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## Session 55PD Results and Applications of the Intercompany LTC Insurance Experience Study

**Track:** Long-Term Care

**Moderator:** MARK D. NEWTON

**Panelists:** WESLEY J. DENERING  
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*Summary: While the LTC Insurance Experience Study provides useful information, not everyone understands what went into the study, the information the study actually provides or what to do with it. The panel discusses: setting objectives—long-term versus short-term objectives: what to study? The panel also discusses communicating (the most important part): preparing the report and delivering the results. Other points covered by the panel include experience studies: How do we apply the results? Comparison to other studies and reasonableness checking are also covered. Finally, the panel will address basis for company-specific pricing and the feedback loop: industry-wide peer review; contributing to future studies. At the conclusion of this session, attendees understand the information provided by the study and how to apply it in practice.*

**MR. MARK NEWTON:** Today we have two folks with us that I'm very happy to have. Kim Tillmann is a fellow member of the committee that put together the Experience Study. Whatever I don't remember, which is probably almost everything, Kim can help us with. Wes DeNering is from John Hancock. He's been their senior pricing actuary for many, many years, and Wes and I go way back. Wes is doing a huge fraction of the work on the valuation tables that you'll all begin to get exposed to today. It will be a process that will last for some time, but we wanted to get started on helping people understand where the data comes from,

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

how it's used, and what effect it will have on you as we go forward in the LTC world together.

Some of you probably are aware of the previous intercompany studies, but not everybody might be because LTC is a new world to some of the folks I know. We wanted to try to do an intercompany study like many of the other intercompany studies that the SOA does. This one would focus exclusively on LTC and insured data, as opposed to some of the data you might find in a nursing home survey or an LTC survey that's more publicly based. We wanted to set up data that was basically on insured lives.

Having said that, insured seems to mean the same thing, but within the study there are data from many companies. The underwriting is different from company to company; how it was sold is different. The plans are different. The time spans from 1984 to 1989. This is basically the lifetime, in many ways, of LTC all the way from its infancy, when almost everybody was making mistakes, to now, when we all hope we're not making any mistakes. It covers the gamut.

Another thing about the intercompany study is that I often get questions such as: "How can I use this? I'm doing this pricing thing." The intercompany study is not and never was intended to be the sole data source for your pricing objectives. You may be able to use some of it for that, but having worked on this committee for many years and understanding the limitations of the data in the survey itself, I would worry if this were your sole data source. So please don't use it that way, but it can be used as a supplement for you.

It can be used as a basis for comparison. Of course, many companies have their own private databases nowadays. There may be some holes in that. You might be able to fill some holes in your own data with data from this report. We want to look at this and compare it and contrast it to public experience because that's a different set of folks who are receiving LTC services, and it may be useful for us to understand how insured data is the same or different from public experience. So it was intended to be a basis for comparison between sets of data.

Also, internally to the data, we want to be able to understand how LTC is changing over time. It will continue to evolve, of course, especially as providers change and as technology takes a different kind of role in LTC than, perhaps, it has in the past. We want to be able to look at groups of business over different time periods, understand how LTC is evolving, and perhaps use that as a basis for projecting forward. Actuaries take different points of view about how worthwhile that is.

The report has many audiences. Actuaries, of course, use it and look at it. Regulators look at it. I've gotten some calls from providers, nursing home groups or publicly traded companies that are looking for data to supplement or to be the basis of an internal report for getting involved in the LTC market, perhaps more

than they have in the past. This is a useful source of data to them. It's not just inside the United States, although it is all U.S. data.

I have also received calls from many actuaries around the world where countries are looking at public policy around LTC, or private companies are looking at what their response should be to LTC, as it seems to have taken hold in the United States. How do they begin to think about LTC, the kind of coverage it is, about what data they should use for pricing, and about how they should approach the whole thing. We had the same kinds of questions many years ago, when we began our career in LTC, as other countries around the world are just beginning their search for how to deal with LTC. Our study is a basis for them to get started with some objective data.

Today, we'll also talk about the intercompany study as a source for industry evaluation. It has advantages, obviously. It's insured data, and it comes from many companies across the industry—the largest as well as some of the smaller ones. It won't be the sole source of data for the valuation tables, but it is a useful source, and we'll be taking advantage of that. We'll be talking about that in a lot more detail as we go through today's session.

