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Session 48PD
Underwriting Concepts For Actuaries – Revisited

Track: Product Development

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Panelists: MR. RICHARD L. BERGSTROM
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Summary: This encore presentation discusses selected concepts that relate to risk appraisal of new business insurance and underwriting. Specific attention is focused on the relative values of underwriting tools, namely fluid collection: blood, urine and oral fluid. Concepts of sensitivity and specificity illustrate why certain testing protocols are "better" than others. Also included is a discussion of empirical tools to support the mortality assumption setting process in connection with underwriting requirements.

MR. RICHARD L. BERGSTROM: Two years ago in San Diego, Jeff Marks of Northwestern Mutual and I put together the first session on underwriting concepts for actuaries. It was well- received. They asked me to put together a second session. This panel put it together and we called it "Underwriting Concepts For Actuaries—Revisited". That was well enough received that they asked me to do yet another one this year.

I'm going to break right into our session by telling you about our speakers. As I said, I'm with the Seattle office of Milliman USA. My peers at Milliman refer to me perhaps conveniently as Captain Mortality, which beats Dr. Death. That's because of the amount of work that I do with mortality and risk appraisal. We've put together some concepts we want to share with the group about how actuaries and

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Note: The chart(s) referred to in the text can be found at the end of the manuscript.

underwriters need to work together in the underwriting process.

Our first speaker is going to be Mary Broesch. Mary Broesch is executive director of research and consulting at ING Re. In her current role, she conducts research and analysis on a variety of topics and issues that impact product development and pricing or reserving. Mary is a Fellow with the Society of Actuaries. She is also a member of the SOA Life Insurance, Mortality and Underwriting Survey Committee, the SOA Individual Life Experience Committee and the Academy's CSO Implications Work Group.

Our second speaker is Doug Ingle. Doug is vice president and chief underwriter for the reinsurance division of American United Life (AUL). He has been an underwriter for 27 years, with his time spent evenly between direct writing companies and reinsurers. He achieved his Fellowship in the Academy of Life Underwriting and Fellowship in the Life Office Management Association in 1987 with honors. He is currently a member of the Mortality and Morbidity Liaison Committee. He also serves as chairman of the Underwriting Experience Studies Committee, which promotes and supports mortality studies performed by the insurance industry at large.

So with no further ado, Mary Broesch.

MS. MARY ANN BROESCH: I'm going to talk about two things. The first part of my presentation will cover the very basics of preferred risk classification. After that, I'll share with you the results of an empirical study we've done using an approach that identifies significant predictors of mortality for preferred risk.

Let's start with a couple of definitions. First, a preferred risk is created from a group of standard (unrated) risks using a specific set of underwriting criteria. It is expected to exhibit lower mortality than the standard group from which it was selected so that discounted premium rates can be offered. You start with a standard group of risks. Preferred risk is all about is trying to look at cardiovascular and violent deaths. Those are the two areas where we can do finer gradation with the standards. The residual class consists of the remaining risks from a standard group of risks that do not qualify for the preferred class and is expected to exhibit higher mortality than the standard group.

The keys to preferred pricing considerations are the number of classes and the preferred underwriting criteria. I'll spend a fair amount of time on this aspect, as well as the qualification percentage and expected mortality. For a long time, there was a trend toward a greater number of classes. This occurred during the 1990s. Now we're seeing fewer numbers of classes and a stabilization of a certain number of classes. More classes could be considered better, especially from the standpoint of looking at competition. More preferred classes will strengthen competition because they allow a company to better position where it wants its rates to be in the marketplace. In addition, there's less premium differential between the classes,

which lowers the not-taken rate, and there's less pressure to make underwriting exceptions when the premium rates are close together.

On the other hand, more might not be better. First, there's less statistical justification when you have more classes. You need additional information or tests in order to be able to classify those risks into the various classes. You spend more time underwriting each case in order to make sure it gets into the right class. More classes add complexity to the whole pricing and product development process. It can be confusing both to agents and to the insureds.

With respect to the preferred underwriting criteria, we want to know which criteria are the most significant predictors of mortality. Tighter criteria results in lower mortality, and we want to make sure the preferred criteria chosen is easy to measure or easy to verify. Another important consideration is the cost. We want to make sure the cost is less than the value the criterion provides. Coming up with criteria that is accepted in the industry, simple to implement and simple to use and understand is important. The last point I want to make, and we'll get into this more later, is exceptions really increase mortality.

I'd like to get into some additional aspects of the criteria such as, medical testing, personal history, lifestyle characteristics, family history, and others. Personal history and lifestyle can almost be combined into one area now.

First, let's go to the common medical tests. There are a lot of different medical tests that are used. I know Doug will get into some of these as well. The most important things that differentiate preferred risk from standard is blood pressure and the cholesterol ratio of total cholesterol to HDL-C. Typical personal history criteria are more reflective of original wording. I don't believe the way that we're looking at personal history today is relevant for the simple reason that a lot of these things might be used to differentiate a substandard risk from a standard risk. Preferred is all about is starting with a standard risk and seeing how we can further find mortality credit differentials from the standard risks. This has evolved. Some of these were done to educate agents. For example, a personal history of non-melanoma type cancer would be something considered under the medical criteria. Personal history should really reflect more of the lifestyle characteristics on this list.

The two main things preferred is trying to cover are the cardiovascular risks and the violent death risks. All of the medical history and the family history are there to help understand the cardiovascular risk factors. The lifestyle factors are much more focused on understanding the violent death component and making sure we can select out the violent deaths, especially alcohol abuse. Has there been a history of alcohol abuse or illegal drug use in the past?

In terms of family history, this is something that's very relevant and important in evaluating a risk for cardiovascular incidence. That's the most important thing. This is also true for cancer and stroke and diabetes. Family history has many

different definitions. One example is that no more than one parent diagnosed or died before the age of 60 of heart disease, cancer, stroke or diabetes. It could be about whether one parent or two parents were diagnosed or died, but typically it's defined using a certain age and specific diseases.

Now, in many cases there are times when you need to do less than full underwriting. In these cases, it's helpful to bring in other criteria to evaluate the risks. Some of the other preferred criteria might be used in situations where you have an older-age population or where simplified issue underwriting is used. Like education and income, activities of daily living (ADLs) or instrumental activities of daily living (IADLs) are typically used to help underwrite the older age populations. Many people believe pet ownership has a positive impact on mortality. Diet, exercise and hobbies are other things that also affect mortality.

Qualification percentage refers to the percentage of the standard class expected to qualify for the preferred class. It's based on the preferred underwriting criteria. The tighter the criteria, the lower the percentage. It's also directly related to the expected mortality. The lower the percentage qualifying for preferred, the better the expected mortality should be. Now, that can be true, but I also want to give you an absurd example to show how that might not always be true. Take an example where we have two preferred criteria, one being hair color and one being cholesterol. Let's say you have a group of people who have red hair and cholesterol under 240, and you compare that to a group that has brown hair and cholesterol under 220. The group with red hair and cholesterol under 240 would have fewer people qualifying, but what group has the lower mortality? It's going to be the group with the lower cholesterol. So, in this absurd example it's not necessarily true that the lower percentage qualifying would result in lower mortality. You have to understand why the risks are going into the class. You also need to understand the relative risk associated with the criteria. The qualification percentages are one of the assumptions that can be easily verified by experience.

In terms of expected preferred mortality, we start with a standard mortality rate and evaluate the screening tools used as well as the strictness and level of the criteria used to qualify. The practice on underwriting exceptions has a very big impact on the expected mortality. It's important to understand how. Here's an example to illustrate what I'm talking about. Let's say you have a nontobacco class, and you allow a cigar smoker into that class. That might be one example of an exception where you allow somebody who doesn't meet all of the criteria in your preferred class. An exception deteriorates the mortality of both classes. Let's take the example of the cigar smoker in the nontobacco class. Clearly, the cigar smoker is going to have worse relative mortality compared to the nontobacco class. The non-tobacco class will end up with worse mortality. However, the cigar smoker is going to have better relative mortality compared to the smokers in the tobacco class. The smoker class will also have higher mortality. Exceptions have a big negative impact on expected mortality. Another impact on expected mortality is lapsation. If you experience high lapses, there could be some deterioration in

mortality of those who do not lapse. This is the classic antiselection example.

Next, a little lesson on the conservation of death principle. If you start with a standard group of risks and carve out the preferred class, the idea is you'll come back to standard mortality when you combine the preferred class mortality and the residual class mortality. In the formula below, the mortality rate for preferred multiplied by the qualification percentage plus those who do not qualify times a residual mortality rate equals the standard mortality rate. The other piece of information you need to do the math is the relationship between the preferred and standard mortality or between the residual and preferred mortality (Table 1).

Table 1

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Conservation of Deaths

$$Sq = QP \times Pq + (1-QP) \times Rq$$

$$Pq / Sq \quad \textit{or} \quad Rq / Pq$$

Where: QP = qualification percentage

Sq, Pq, Rq = standard, preferred and residual mortality rate

In this example, assume the preferred criteria is expected to give a 40 percent qualification from the standard class. We are going to assume the expected mortality of the standard class is 50 percent of the Society of Actuaries' 1975-80 Basic Mortality Table. What's the expected mortality of the preferred and residual classes? We also need to understand the relationship between the standard and preferred classes. That can either be determined by knowing what your preferred mortality discount is or by knowing the relationship between residual to preferred or standard mortality. Let's assume a 20 percent discount. In this case, preferred mortality is going to be 80 percent of standard or 40 percent of the SOA 1975-80 mortality. You can now plug in this information to solve for the residual mortality. Table 2 below shows the derivation of the assumed residual mortality is 56.7 percent of SOA 75-80.

Table 2

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Expected Mortality Example (con't)

$$Sq = QP \times Pq + (1-QP) \times Rq$$
$$0.5 \times (\text{soa } 75\text{-}80) = 0.4 \times Pq + 0.6 \times Rq$$

$$0.34 \times (\text{soa } 75\text{-}80) = 0.6 \times Rq$$

$$\rightarrow Rq = 0.567 \times (\text{soa } 75\text{-}80)$$

In this quick overview on the basics of preferred, we discussed each one of the interrelated decision points: the number of preferred classes and for each class the underwriting criteria, the qualification percentage, the expected mortality and the underwriting exceptions.

Let's turn to an empirical approach. You can use an experiment or an observation to try to come up with some understanding. We're trying to understand the predictive capacity of the preferred criteria for mortality. First, we're going to identify significant predictors of preferred mortality using a Cox model. Then, we're going to explore the mortality differentials between the preferred and residual classes using survival curves based on a Kaplan-Meier estimate.

