes that practitioners would carefully review the findings of this report and extend them. Following is a brief list of known limitations of the research methodology and data. Recommendations for further study naturally follow from the discussion regarding limitations of the current study and are also included in the list below.

1. MEPS data is not very large. Although the data design that appends ten years of overlapping information mitigates issues of credibility, they will still exist – especially in relation to some variables with missing information.
2. MEPS data is collected through a survey-based design, and has inherent differences and limitations relative to transactional claim data. For instance, the reported healthcare utilization may not be complete (Zuvekas & Olin, 2009).
3. The nontraditional variables have varying proportions of cases where information is unavailable or respondent failed to respond. This issue of completeness will affect to an extent the conclusions drawn regarding these variables.
4. The study tests essentially a linear model for the nontraditional predictor variables. Non-linear modeling is considered beyond the scope of this proposal, although it may be a useful extension of the proposed research.
5. This research used a commercially available risk adjustment model. Ideally one would use the HHS ACA risk adjustment model. The details of this model were recently released as of the writing of this paper.
6. This research does not make a distinction between individual, small group, and large group commercial data. A useful extension may be to examine LRA effects in relation to group size.
7. The research treats group and individual commercial coverage essentially as a singular risk pool. Small group and individual insurance comprise two separate risk pools, within a state, for

purposes of ACA risk adjustment. A useful extension of this research will be to analyze the impact of nontraditional variables separately for small group and individual risk pools.

8. The data from MEPS may not be representative of the post-ACA commercial risk population. While we attempted to gather data from uninsured and commercially insured – only about thirty thousand individuals are surveyed each year, and the statistical extrapolation of this sample will reflect the post-ACA market with variable success. Also, it is not possible to distinguish between small or large group policies in the publicly available MEPS data, further limiting the extent to which this data may be representative.
9. ACA includes many reforms that potentially will impact cost and utilization of healthcare services. Conclusions drawn from a historic look (for example, through MEPS) may not translate well into the post-ACA market as utilization patterns and associated cost may materially be different.
10. This research includes several nontraditional variables, not all of whom may automatically be used towards any application. Readers should be aware that use of any such factor for underwriting or rating purposes may be prohibited by applicable regulations and other considerations. In this research we have *not* considered such limitations, and the legal environment must be taken into account with any application. Furthermore, there may be significant cultural sensitivities towards the use of nontraditional variables, and besides legal risk, reputation risk should be considered as well. Attitudes towards privacy are rapidly evolving and it would be prudent to pay close attention to them when developing or using nontraditional variables in any application including risk adjustment.

Appendix: Literature Review

The following reviews are a continuation of Section 1.4:

Hadley (1982 and 1988) presented a small area econometric analysis of mortality rates that examined the impact of medical expenditures on mortality outcomes. He noted that both income and education exert a negative and significant impact on mortality. He also found that areas with increased medical expenses have lower mortality rates: he estimated that a ten percent increase in expenditures "per capita" will reduce mortality between 1 and 2 percent (Hadley, 1982).

Adler and Newman (2002) stated in their study that socioeconomic status (SES) has three major determinants of health: health care, environmental exposure, and health behavior. In addition, chronic stress associated with lower SES may also increase morbidity and mortality. Reducing SES inequalities in health will require policy decisions addressing the mechanisms of socioeconomic status (income, education, and occupation) as well as the pathways by which these affect health. Socioeconomic status, whether assessed by education, income or occupation, is associated with a wide range of health problems, including low birth weight, heart disease, high blood pressure, arthritis, diabetes, and cancer. Lower SES is associated with higher mortality, and the greatest disparities occur in middle adulthood (ages 45–65) (Adler & Newman, 2002).

McGinnis and Foege (1993) carried out an analysis of the actual causes of death in which they found out that the majority of the deaths in the US were caused by factors such as tobacco, diet and lack of activity, and toxic agents.

In one study (Ross & Wu, 1995) education was found to be the most important and fundamental SES component as it determines future occupational opportunities and earning capacity. Education provides information and life skills that enable people to gain more ready access to information and resources to promote health (Ross & Wu, 1995). Winkleby and colleagues examined the role of education, income, and occupation as risk factors for cardiovascular disease; and when these were taken in combination, only education was found to be a significant predictor (Winkleby, Jatulis, Frank, & Fortmann, 1992).

When it comes to obtaining health care, increased income can give access to better facilities. "Independent of actual income levels, the distribution of income within countries and states has been linked to rates of mortality. At lower incomes, the relationship between income and health is stronger" (Backlund, Sorlie, & Johnson, 1999). Occupational status is a more complex factor and its measurement varies depending on one's perspective about the significance of various aspects of an occupation. It has been observed that to be unemployed and the length of unemployment affect one's health. The threat of unemployment and job insecurity can affect health as well. Catalano and Serxner (1992) found increased rates of low birth weight in geographic locales exposed with high rates of unemployment. Moreover increased rates of blood pressure have been linked with unemployment threats. However, the increase tends to be temporary (Catalano & Serxner, 1992).

Angell (1993) has observed that education, income and occupation are influential yet mysterious factors of health; they are not likely to have a direct effect rather they serve as substitutions for other determinants (Angell, 1993). There are three causal factors of SES which are associated with eighty percent of premature mortality. The major determinant is behavior and lifestyle, which accounts for about half of premature mortality, followed by environmental exposure which accounts for another 20 percent, and health care 16 percent (Lee & Paxman, 1997).

Direct contact with the toxic agents in the environment, including phthalates, carbon dioxide, and industrial waste, also varies with socio-economic status (SES). Those scoring lower on the SES measures are more likely to live and work in worse physical environments. Low-SES persons also experience greater residential crowding and noise. Area density is less problematic for health as compared to living in a crowded home environment. Poor long term memory and reading difficulty have been linked to noise exposure among children and to hypertension among adults (Saegert & Evans, 2003).

Berkman and Glass (2000) found out that SES-related health effects of social environments may be even more significant than those of physical environments. Lack of engagement and isolation and lack of engagement in social setups are strong predictors of health (Berkman & Glass, 2000). People who are socially isolated are at greater risk in terms of mortality than those with better social connections. As far as sexually transmitted diseases are concerned, diffusion is quick in networks which are at elevated risk, thus placing lower-SES people at higher risk.

Furthermore, it has also been observed that the quality of health care varies by socioeconomic status. Among adults, forty percent of those who have not graduated from high school are uninsured, compared with only ten percent of college graduates; more than sixty percent of the uninsured are in low-income families (Monheit & Vistnes, 2000). Hafner Eaton (1993) noted that about forty percent of those who lack insurance receive less remedial care than those who are insured (Hafner Eaton, 1993).

McGinnis and Foege (1993) noted that behavioral factors are related to about half of premature mortality, and almost all premature mortality was affected and influenced by socioeconomic status. The use of tobacco has proved to be the greatest behavioral risk for premature mortality (McGinnis & Foege, 1993). Further, those with less education and less income are more likely to smoke (Pierce, Fiore, & Novotny, 1989). Low socioeconomic status is similarly linked with more inactive lifestyle and lower consumption of fiber and fresh fruits and vegetables.

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