I view the communication of the results as the most important part of this. In preparing the report, probably the piece of it that we spent the most time on was the data itself. Having worked with and asked for data from so many different companies at so many different levels of expertise in LTC, it was obvious right from the start that scrubbing the data was going to be a high priority for us. Between the committee and the Medical Information Bureau (MIB), who did most of the processing work, there are a lot of internal rules in place about cleaning up data before it even gets entered into the study. That's something that we needed to work on, and you need to be aware of, but I don't know if it affects your conclusions about it. I just want to put that out there for you and let you ponder that issue as you see fit.

Before any studies are published, there are peer reviews. There are a variety of actuaries who have long histories in the LTC industry. We finished the report and sent it to them. They make their comments, and then we fold the comments back into the report that's published. It's just not a matter of a few people on the committee writing this big report and sending it out there. It goes through a peer review process before it is published.

Over time, there's been a shift in emphasis on what was studied. In the beginning, in the first study and even the second study to some extent, all we wanted was any kind of knowledge. It didn't matter what it was; we just wanted to get something down on paper and get it out there so we could start to think about what this data looks like. In the beginning, there were certain companies that were able to provide data; most of them on a quite limited basis relative to what we asked for, and that is still true today. We have scaled back drastically the amount

of data that we ask for from companies. This is because, in many cases, it's not available at all. In other cases, available means a program or putting down what they thought was wanted, which may or may not be, and then we had to work with it from there. Therefore, we've scaled back the amount of data that we ask for. We've scaled back the amount of data that we actually use, and, obviously, that means we've scaled back some of the original hopes that we had for the study into what was available today.

As for delivering the results, the study is on the SOA Web site. It's massive. If you actually print this thing off, it's gigantic. I would not recommend that; you would be going through several toner cartridges before you get done with that part of it. Just go to the Web site, and there's a place on there called " Actuarial Library Search." Click on that, type in "intercompany study" on the search results, and you'll get the LTC intercompany study. It's quite obvious which one you want, but it's available 24/7, and you can get the whole thing or pieces of it any time you want.

Little pieces of the study are published from time to time in articles. We have sessions at meetings like this to go over it so that we can help you through what is in there and how you should use it. In addition, and this is the most important part, we get your feedback on what it is you want next. As I said, over time, it's changed its nature. It's changed its nature because you said you wanted this or that this way, and that's the basis of what we used to try to change it. Therefore, we need and we want your ideas for improvements.

As for applying the results, we covered some of this already, but I'll just go through it briefly again. We're using this in comparison with other studies. If you're working with LTC data and you want a place to do a reasonableness check or a gut check, or you want some fill-in-the-hole data, you can probably use some of this study or one or the other of the tables to fill in some gaps that you might have in your own experience or your own data. As I said before, it might be theoretically possible to use this as your primary pricing source, but I would be very careful about doing that, and I'll go through some of the reasons in a little more detail in a few minutes. Also, it's being used for industry valuation tables.

Some people have commented to me from time to time on how long it takes to get one of these reports out, which is fair. On the other hand, there's an enormous amount of time that people fill out of their own nights and weekends to get this done, and it goes through several iterations on the committee before it even gets to you. The full committee is reviewing this several times. Then once we feel it's basically right, we send it out for peer review. That's another formal process that we use to try to get this right before we publish it. All of these things take time, and it's all volunteer time. We're trying to keep the data up-to-date and get it to you as fast as we can, but please be a little patient with that. We need your user feedback. I can't say it more than that. Our ideas for what this looks like come from you. If you have suggestions on what you want to see next, then we can try to take that into account.

Let's go into the study itself for a few minutes. I covered the background already. There's a section on morbidity, which is basically an incidence section, a set of tables on incidence and a set of tables on continuance. These are all in the appendices: claim characteristics, cause of claim, a section on mortality and lapse and a new section on total terminations, which was based on feedback that we got from meetings. People said, "Well, I understand what you're saying about mortality and what you're saying about lapse, but I don't really care; just give me the total terminations and I'll work with it from there and separate those two out as I'd like to do."

It's the third study. It was published in September 2002. As I said before, it covers data from a wide variety of issue years; it includes 21 insurers and millions of exposure records and years. A lot of the data is still very new. Because the sales of LTC are heavily weighted in the mid-1990s and late 1990s, a lot of the exposure records are still very new.

Incidence is measured over several variables. We always try to do attained age and elimination period feeling like those are really central to any reasonable conclusions about what incidence rates are. You always have to separate the data at least by attained age and elimination period. Once we do it by attained age and elimination period, then we can start to add on other kinds of variables including those two, and then try to strip out and look at data over different kinds of variables. There's attained age, elimination period and then policy duration. Policy duration, I think, goes up to 15 years at this point, although there is not very much data in the 10- to 15-year grouping.