First, here's some background on the Cox model shown in Table 3 below. It's a proportional hazard model and fits time to death as the outcome. It's widely used in medical and clinical research to identify risk factors. Since it is a semi-parametric approach, you don't have to assume what the distribution is for the time to death. The Cox model is very easy to apply and it's easy to interpret the results. The formula can be rearranged and presented as a hazard ratio, where it represents the relative mortality of the predictor compared to the baseline example. This will become more obvious as we work through the examples and interpretations.

Table 3

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Definition of Cox Model

- Cox model can be written as

$$h(t) = h_0(t)e^{\beta x}$$

t: time to event (e.g., death)
h(t): hazard function
$h_0(t)$: baseline of hazard function
x is the row of potential predictors,
β is the vector of parameters to estimate

One other concept needs to be introduced before we proceed. While every risk factor provides some kind of information, some information is more valuable and relevant than other information. We want information that is statistically significant. The "p-value" used in this approach determines how significant the results are. The lower the p-value, the more significant it is.

In our example, we're going to start with some generic industry preferred criteria. The criteria is the same for all ages, as most companies don't vary their criteria by age. This is a standard nonsmoker group and we're going to assume there has been no tobacco use in the past five years. We're also going to assume the person is not a heavy drinker, blood pressure is under 145/85, total cholesterol is less than 240 and a body mass index (BMI) between 22 and 28. BMI combines height and weight into one calculation. BMI is more predictive than just using height and weight. The results are shown as a hazard ratio— the risk of dying among persons with the value of the preferred criteria relative to those who do not qualify on that criterion, among all of those who are standard nonsmokers. Let's see how to interpret these results.

Table 4 shows what we found using the generic criteria. Only the statistically significant values are shown in the table. The first criterion is no tobacco use in five years. Those between the ages of 40 and 69 that have not used tobacco in the past five years would have 61 percent of the mortality of the nonsmokers who did use tobacco in the past five years. We're basically comparing someone who is a non-smoker that quit more than five years ago to someone who is a nonsmoker that quit less than five years ago. The 61 percent is the relative mortality between

those two situations.

Table 4

[31]

Generic Preferred Significant Predictors

Hazard Ratios for Generic Industry Preferred Criteria by Age Group

Criteria	Ages 18-39	Ages 40-69	Ages 70+
No tobacco use in 5 years	-	0.61**	-
Not a heavy drinker	0.23***	-	-
Blood Pressure <= 145/85	-	.77**	-
Cholesterol <= 240	-	-	1.78**
BMI 22-28	-	-	0.49***

*** very significant (p-value <=.01)

** signifcant (p-value <=.05)

* marginally significant (p-value <=.10)

For ages 18 to 39, someone who is not a heavy driver would have 23 percent of the mortality of a heavy drinker. This is a very significant result for this age group. This makes sense, because, at the younger ages, we're trying to look at criteria that predict violent deaths. Heavy drinking is associated with those kinds of accidents and violent deaths. For the middle-age group of 40 to 69, someone with blood pressure less than 145/85 would have 77 percent of the mortality of someone with blood pressure greater than 145/85. Cholesterol less than 240 is statistically significant for the oldest age group—those over age 70. Someone with cholesterol under 240 would have 178 percent of the mortality of someone with cholesterol greater than 240. That result seems a little counterintuitive, because typically we tend to think the lower the cholesterol the better. However, in the older-age population low cholesterol will sometimes be an indication of other diseases such as cancer. Another significant predictor for ages 70+ is BMI. Someone with a BMI in the 22—28 range will have 49 percent of the mortality of someone with a BMI less than 22 or greater than 28. Please note the entire grid could have been filled in with values, but I'm only showing the ones that are significant to aid in our discussion.

While we ended up with some significant predictors, does this help us to differentiate a preferred class from a residual class? The Kaplan-Meier(K-M) estimate is a product limit estimate of the survivor function (Table 5). It uses the exact time of death. Chart 1 is a graph of the preferred and residual survival functions for the age group of 18 to 39where a heavy drinker is a significant

predictor. One line is residual and the other line is preferred. The p-value of 0.028 is statistically significant, which means there is a significant difference between the preferred and residual class mortality using the given criteria for this age group.

Table 5

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Kaplan-Meier (K-M) Estimate

n_j: the number of subjects alive just before time $t_{(j)}$

d_j: the number of deaths at time $t_{(j)}$

$$S(t) = \prod_{j=1}^{k} \left(\frac{n_j - d_j}{n_j} \right)$$

For the next age group of 40-69 (Chart 2), not using tobacco for five or more years and having blood pressure less than or equal to 145/85 was not enough to see a mortality differential between the preferred and residual classes. The p-value of 0.307 says this is not statistically significant, and on the graph it looks like there is no difference between the two lines. The same situation occurs for the 70-and-older age group (Chart 3). In fact, the preferred line crosses over the residual line. So even though we found significant predictors of mortality, they did not give us a statistically significant mortality differential between the two classes. Is there a better way? Is there a better way to get at this and show that mortality differentials exist?

We tried to find specific predictors for the three different age groups. We tested each age group separately as opposed to all the ages together. For the age group of 18 to 39, there were two significant predictors—a BMI of 20 to 24 and not being a heavy drinker. That means someone with a BMI in that range would have 29.4 percent of the mortality of someone who has a BMI less than 20 or greater than 24, and someone who is not a heavy drinker would have 28.6 percent of the mortality of a heavy drinker.

The resulting significant predictors based on age-specific criteria are shown in Table 6. Table 6 does not show a list of all predictors. The predictors are identified

through an iterative process of testing various thresholds and running it through the computer programs. Every time you run it, you get different results.

Table 6

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Significant Predictors
Age-specific Criteria

Hazard Ratios for Age-specific Preferred Criteria

Ages 18-39	
BMI 20-24	0.294**
Not a heavy drinker	0.286***
Ages 40-69	
BMI 19-24	0.681**
Blood pressure <=145/85	0.631***
Serum albumin >=4.2	0.685***
Ages 70+	
Serum albumin >=4.2	0.532**
No weight change	0.535*
Active	0.443***

***p<=.01 is very significant

**p<=.05 is significant

*p<=.10 is marginally significant

For ages 40 to 69, there were three significant predictors. BMI is one of them. Blood pressure less than 140/85 would have 63.1 percent of the mortality of blood pressure greater than 145/85. We used serum albumin instead of cholesterol and found someone with serum albumin greater than 4.2 would have 68.5 percent of the mortality as compared to someone with serum albumin less than 4.2.

For the older-age group, ages 70+, there were three criteria that showed up to be significant. First, serum albumin of greater than 4.2 would have 53.2 percent of the mortality compared to serum albumin of less than 4.2. Second, no weight change was significant. Someone that does not have any weight change would have 53.5 percent of the mortality of someone that would have weight change. Activity was also a significant criterion for the older-age group. We found that people who are active would have 44.3 percent of the mortality compared to people who are not active.

Let's see how well these predictors did in terms of differentiating between the residual and preferred classes, see Charts 4, 5 and 6. Using our Kaplan-Meier curves again, we see that for ages 18 to 39 (Chart 4), our p-value is extremely small, suggesting these results are very significant. The next age group, 40—69 (Chart 5) again shows a difference and it is very significant on a statistical basis. For ages 70 and over (Chart 6), the result is that those three criteria that we found

produced a statistically significant difference between the preferred and residual class.

Here are some points about this example. The results are very sensitive to the criteria included in the model, so every time you change the criteria, the results will change. As I mentioned, this is not a complete list of significant predictors. Clearly, there are more, and testing must be done to figure out which ones they are. This whole approach was done using U.S. population data, but we did make some selections to simulate an insured population. If different data is used, the results would be different as well. In order to capture enough data to see the mortality implications of it, you have to go back and study behaviors from many years ago to be able to follow them through time and see what the mortality results are. Much of the data was collected in the 1980s and followed through to the current time, so it may not reflect all of the benefits and medical advances that occurred in the 1990s for cardiovascular disease. These caveats are presented so you better understand the limitations of the results.

In summary, it is possible to choose preferred criteria that are significant predictors of mortality and that result in a statistically significant difference in expected mortality between the preferred and residual classes. Furthermore, we found through this example that preferred criteria should vary by age.

MR. DOUGLAS A. INGLE: I was so excited the first time I had a chance to hear Mary's presentation on the Cox proportional hazard model. It's a regression model that's near and dear to my heart, and one that I have been extremely interested in for many years. I actually heard her give a presentation on the proportional hazard model back in the late 1990s. We thought this meeting would be a great opportunity to collaborate and talk about this in a little more detail.

The reason I'm so excited about it is because I'm going to take you down a different road. I'm going to take you on the path that I took finding out about multivariate regression. I'll show you how she and I ended up arriving at the same place.

One of the things Mary mentioned was she was using an empirical approach, and that's absolutely a true statement. Empirical is defined as "statistical analysis relying on experience through observation alone, often without due regard for system and theory."

In other words, she was using data to determine if the life insurance industry was using the right criteria today, or if it should be using a different approach. That's fantastic. That leads to the question: Are underwriters using the correct criteria? So, where, did preferred really come from? I believe much of it came from the Framingham study. I suspect almost everyone in this room has heard of this study. There's probably not an underwriter who has not heard of this study. Framingham, Massachusetts was a sleepy little town in 1948. At that time the

United States Public Health Service was interested in determining why cardiovascular disease was killing so many Americans and if we could do anything to modify our risk of dying from this disease. The U.S. Public Health Service asked the residents of Framingham if they would be willing to volunteer for a program to help us identify the risk factors for coronary artery disease. Approximately 20 percent of the population stepped forward and said yes, include me in your study. It started in 1948. It is still going strong today.

What was the focus of the Framingham study? Their charge was to identify a cohort of healthy, asymptomatic people with no history of coronary artery disease. In many ways this is similar to what we're doing in the insurance industry. Once identified, these individuals were tracked over time to see who developed coronary artery disease, and if we could discover the key predictors associated with the disease. Framingham came up with some really awesome discoveries. What's intriguing to me about this is this whole room is full of people that know most of the results from the Framingham study. For example, when we discuss things like "risk factors," we are, in reality, discussing a phrase that was introduced by the director of the Framingham Institute in 1961, Dr. William Kannel.

Table 7 reveals a list of Framingham discoveries. Does this look at all familiar to anyone in the room? Does anybody know that high blood pressure causes strokes? Did you know that smoking is not good for you? Voila! This came from the Framingham study. Another finding was that physical exercise reduces the risk of heart disease. I'll bet the majority of the people in here run. At dinner last night, the majority of the people at the table were telling me about how they had just run a couple hours before coming to sit down to dinner. People eat low cholesterol diets and low fat diets. All of these things are due to results reported out of the Framingham study.

Table 7

Framingham

- The term “Risk Factor” coined by Dr. William Kannel in medical paper 1961
- Discoveries include:
  - **High BP causes strokes**
  - **Cigarette smoking causes heart disease**
  - **Elevated cholesterol raises risk of heart attack**
  - **HDL protects against heart disease**
  - **Physical exercise reduces risk of heart disease**

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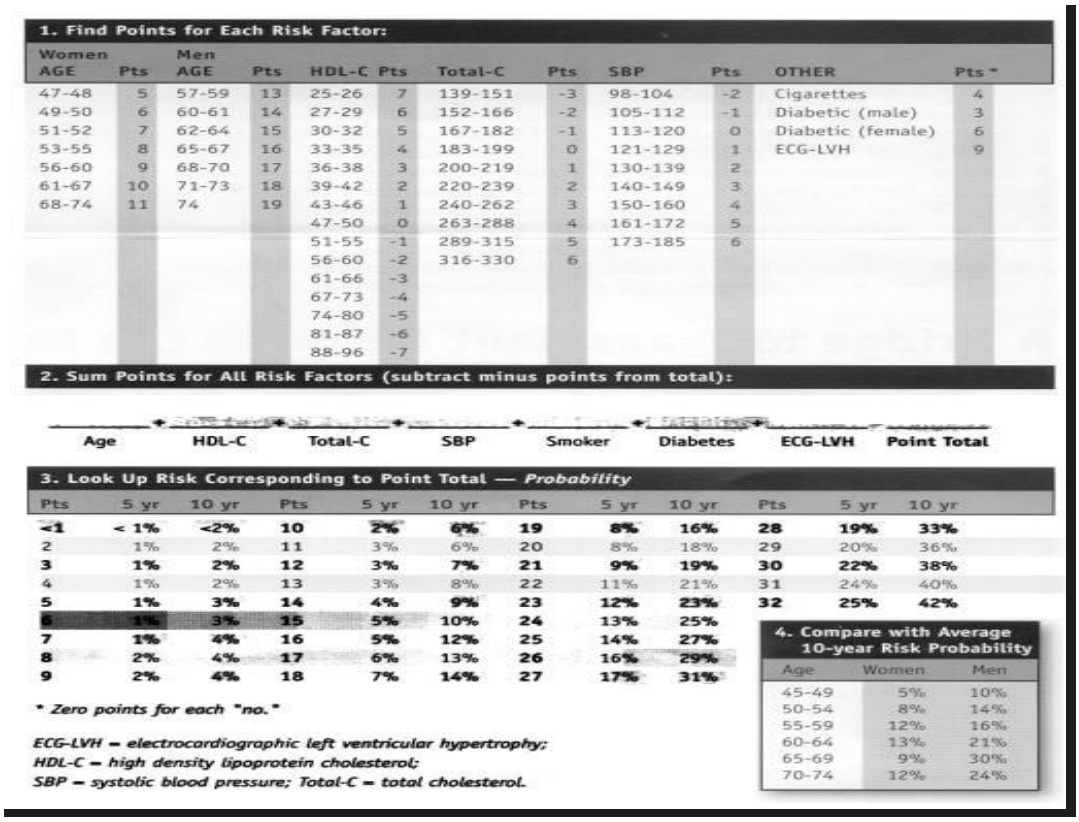
Let's go back to what Mary was talking about in terms of quantifying statistically significant findings. Back in 1948, the researchers, the physicians, the statisticians, and epidemiologists studying the Framingham population, did not know what the coronary risk factors were going to be in a healthy, asymptomatic population.

In 1991, the American Heart Association commissioned researchers associated with the Framingham study to create a point system that would help healthy asymptomatic people predict their risk of coronary heart disease. The magazine *Circulation* published an article in 1991, by Andersen et. al that published the point system to help individuals identify what their risk of heart disease was going to be in the next ten years. The Framingham study, early in the 1950s, actually started presenting that sort of information to the public in logistic regression formulas. They revised their models as they collected more data through the 1950s, 1960s, 1970s, and 1980s. In the 1990s, once again, they built the model just mentioned. In 1999, I received a quarterly newsletter called *Heart and Health* from Clarian Health Network. It contained an article titled, "Calculating Your Risk of Coronary Heart Disease."

Clarian is a medical group in the Indianapolis area. The magazine made it sound like this was a new concept, but I recognized the table from a publication eight years earlier.

Table 8



1. Find Points for Each Risk Factor:

Women AGE	Pts	Men AGE	Pts	HDL-C	Pts	Total-C	Pts	SBP	Pts	OTHER	Pts *
47-48	5	57-59	13	25-26	7	139-151	-3	98-104	-2	Cigarettes	4
49-50	6	60-61	14	27-29	6	152-166	-2	105-112	-1	Diabetic (male)	3
51-52	7	62-64	15	30-32	5	167-182	-1	113-120	0	Diabetic (female)	6
53-55	8	65-67	16	33-35	4	183-199	0	121-129	1	ECG-LVH	9
56-60	9	68-70	17	36-38	3	200-219	1	130-139	2		
61-67	10	71-73	18	39-42	2	220-239	2	140-149	3		
68-74	11	74	19	43-46	1	240-262	3	150-160	4		
				47-50	0	263-288	4	161-172	5		
				51-55	-1	289-315	5	173-185	6		
				56-60	-2	316-330	6				
				61-66	-3						
				67-73	-4						
				74-80	-5						
				81-87	-6						
				88-96	-7						

2. Sum Points for All Risk Factors (subtract minus points from total):

Age + HDL-C + Total-C + SBP + Smoker + Diabetes + ECG-LVH = Point Total

3. Look Up Risk Corresponding to Point Total — *Probability*

Pts	5 yr	10 yr	Pts	5 yr	10 yr	Pts	5 yr	10 yr	Pts	5 yr	10 yr
<1	**< 1%**	**<2%**	**10**	**2%**	**6%**	**19**	**8%**	**16%**	**28**	**19%**	**33%**
2	1%	2%	11	3%	6%	20	8%	18%	29	20%	36%
3	**1%**	**2%**	**12**	**3%**	**7%**	**21**	**9%**	**19%**	**30**	**22%**	**38%**
4	1%	2%	13	3%	8%	22	11%	21%	31	24%	40%
5	**1%**	**3%**	**14**	**4%**	**9%**	**23**	**12%**	**23%**	**32**	**25%**	**42%**
6	**1%**	**3%**	**15**	**5%**	**10%**	**24**	**13%**	**25%**			
7	**1%**	**4%**	**16**	**5%**	**12%**	**25**	**14%**	**27%**			
8	**2%**	**4%**	**17**	**6%**	**13%**	**26**	**16%**	**29%**			
9	**2%**	**4%**	**18**	**7%**	**14%**	**27**	**17%**	**31%**			

4. Compare with Average 10-year Risk Probability

Age	Women	Men
45-49	5%	10%
50-54	8%	14%
55-59	12%	16%
60-64	13%	21%
65-69	9%	30%
70-74	12%	24%

** Zero points for each "no."*

ECG-LVH = electrocardiographic left ventricular hypertrophy;
HDL-C = high density lipoprotein cholesterol;
SBP = systolic blood pressure; Total-C = total cholesterol.

Researchers associated with the Framingham study must have a fantastic PR department. There is no doubt that their information has been disseminated over numerous communication modalities. I'm not going to go in any detail about what is on this Table 8 but, suffice it to say, as an underwriter this is what I do day in and day out. This slide calculates a person's risk of getting coronary artery disease, and as an underwriter, I calculate an individual person's risk of death. This is a point system and the underwriting process is a process of aggregating debits and credits, which is also, in essence, a point system. We do much the same thing that a coronary risk factor point system does.

I want to read a couple of things from the *Heart and Health* newsletter. "Calculating your risk isn't easy. There are about 300 cardio vascular risk factors. There is no consensus about the predictive value of a great majority of these risk factors. Coronary heart disease prevention strategies focus only on the clearly established risk factors, such as age, gender, high-density lipoprotein (HDL) cholesterol, total cholesterol, systolic blood pressure, cigarette smoking, diabetes mellitus and electrocardiogram left ventricular hypertrophy (ECG-LVH)." Framingham has done tons of research and we use the preferred risk factors we do

today because of the research produced by the Framingham community. They found that these things are extremely important in reducing your risk for coronary artery disease. Why do I mention that? Not only are we aware of that, but the rest of the population is aware of the importance of these risk factors. I would suggest that part of the reason we have a preferred product today is because there was an applicant sitting in front of Joe Agent and the applicant was telling Joe "I watch what I eat, I exercise every day, my blood pressure is great, my HDL is high, I take really good care of myself. Joe, can't you find me a life insurance product that's a little bit cheaper?" I really think that was a lot of the impetus behind preferred risk classes. Healthy Americans knew they should qualify for cheaper life insurance. Much of the push for the preferred product came from hearing our customers. What do our customers want and is there something that we can give them? Lo and behold, these factors are the preferred risk factors.

Now I'm going to take you down this path toward my proportional hazard model. Remember, in 1948, Framingham started their analysis not knowing what the important risk factors were. By the mid-1980s, build, blood pressure, cholesterol, smoking, and age were established as important factors, but it wasn't until the 1970s and 1980s that the researchers started collecting data from the Framingham population on HDL cholesterol. HDL stands for high-density lipoprotein. It's also referred to as the "good" cholesterol. It's cardio-protective. The researchers complete their studies and are now ready to state that HDL or "good" cholesterol is cardio-protective. But, the researchers associated with the Framingham study now have a conundrum. By the mid 1980s, they had already created their list. How are they going to add in another important coronary risk factor? The first question from the population is going to be, "If all these other things are already established as important , then is HDL worth anything more?" Obviously, we're dealing with extremely bright people. They know how to answer that question as well as we do in this room. The answer: use a multiple variable regression formula to figure out how important each of the components are in predicting mortality or, in this case, coronary artery disease.

Professor Cox wrote his paper on the proportional hazard model for the Royal Statistical Society in 1972. Professor Cox has been knighted and his paper was considered one of the top 100 papers of the twentieth century. Recall, the Framingham study started in 1948. Prior to the 1970s they were using multivariate logistic regression formulas to adjust for confounding variables. These mathematical formulas take all the important predictive characteristics into consideration and appropriately weigh each factor according to its contribution to outcome. This concept is very interesting to underwriters and actuaries throughout the world. What are the big sticks? What is important? Multivariate logistic regression does the same thing the Cox proportional hazard model does, and that is to create a formula that can be used for multiple risk factors.