There's a section on gender. There are issue-year groups. That was another feedback item. How can we understand whether the incidence rate is changing over time? We feel like it should be getting better, and it is getting better; still we want to try to quantify that and understand how the benefit of better underwriting, more mainstream coverage and things like that affect the incidence rate.

We wanted to look at anti-selection, and so the incidence rates are looked at by benefit period. Are the incidence rates for longer benefit periods any different than those for shorter benefit periods? If so, how? Does daily benefit matter? Does somebody who buys a ton of coverage make any difference in incidence rate versus someone who buys a more modest amount of coverage? You can draw your own conclusions about the tables when you see the data there.

Then we did a set of tables based on feedback from actuaries at large around issue age. This was primarily to try to get at selection factors. I have chosen one of the tables in the study out of all the tables in the appendices here, and I think Chart 1 highlights some of the usefulness of the data, perhaps, but also some of its limitations. The pink line at the top is issue age 40 to 49 years, and it seems apparent from this that there is no selection based on underwriting for very young

people, and no value of it. If you looked at this graph, you might conclude that. You can see all the other lines. The yellow, light blue and maroon lines all seem to show that there is a value to underwriting except for the 40- to 49-year age category, where it seems like it's almost the opposite. If you just looked at this graph by itself without really thinking about where the data comes from and how the nature of the data has changed over time, you might draw the wrong conclusion.

I would say that the data has shifted over time, especially in this latest study, to being much more group-oriented than individual-oriented, as it was in the past. Since the group data is basically guaranteed issue and most of it is at the younger issue ages, you're not even looking at selection in the data here. It's basically what's happening with the group data in the early durations relative to duration 8, which is where everything is assumed to be 100 percent and on an ultimate basis. It's with those kinds of things that you need to think through some of the limitations of the study and try to understand a little more deeply what's going on in some of the graphs and tables in there.

Let me make some cautionary statements about some of the things you might see in the morbidity tables and ask you if you happen to use the data to keep these things in mind. First, different companies have submitted this data over time periods. Some of the companies that gave us data initially are no longer in the study. Some companies gave us data in the second study, but not the first or the third, and the nature of the companies and the quantity of data that they submit tends to change over time. We felt like it was inappropriate to say which companies contributed how much data in each of the studies. A lot of companies give us data only because of extreme rules on anonymity. You need to keep that in mind as you're using the data.

Second, as I just mentioned, group insurance data is taking a larger share of the overall amount of data that's in the study. If you look at incidence rates by age, then you might want to consider that the group insurance data is largely group insurance versus the individual data, which is largely underwritten. The experience is still highly underdeveloped. Forty-eight percent of the data is still in the first two years of its durations. Data has changed to be more in longer elimination periods over time. What I mean by that is, in the first study, there was a huge amount of zero-day elimination data in the study. In the second, it tended to shift to 20-day and 30-day kinds of things.

In the latest study, the shift in what's submitted to us has changed to more 90- and 100-day elimination periods. If you're looking at incidence rates without necessarily looking at the elimination periods they represent, you can see that the incidence rates appear to be declining rapidly over time, and some of that is because of a shift in the data itself from shorter elimination periods to longer, meaning more 90-day and fewer zero-day periods than there used to be. Some of it is because the average age of the data has been less. There has been a shift from 60 years old on the average in the first study down to something much smaller in

this latest study. Elimination period is shifting over time, and issue ages are shifting over time.

That's it for general comments. Let me welcome Kim Tillmann, who can take you through some of the claim and lapse mortality part of the study.

**MS. KIM TILLMANN:** This is only the second time I've been a speaker at one of these meetings. The first time was several years ago, and my topic was state regulation of LTC insurance. Dawn is laughing because she was in my panel. I had all this material and I thought, "Well, it's going to be really easy. I'll just watch my watch and I'll just skip over some if I start taking my time." Of course, that's easier said than done. I ended up using all my time plus a good chunk of Dawn's time. I'm not going to do that today. I learned my lesson.

I think my role on this panel is to give you just a little more information on the Experience Study. I'm going to give you a few tidbits of information from the different sections in hope that it will whet your appetite to go out to the Web site and dig into the study further.

The section on claim characteristics looks at the data in the claims a few different ways. It tells things like average age at claim, some gender split, elimination period splits, benefit periods, length of stay and all sorts of different interesting statistics. There are a lot of claims in the study. There have been 3,000 to 5,000 incurred each year since almost the beginning. The average age at this study in claims was in the upper 70s. I would expect that we would see that going up as time goes on. I don't think we have even many people with attained age much in their 80s and 90s, so I would think this is another thing that will change as time goes on.