Back in the mid-1980s, the labs that provide their services to the insurance industry were eager to garner more business, and when results from the Framingham

study reported that HDL cholesterol had been found to be an important risk factor in predicting cardiovascular disease, the labs began telling the insurance industry that they could test for HDL and the industry should include it in their blood profiles. They would often bring a copy of one of the articles espousing the importance of HDL to an underwriter's office and say, "Here's proof that HDL cholesterol is really important, and you should not only get total cholesterol, but HDL cholesterol measurements as well." Being the sort of obsessive-compulsive, analytical person that I am, I read these articles over very carefully, and I discovered that while the labs were promoting the graphs published with the articles, I was interested in the tables.

Table 9 presents the importance of HDL cholesterol as a component to the model. The table presented here is a list of regression coefficients. The article stated, the appropriate regression coefficient to apply to HDL is -.032. The researchers presented the mathematical model in such a way that the numbers speak for themselves. Once it was stated that the regression coefficient was –.032, they were in essence saying "Thus, we rest our case." From my perspective as an underwriter, I needed a little more than that to be able to understand what that regression coefficient meant. Thus, it led me down a path many years ago, to discover the Cox proportional hazard model. I learned that multivariate regression is the way to go for classifying preferred criteria. Note the criteria in the table are: HDL, total cholesterol, blood pressure, cigarette smoking, BMI (kilograms divided by meters squared) and age. It's interesting to note these are also the factors we review in stratifying preferred risks.

Table 9

Cox Regression Coefficients

Table 4.—Proportional Hazards Model Coefficients for Multivariate Regressions Based on Combined Four-Year CHD Following the Two Measurements of HDL-C for Subjects Free of CHD*

	Men		Women	
	Regression Coefficient β	Relative Risk†	Regression Coefficient β	Relative Risk†
HDL-C (mg/dL [mmol/L])	−.032	0.5 (0.4-0.7)	−.026	0.5 (0.4-0.7)
Total cholesterol (mg/dL [mmol/L])	.006	1.4 (1.1-1.8)	.005	1.4 (1.1-1.9)
Systolic blood pressure (mm Hg)	.014	1.6 (1.2-2.1)	.009	1.4 (1.1-1.9)
Cigarette smoking	.049	1.1 (0.8-1.5)	.200	1.2 (0.8-1.9)
Body mass index (kg/m²)	−.041	0.8 (0.6-1.0)	.025	1.2 (0.9-1.5)
Age	.031	. . .	.018	. . .

*CHD indicates coronary heart disease; HDL-C indicates high-density lipoprotein cholesterol.

†Based on a comparison of estimated risk for a person at the 80th percentile vs 20th percentile of the sex specific distribution of the risk factor. For cigarette smoking, estimated risk for a smoker is compared with that of a nonsmoker. Numbers in parentheses indicate 95% confidence limits.

Lipoprotein Incidence. Castelli et al *JAMA*: Nov 28, 1986 Vol. 256 No. 20

So, in essence we really need to use the Cox proportional hazard model in the process of doing preferred risk underwriting. As Mary was pointing out earlier, what you end up doing is ratioing two of something against each other. Why do I say "of something"?

These w and z vectors can be anything you want (Table 10). The baseline reference value, z, can be for example, the average cholesterol, average blood pressure, average HDL and so on for a standard population. Let's ratio that against what either an individual or a preferred cohort's average cholesterol and average blood pressure, and so on are.

Table 10

Cox Model Assumes Proportionality

z = vector of reference parameter values

w = vector of focus parameter values

$$\frac{l(t,w)}{l(t,z)} = \frac{l_0(t) \times e^{(b_1 \times w_1 + b_2 \times w_2 + \ldots + b_n \times w_n)}}{l_0(t) \times e^{(b_1 \times z_1 + b_2 \times z_2 + \ldots + b_n \times z_n)}}$$

$$\frac{l(t,w)}{l(t,z)} = e^{(b_1 \times \Delta x_1 + b_2 \times \Delta x_2 + \ldots + b_n \times \Delta x_n)}$$

By using the formula you can compare the average values in the standard class to the average values of a preferred class. You can statistically define an improvement in mortality that would be mathematically justified based on using the Cox proportional hazard model. We've been talking about coronary artery disease risk factors all through this presentation, and the first question is: That's fine for coronary heart disease, what about all-cause mortality? There are many examples in the literature using all-cause mortality. For example, Mary was doing all-cause mortality to find her regression coefficients.

Finally, I'd like to cover a little bit of the protective value of blood. We in the underwriting community can be defined as debit mongers. Debits are us. If you go to an underwriting national meeting and you see the underwriters talking to each other, they'll be talking about how something was 50 debits, or 150 debts, and we all know what we're talking about because one debit means a one-percent increase in mortality. This would be similar to how actuaries refer to Society of Actuaries mortality tables. If you talk about a Bragg table, the 90–95 Select and Ultimate table or the 75–80 Basic table, you know what each one means.

The reason debits are important is that they help you define the protective value of blood. You want to collaborate with your underwriters. What is it that these blood profiles are doing for us as far as helping us in terms of mortality at our company? All of us presenters are really big proponents of underwriters and actuaries getting

together and talking. The work we can do together is fantastic. When speaking with underwriters, I suggest they identify the debits found in the blood profile component of a risk selection process. By identifying the debits, you're actually identifying how much mortality there is. Therefore, if we either eliminate or add blood testing to a cohort of insureds, we know what the change in mortality is going to be. So get your underwriters involved in that process. That's what they're all about.

A little more about the underwriters. When I see a blood profile, it's not a simple matter of saying, "If the cholesterol is 357 mg/dl, it gets 33.5 debits." As an underwriter, when I see a blood profile, it's telling me a story about the individual. Six of the tests on a blood profile are actually related. These are all liver function tests. There are other related tests on a blood profile. The BUN and the creatinine help tell me about kidney function. There are three tests for glucose metabolism to diagnose or find out whether or not a person does or does not have diabetes. We've already discussed cholesterol and triglycerides in a preferred risk setting. The proteins help you define whether or not a person has kidney or liver disease. When I'm in the process of doing my protective value study for the actuaries, my job is to aggregate the debits or find out what the mortality change is going to be by aggregating the debits. I'm going to run into some complicating factors. The upper limit or normal for fructosamine is 2.1, and for Glycohemoglobin it is 6.0. If both of those test results are elevated above the upper limit of normal, how do I distribute the debits? Although individually both tests would warrant debits. I'm not necessarily going to double the debits. Both of these tests say the person isn't metabolizing glucose properly. Which test will receive the mortality debits? That's a decision that has to be made. Fructosamine tells you what your average blood glucose level has been over the last three weeks. Glycohemoglobin tells you what the average blood glucose level was over the last three months. I suggest this creates the need for a dialogue to knowingly parse out the debits to the tests in such a way that everyone understands the underlying methodology.

What about debits for cholesterol or triglycerides? These are fats, and, although they are different tests, they are testing components of the same family of disorders. Which one am I going to apply the debits to? Plus, the combination is going to affect the rating and the mortality study I'm going to do for you. If only one of the tests was elevated that would not be as bad as both tests being elevated. Is the relationship of both tests being elevated additive or multiplicative, and if so, which test receives the multiplicative debits? So this gives you some insight into what the underwriters are doing. They're seeing more than debits and credits—they're seeing a living, breathing individual that they're analyzing. Chart7 shows the results of a study I performed.

I analyzed 8,500 insured lives from American United Life's direct side back in the 1990s, and I awarded debits to the different blood profile analytes. For example, if you no longer obtain the cholesterol values on your insureds, the mortality would go up by three percent. How did I do that? I just added up all the cholesterol

debits I found and divided by the number of people in the cohort. The average number of debits have been converted to the change in mortality. The one interesting component or warning, is fructosamine is way down here. and A_1C (which is an abbreviation for glycohemoglobin) is up here. it might seem like the A_1C is much more valuable than fructosamine is. That's why the communication between the underwriters and the actuaries is important. Knowing how the underwriter awarded the debits will help you understand how you want to convert these data.

There is another way to look at it. Intuitively, we all know blood profiles ought to be identifying more mortality as your population gets older. By running the raw data, the numbers seem to prove that out (Chart 8). Blood profiles don't find a lot of mortality on 15- and 20–year-olds. As you get into the 60s and 70s, there are a lot more diseases. The blood profiles are detecting a lot more. You will notice an aberration on the graph where, at age 65, the bar drops way down. What's going on? One of my favorite sayings is "the numbers are what the numbers are." This is just a presentation of 8,500 cases. There were not that many individuals that were age 65. Therefore, rather than skewing the data or smoothing it, I chose just to report it.

Rick is going to go into break-even analysis in greater detail, but I thought I might display a quick break-even graph on what I have (Chart 9). This was done a couple of years back, so the data uses the 1975-1980 Basic table. For the cost of testing, assume $65. Here are your break-even points for the protective value of blood. Rick did a similar study like this a number of years back, and we ended up with fairly similar results, even though he looked at a totally different population than I looked at.

In closing, I would like to suggest you keep track of what mortalities are under discussion. When I did this protective value of blood study, it was in the mid-1990s when people were talking about surrogate blood testing mechanisms. The discussions focused on getting rid of blood testing and instead doing urine and saliva testing. The intent of my analysis was to show what the value of the blood is separate from the protective value components you get out of saliva or urine. My analysis does not include protective values from cocaine, HIV or nicotine. You also find those analytes in saliva or urine. Much of the protective value for saliva or urine comes from these things. It is important to break down the protective value study into its component parts. What are you getting from blood and what are you getting from these other things? That was the reason I did that study.

Finally, here's a little plug for us poor reinsurers. If you do decide to go to a different testing protocol that saves money on the expense side, we in the reinsurance community don't receive any of those dollar savings. We have to look at what the change in mortality is going to be to our block. So, if you're changing requirements on any of the business you are reinsuring, we need to do this analysis ourselves to see what mortality implications are associated with our block of

business. Now I'll turn it over to Rick.

MR. BERGSTROM: The reason I'm doing this is because this is another dimension from which actuaries and underwriters get together to try to quantify the value of tests. Doug just mentioned that serum blood testing has a certain amount of value. If someone were to ask me directly, is oral fluid, formerly known as mucosal transudate, informally known as spit, more valuable than blood? The answer would be a qualified no. It's a lot cheaper than blood. There are places in the face amount spectrum where it would behoove a company to actually look closely at fine-tuning its current underwriting paradigm by age and by face amount, to take advantage of the evidence you get from each of the various fluids—blood, urine and oral—to consider whether it would be worth your effort or your cost to do this. If you ask an underwriter, what is the one most important variable in making a decision to change a traditional paradigm, do you know what the answer is going to be? It will be cost. It will not be value, but cost. Underwriting departments work on very narrow budgets and they try to squeeze what they can out of those budgets. They need to look at the cost factor, and not necessarily the value factor. Perhaps the actuary and CFO should look at that. The underwriters are starting to look at costs because they're stuck with the budgets they have.

I want to do two things. First, I chose the oral fluid because of the limited number of markers that it has in it. This is just an example of the type of analysis anyone can really do to try to determine the value of certain tests at various ages and at various face amounts. I use the word *protective value* as opposed to *cost-benefit analysis*, only because a protective value study tells you, given the assumptions that you're using, what the face amount threshold is above which it financially makes sense to test. On the other hand, a cost-benefit study says, if we want to test at $50,000, what's the return on our investment to do this? They're the same equations. It's just a matter of what is the one variable—face amount, interest rate, or discount rate—that we use.

Doug just pointed this out, too. There used to be three things, but now we have a fourth area that oral fluid can be used for. Oral fluid can be used to discover cotinine. Cotinine is the metabolite of nicotine, so this would give an indication of smoking status. There might even be some other illegal drugs, but certainly cocaine is one that could be found. HIV is another. Up until about four years ago, that was not FDA approved. It now is approved, and what actually spurred the whole oral fluid movement was the fact that they could actually test for HIV. It has very positive sensitivity values. The most recent is glycated albumin, which is a diabetic marker. So companies now have an ability to find markers for diabetics.

The real question with a protective value study is at what face amount does any particular test make fiscal sense to perform? And that's not just for oral fluid. It can be for any underwriting component, like motor vehicle records (MVRs), for example. If you can define certain parameters that you can quantify, you can actually go through the same analytical process. At what face amount does it

become cost effective, under the assumptions you choose to use, to do the testing? In other words, when does savings exceed cost? Mortality savings, very simply put, is R x S x T x PVB. R stands for prevalence. What is the prevalence of the parameter that you're looking for in the population being tested? Sensitivity (S) is rated to the ability of the test to detect that prevalence. T is a funny variable, but it's necessary. It's called the attribution factor, and it's necessary because it says to the underwriter, what is the ability of this test to be the *only* way I can find out if this person has this impairment? A good example of that is we can use oral fluid in an environment to discover smoking status. What if an applicant admits that he or she smokes? What's the value of the test? It's nothing. There's maybe a small confirmatory value, but the attribution ratio in that situation, would be zero.

If everybody who is HIV-positive knows they are and denies it, what's the value of that? About one. Okay. So it's the ability of the test to be the exclusive way to uncover the impairment. Finally, the PVB is the present value of excess mortality associated with that impairment.

The following are assumptions that I use. These are risk assumptions:

Mortality:	Unisex 2001 VBT
Lapses:	15%, 12, 10, 8
Discount rate:	8%
Sensitivity(s):	99%
Study period:	20 years

Do not go back to the home office and say Mr. Bergstrom told us this is what oral fluid is worth. This is just my approach. Nobody ever questions the approach; they question my assumptions all the time. Don't question my assumptions. If you don't like my assumptions, then I can say I don't like your tie, right? It's very simple. In this study, I'm going to use the unisex 2001 Valuation Basic Table (VBT), which just came out in 2001. It's the basis for the 2000 Commissioners Standard Ordinary (CSO), which I think is still being worked on. In any event, that's the basic table, so there are no margins built into that. It's an experience table. The lapse rate I chose to use is probably conservative. The higher the lapse rate, the less the present value. If I use five percent levels, people would question that assumption. Now I brought it up to 10 percent. I'm going to use 15 percent the first year, 12 percent the second, 10 percent the third, and eight percent for 20 years. I'm going to assume a discount rate of eight percent. I used eight percent in the protective value date because where does the money really come from for underwriters to do testing? Does it magically appear in their budget? It comes out of what's called surplus. What does surplus earn in a given company? Five, four, or whatever. It could be less in some cases. Hopefully, it is a positive number in most cases. So I chose to use eight percent. I don't think eight is an overstatement, but again, the lower the rate I use, the higher the present value, so I want to use something higher than general surplus, so I chose eight percent. Finally, just for interest and simplicity, I chose a sensitivity for each of these tests. The ability of these tests to discover the impairment, although not exclusively, is

99 percent. You don't have to use that number. You can use whatever number you wish.

Table 11 shows some real statistics. I wouldn't even argue with these. These are facts. These are taken from a million or more tests that Lab One does. It used to be the Home Office Reference Laboratory, and is now probably the laboratory that does about 80 percent of testing in North America. Table 11 is taken from their year 2000 database. This is not broken down by face amount, but they do have the ability to break these down by face amount if someone wanted to look at it like that. If someone were interested in doing a detailed study, that would be the thing to do. For example, with cotinine, you can see overall all amounts combined for these ages, roughly 20—25 percent of the individuals tested, tested positive for cotinine. That didn't necessarily mean they smoked. They might chew. They could be an occasional cigar smoker who happened to have a test the next day. These are the people who actually pop up as testing positive for cotinine, which is a metabolite of nicotine.

Table 11

Prevalence: R

Age	Cot.	Coc.	HIV	GA
25	23.3%	0.84%	0.12%	0.6%
35	23.4	0.78	0.23	1.0
45	24.2	0.95	0.25	2.1
55	20.5	0.47	0.12	4.0

R/staff/Rbergstr/OralFluidTesting 08/15/01

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One interesting thing about cotinine is that if we were to look at it by face amount, we would find that face amounts tested under $50,000 (and not many companies do that) have a number that is closer to about 35 percent. If it were $500,000 or higher, that number would be about nine percent, so there is an economic status involved with tobacco usage.

Cocaine, except in older ages, is pretty close to a little under one percent. I was surprised at that, too. HIV has come down dramatically from the mid-1980s when this was about two percent, and that is because of a couple of good reasons. Namely, people who were HIV-positive discovered that they could get a test. Maybe many of these people here do not know that they were HIV-positive. In addition, there are more women testing positive this way than men. The dynamics and the demographics changed in this regard. For glycated albumin, our diabetic marker, the attribution ratios are listed blow.

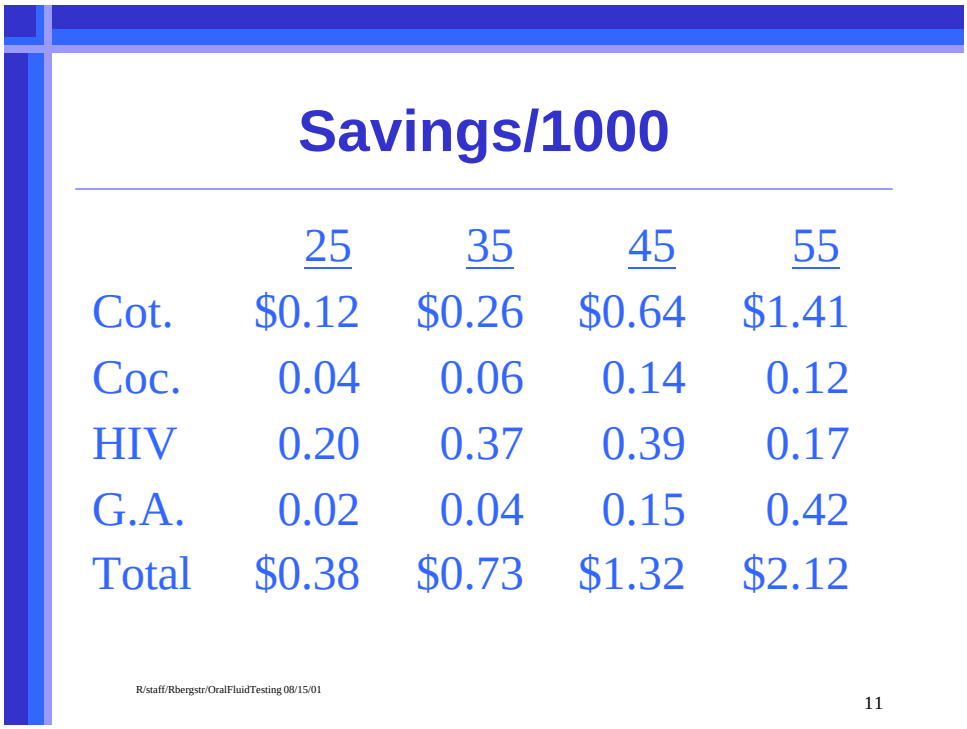
Cotinine:	8% applied to NS
Cocaine:	95%
HIV:	90%
G.A.:	90%

I'm going to just skip over these numbers. They are really just my feeling for the exclusive way of finding a test. Just accept these.

What is the sentinel effect? I didn't put that in my formula because it's another one of these funky ones that really requires some thinking. The sentinel effect happens when an applicant, for example, knows that if he or she applies for insurance and gets tested, there's a possibility that the person's impairment, like HIV for example, might be discovered. I would suggest that most people who knew they were HIV-positive would not take a blood test or a urine test or an oral fluid test if they were not going to disclose on the application that they're positive. You know what happens if they disclose on an application that they're positive? They're not going to get the insurance. About 35 percent of the people that apply, don't apply for face amounts above which they'll be tested. Or they'll go to a different company where maybe the face amount for testing is higher. Glycated albumin, as I said, is 10 percent extra, and cocaine is maybe 20 percent. I already factored cotinine in the prior numbers, so we won't go into that. The sentinel effect really does have value because it discourages people to apply if they know something. There's no cost to test if they don't apply, but at the same time, there's value because, if they did apply for a new product, you did not issue a standard policy to somebody who is a substandard risk. So there's value in the sentinel effect.

When you run the equation through all of my assumptions, you get something that looks like Table 12. For each of these ages and each of those tests, this is the value of the testing for each of these components. You can see for age 25 that the most important test is still the HIV test. It's not because it is so prevalent, but the results are so disastrous. So when you put them all together, until about age 40, that's number one. After age 40, tobacco is number one. There is certainly some element to glycated albumin. I wouldn't deny that. The cocaine is not much, but it effectively comes with the test. If you ask to strip cocaine out of your test, you'd probably save a nickel, so it's just not worth doing it.

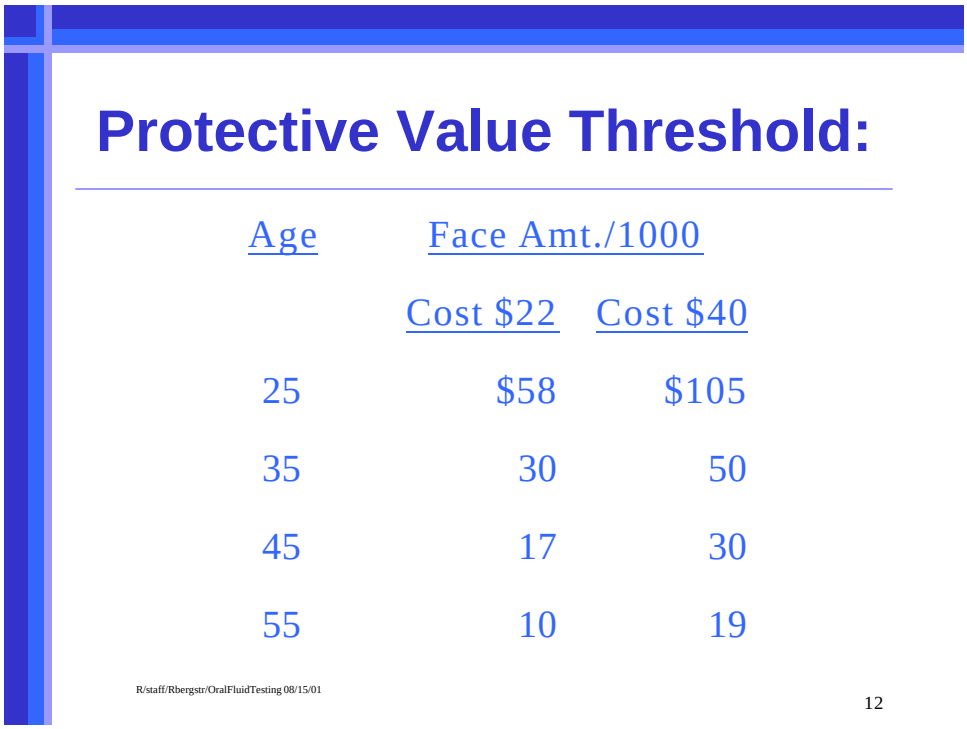
Table 12



If you look at the bottom and add all the columns up, the values per 1,000 are between $0.38 and about $2 at age 55.

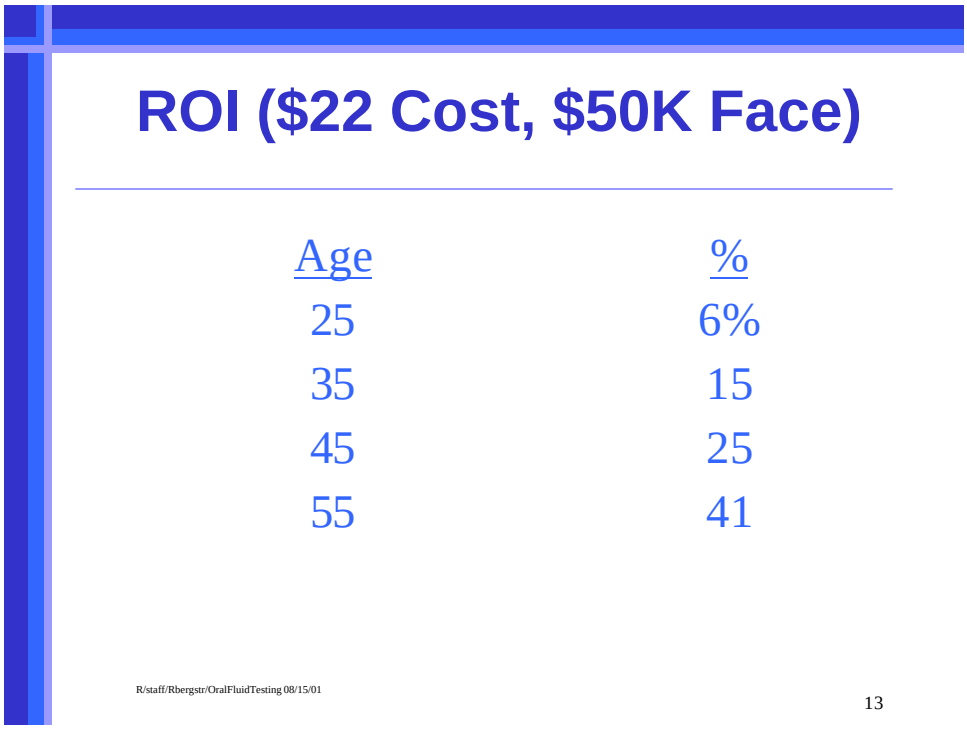
The way we come up with the protective value threshold (Table 13) is we divide the cost of the test by the savings. You don't pay an agent to do the collecting of oral fluids. You pay a paramedical something up in this range to do that. If you could do agent collection, and it costs $22 to do that, $22 divided by $0.38 is $58,000, so that's your breakeven threshold for oral fluid under that scenario. It, of course, goes down as age goes up, because you saw the value goes up as age increases. If the test costs $40, however you had it collected, the same equation follows. At $40, the test is cost effective for $100,000 at age 25.

Table 13



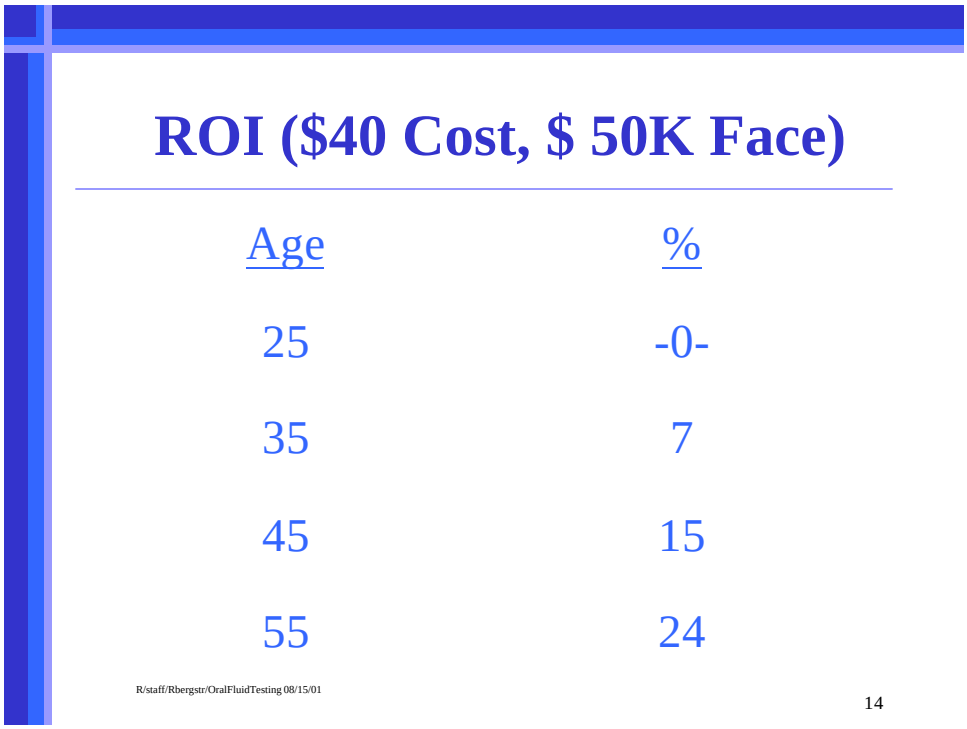
The flip side of the protective value is to do a return on investment (ROI) (Table 14). I defined my ROI as eight percent to find out a face amount. I can choose a face amount and then go back to try to find out what the ROI is, I find that age 25, at $58,000, the break-even amount is at eight percent and $50,000 is only six percent. Of course, it gets a lot larger as age increases.

Table 14



These are returns that might impact what you do to choose a test or not (Table 15). If you invest your testing dollars, these are the returns you get. That's much better than sticking to surplus, isn't it? If it costs you $40, and you want to test at $50,000, it probably doesn't do you any good to do it with oral fluid. At ages older than 30, it does. So this is the type of back-of-the-envelope analysis you need to do if you want to try to fine-tune your testing requirements for the various products that you have.

Table 15



This particular session is the first of a trilogy or a track. The other sessions are 63PD and 76IF. I will be getting into a much more comprehensive development in 63PD. One of the thoughts I'm going to leave you with, though, is going to kind of fly into the face of the way the life insurance industry, at least the actuaries, have been looking at preferred risk mortality. I'm not particularly a proponent of conservation of deaths. The algebra works, but I'm not sure the reality is there. I'll leave you with the thought that even though we have done things a certain way for ten years or more, I'm not sure we've done the best we can do. Maybe we ought to sit back and take a different look at whether it is really right, or whether it can be accomplished this way.

Chart 10 shows a normal curve that reflects 45. Let's assume that we have a distribution of the traditional standard risk class. The mean mortality of a standard class is one per 100 percent. Underwriters will find that the range of mortality in a standard class might be 50 percent of standard or it's up to 150 percent, because sometimes there are exceptions made as to at what range we'll allow risk to come into standard. Some companies go up to standard two just naturally, or Table 2, and we will accept that. Sometimes certain things aren't disclosed, and the risk is really 150, but we don't know. Think of the area under this curve as being the standard mortality class. This is where we're starting.

Let's look at a different age—age 25 (Chart 11). Does it look a little narrower to you? Does it make sense why it might look a little narrower? Age 65 is reflected in Chart 12. At older ages, it's more important to uncover the medical aspects of mortality and the impairment that leads to that mortality. Ninety percent of the people under age 30 die of nonmedical risks. We can't underwrite them out. About 85 percent of people over age 65 die of medical risks. I don't care if you use my curve or your own curve. At the young ages, it's going to be narrower, and at the older ages it's going to be wider.

I'm assuming a normal curve in this specific case just to give you an example. You don't have to choose my distribution. You can use your own. I'm going to assume that we're going to break our standard class into two pieces: preferred and residual standards. We want 65 percent of the traditional standards to be preferred, with the remaining 35 percent as the residual standard. We're going to say we'd like the standard-to-preferred mortality ratio to be 150 percent. The question is, it's 65 percent achievable at all ages. At the same time, can we achieve that mortality ratio at all ages? Many companies, if not most, still pick and choose their ratios and the percentage qualifying, irrespective of age groups. I'm not going to tell you what's right; I'm just going to tell you that's wrong.

If our preferred mortality is 65 percent eligible, and we want 150 percent differential mortality, this is what we have to come up with. So our assumption for the preferred mortality is 85 percent, and our residual standard is probably 120 percent of the traditional standard, whatever that was.

This is my pictorial representation of what our two subsets looked like (Chart 13). You cannot clinically slice this like I have done here. If you actually put 65 percent into this class, you're going to get some skewness over here. Your residuals are going to skew over here. To make it easy to understand and to visualize and to calculate, I sliced it with a knife. So some are preferred, and some are standard. This is the mean of my preferred, whatever that number is, and this is the mean mortality of my residual standard. At age 25, it looks different again doesn't it ? At age 65, it is even more different (Chart 14).

So the question I have is, can we actually do what we've been doing for the last ten years? To complicate matters, what if we have three preferred risk classes or four or five? At what point does the law of large numbers fall apart? I did the calculations. This is what I came up with. Under the normal curve approximation, the mean mortality is 85 percent of standard for preferred and 128 percent for the standard plus. At age 25, we're narrower with 90 percent for a mean. That's not 85; it's less. That's closer to the middle; therefore, we don't have as much to play with. At age 65, we're at 80 percent, so we have a little more to play with. My point is, if we're doing something beyond 80 percent or 90 percent, we can't do it. It can't be done under a normal curve distribution of deaths.

MR. DAVID WYLDE: Those last two slides were very interesting. AUL's PRiMA

mortality system has been doing that very thing for almost ten years now. We actually have a whole set of normal curves. We've actually shown, through our own data, that mortality in the standard class is normally distributed. We actually have the mean and standard deviation.

MR. BERGSTROM: Why have you been hiding it?

MR. WYLDE: I've given my talk about five or ten times in the last ten years. Doug Ingle is the co-author of the system, and he'll probably be showing you some slides from that system tomorrow, so I didn't want you to think that Rick was out there doing some brand new things. We have a system that does that. We truly do the calculus and take the weighted average of the mortality within those normal curves. You're exactly right in saying that the algebraic method is, in fact, severely flawed, because it makes two huge assumptions. One is your preferred discount, and the other is the number of people that will qualify. What you really need to do is find out how many will qualify. Mary said the fewer that qualify, the better the mortality. You're exactly right in that you just can't pick and say, "I want to design a class in which 50 percent qualify. I'll have a 32 percent mortality reduction, and I'll use the normal curve that we've shown to be correct." Actually, it's more of a gamma, but the normal is a really good approximation. You can actually show that the outbreak conservation of death is really flawed. I think you guys will probably get into that a lot at the next presentation.

MR. BERGSTROM: You can pick one, but you can't pick anything more than that. Even if you can't make an equation out of it, you can draw it. For a two-class scenario, once you pick the mean, everything else is defined for you. You cannot pick the percent to qualify and you cannot pick the ratio of standard to preferred.

FROM THE FLOOR: I have a question. Let's suppose that an insurance company comes up with a new rating criterion. If you look at the client or the customer who is actually one of the target customers, he's actually facing the intersection of all the criteria of all the major components in the market. To a great extent, the mortalities that will be faced by this company would depend not only on its rating criteria, but it will be very much dependent on the rating criteria of the other companies as well as the exact cost of the products, right? Depending on that, won't there be a movement? Is there any literature that takes this complexity into account?

MR. BERGSTROM: I'm not sure about literature, but I'll just say one thing, there's no free lunch. So whenever that happens, there will be some immediate movement to certain things. Whatever happens with new tests, through competition, people will either pick up on it or they won't. There will be a natural leveling of the playing field that way.

FROM THE FLOOR: Not specifically.

MR. BERGSTROM: You raised a good question, I'm just not sure we can give you a specific place to go to.

MR. INGLE: Let me add one thing to that. I think the paradigm of the market itself is a factor. The normal curve is the starting point for actually coming to what you think your resulting mortality is going to be. We'll get into that a little bit tomorrow. There's some migration and agent field selection, which also adjusts what your resulting mortalities are going to be. We'll talk a little bit about that in session 63PD.

MR. BERGSTROM: Doug brought up something that goes back to the Framingham studies. Obviously, as information over the years has come out from the clinical studies, some of the insurance studies and the underwriters have asked us for more information that allows them to fine-tune their underwriting process with that. It was actually HIV that allowed us to do preferred. For those of you who are old enough to remember, prior to 1985, a blood test was not performed on an individual unless he had a million dollars of coverage being offered. Within literally six to eight months, that amount dropped to $100,000. Clearly, the community was worried about the problem with HIV, but the flip side of that is that the underwriters had access to all this other stuff that they didn't have access to before. They could look at cholesterol, diabetic markers and liver enzymes, and because of the Framingham studies they were then able to move that out of a clinical environment into an insurance underwriting environment and actually make some sense out of it. The continuation of that process into the 1990s with the preferreds has allowed us to continue to do this as well.

I will say one other thing, too. I think we're getting to the point where, once we reach six risk classifications for preferreds, that might be too many. There is a point below which mortality cannot go. Some of the preferred assumptions I have seen have zero. For any one individual, it's either zero or one—there's nothing in between. But there is a baseline below which mortality simply cannot go. If you think it's 19 percent of the 1975/80 tables, I think you're kidding yourselves. However, I have seen companies do that. At a minimum, you're going to have some accidental deaths in which you will have no control in underwriting out. If we're going to add extra classes, let's not keep chopping off the bottom end. Let's go in the other direction. Does anybody else have comments?

FROM THE FLOOR: What would be the database that you were using in doing a Kaplan-Meier? You said it was population. Was it NHANES?

MS. BROESCH: NHANES, yes.

FROM THE FLOOR: Was it the first one, the second one or the third?

MS. BROESCH: I think it was the first one.

MR. BERGSTROM: Do you want to give them a 30-second explanation of NHANES?

MS. BROESCH: NHANES is a U.S. government-sponsored study that has been going on since the 1970s. There are now three NHANES—one, two, and three. One and two include mortality information. The studies are used to help understand health characteristics in our society. For example, if you go to a pediatrician's office, the height and weight for kids is based on these studies. They're used in all sorts of ways, and it's one of the studies we found that tracks data from asking questions related to all those criteria we listed. The main advantage is it has the mortality associated with the questions. What's important is to be able to track people until they die so you can have some estimates about mortality based on those characteristics.

Chart 1

34

Generic Criteria Ages 18-39

Survival Curves

The difference in mortality between the preferred nonsmoker and residual nonsmoker classes according to this data is statistically significant

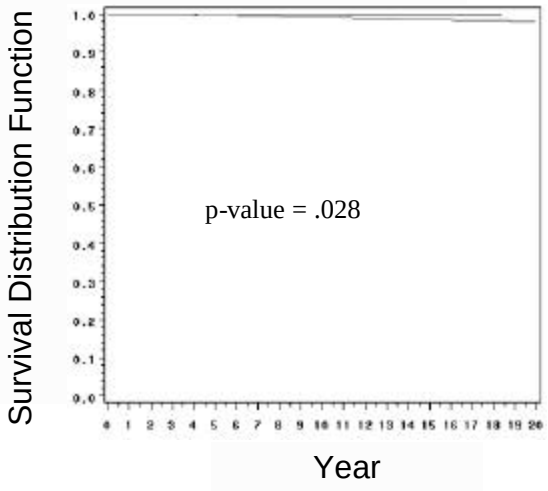


Chart 2

35

Generic Criteria Ages 40-69

Survival Curves

The difference in mortality between the preferred nonsmoker and residual nonsmoker classes according to this data is statistically NOT significant

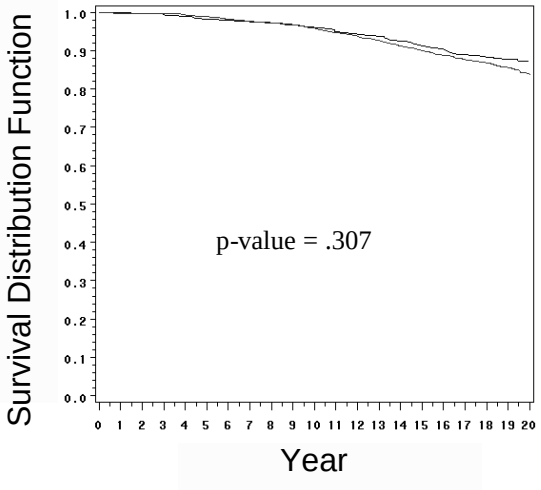


Chart 3

36

Generic Criteria Ages 70+

Survival Curves

The difference in mortality between the preferred nonsmoker and residual nonsmoker classes according to this data is statistically NOT significant

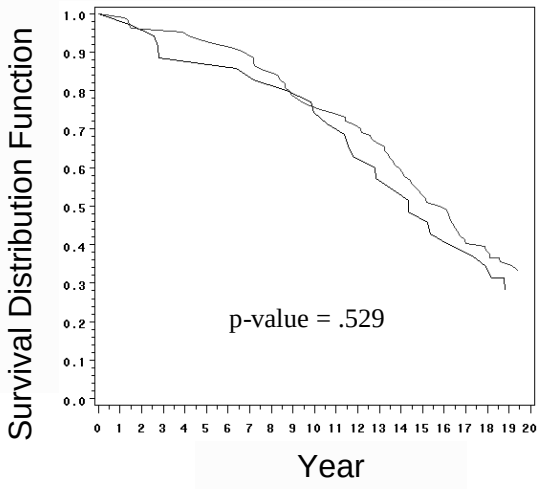


Chart 4

38

Age-specific Criteria Ages 18-39

Survival Curves

The difference in mortality between the preferred nonsmoker and residual nonsmoker classes according to this data is statistically VERY significant

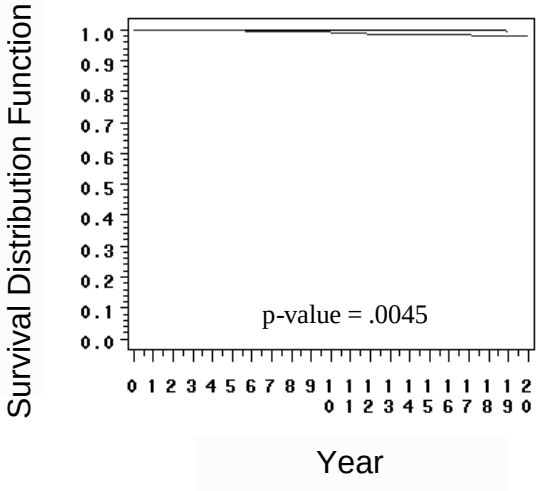


Chart 5

39

Age-specific Criteria Ages 40-69

Survival Curves

The difference in mortality between the preferred nonsmoker and residual nonsmoker classes according to this data is statistically VERY significant

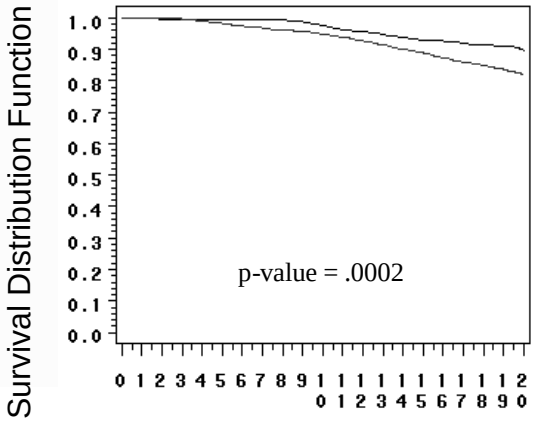


Chart 6

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Age-specific Criteria Ages 70+

Survival Curves

The difference in mortality between the preferred nonsmoker and residual nonsmoker classes according to this data is statistically VERY significant

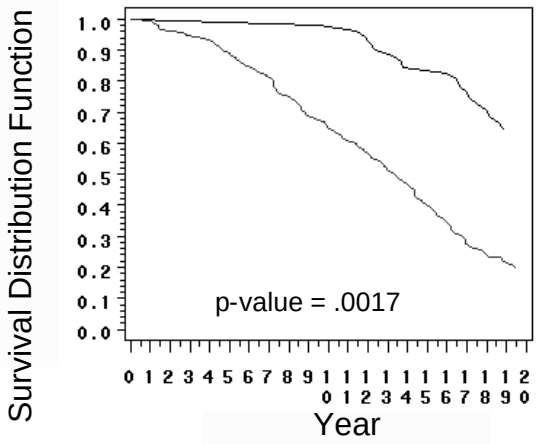

Chart 7

Mortality Attributed to Individual Tests

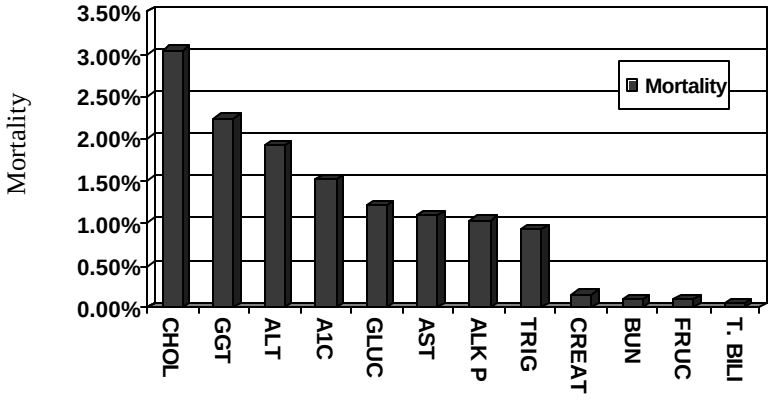

Chart 8

Percent Increase in Mortality by Quinquennial Age Band

Chart 9

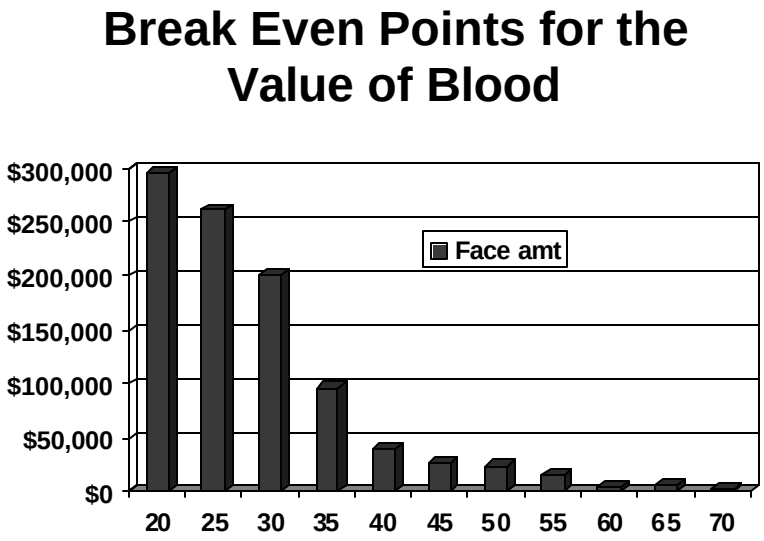

Chart 10

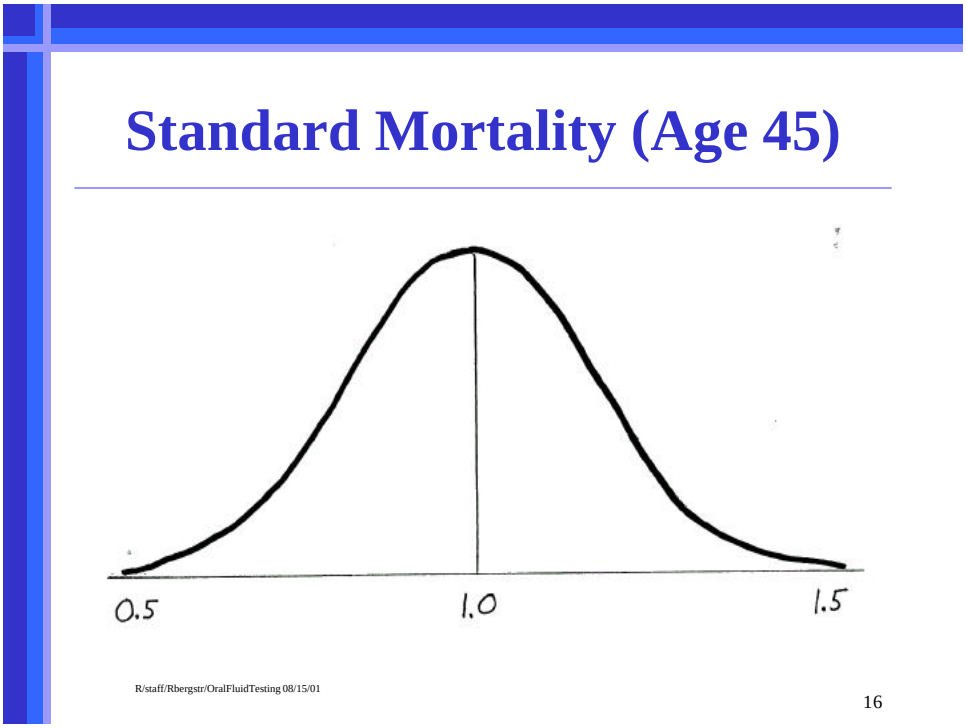

Chart 11

Standard Mortality (Age 25)

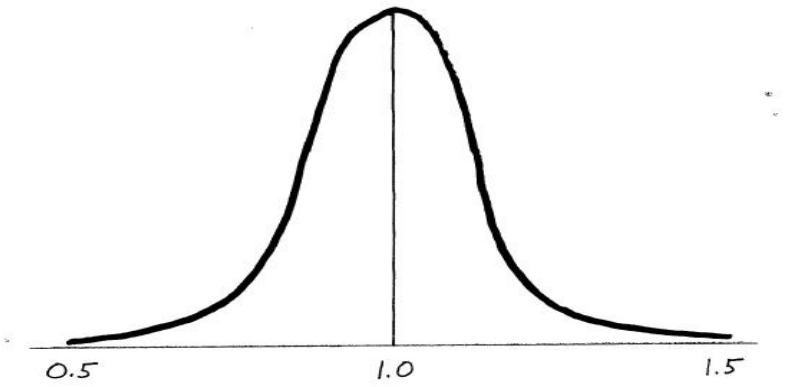

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Chart 12

Standard Mortality (Age 65)

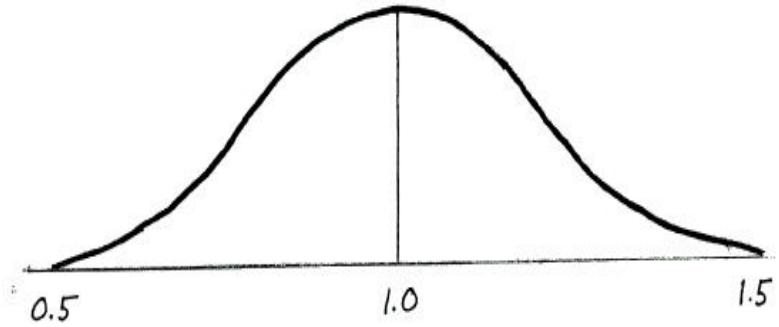

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Chart 13

PRFD/STD Mortality (65%/35%, Age 25)

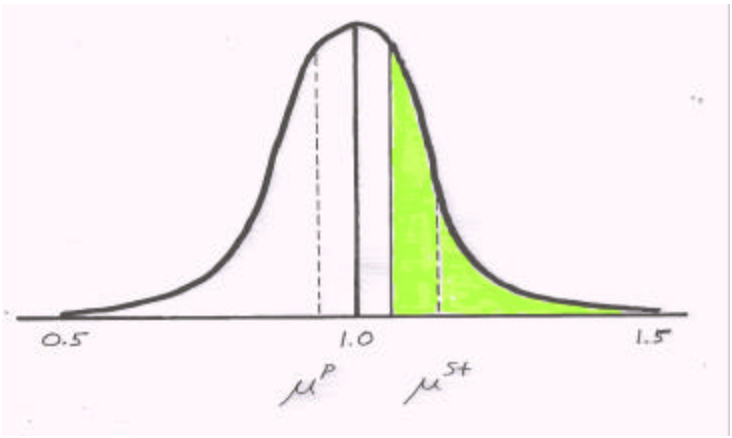

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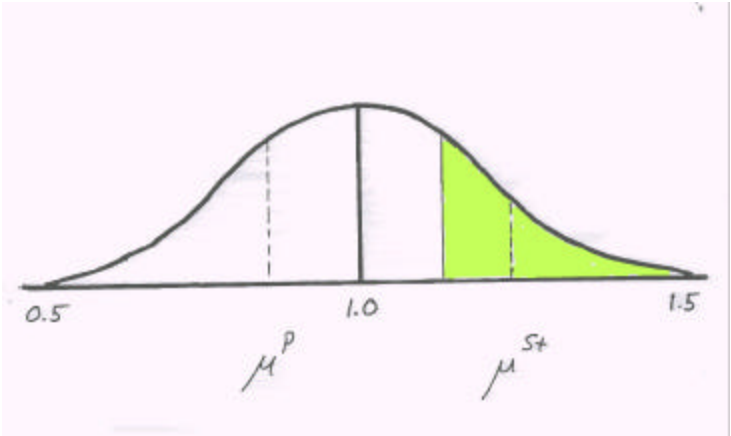
Chart 14

PRFD/STD Mortality (65%/35%, Age 65)



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