As Mark pointed out, the whole product is still pretty young. You can see that 75 percent of the claims in their database are less than 1 year old. When we start looking at lengths of stay and continuance, maybe we aren't seeing a lot of that tail yet. The average nursing home claim is just over one year. The average home-care claim is just under one year. Those are a lot shorter than that famous 2.5 years of nursing home that you see quoted in a lot of places.

The cause of claim looks at the diagnosis categories. It uses the codes for the different diagnoses, and then they're categorized in different ways. The leading causes of nursing home claims have been Alzheimer's disease, injury and stroke. The longest claims have been Alzheimer's disease and mental/nervous-type claims. The leading causes of home-care claims are Alzheimer's disease, injury again and cancer, and the longest home-care claims are nervous system and Alzheimer's disease. I think this section might be particularly interesting for underwriters to look at. It emphasizes the importance of underwriting for cognitive impairments, as these are the biggest, most expensive and longest-lasting claims. This section also gives some information on how the causes have been changing over time. It does some splits by age and gender, which also are kind of interesting.

The last three sections are on persistency, mortality lapse and then looking at them together. We looked at the mortality by itself. It was dramatically lower than any of the industry tables that you might see commonly used in pricing. On top of that, it seemed to be improving over time, although in this last study, when we separated by exposure period, it seemed to be flattening out a little. We see an underwriting selection in the mortality as well, and there is information on what might be some appropriate factors in this study. The disabled lives mortality was significantly higher than active lives. I think in this last study it was 17 times as much, which was fairly dramatic.

We looked at it by the different underwriting types. There was guaranteed issue, which was mostly the group business, simplified issue and fully underwritten. It varied in an interesting way. Actually, the guaranteed issue as far as mortality went was much more similar to the fully underwritten than to the simplified underwritten. That might bring some interesting thoughts or trigger some more studies of people who are using the simplified underwriting and look to some of the things that are inherent in the group business that guaranteed issue would hit.

There was a section on voluntary lapse. Lapse rates are a lot lower, as everyone knows, than anyone expected, and they seem to be going down over time. We saw a selection lapse—selection or anti-selection you might call it. People who bought the higher benefits or unlimited benefit period and some of the increasing benefit things actually had lower lapse rates than average. Not surprisingly, the lapses tended to grow in the premium payment data, and I did some charts looking at that.

The study showed, as you would expect, that the lapses went down over the first few durations, and then after a time, they started to go up a little bit. Looking at that data, we got some feedback from studies. Looking at how low the mortality rates were, we thought, "Hmm! I wonder if maybe some of these lapse rates are really deaths; that people have just coded in the wrong bucket or they didn't really know whether they died or just left." Therefore, we did some further digging. We added this last section that looked at total terminations, and we did a little further digging and saw that it's pretty clear that that is the case. There are likely quite a few deaths that are being counted in the lapse section. Of course, there's no death benefit, so a lot of times there's no reason for a company to keep track of who dies and who lapses.

We've gotten some ideas and would welcome any others about how to try to get a handle on this. For this first study, we did some of the same comparisons that we had done in the mortality section and in the lapse section to get a handle on the total termination. I think this is something that would be a good idea for pricing actuaries to look at as they go, because the total number of people who are leaving the population is what really matters, rather than how many are deaths and how many are lapses, unless you get into the nonforfeiture benefits.



As Mark mentioned, this study is available on the Web site, I found it under the LTC Section, so that might be another way to get there.

**MR. WESLEY DENERING:** Kim talked about the data. I'm on the subcommittee of the LTC Valuation Task Force that is charged with putting together the intercompany data into base tables and taking that data and seeing what we can do as far as anything else that might be useful for valuation. I'll go through the goals for the basic tables, the initial directions that we took with that data from the Experience Committee, and how we wound up using regression. I'll talk a bit about some regression modeling through the simple example. I'll spend a fair amount of time on that since, up until about two or three weeks ago, I didn't think we were going to have any data to present. Fortunately, the MIB came through with a pretty good amount of data for us. I'll also be talking about the preliminary nursing home incidence results.

The goals we had were to try to simplify everything that the Experience Committee had into a simple set of nursing home and home-health-care baseline tables that varied by key drivers. We also wanted to have other factors that would allow easy modification away from the baseline tables for a wide range of the demographic and product features. Also, we would want to do the same for the continuance and for the salvage, which is the difference between the actual charges that are in maximum daily benefit that the companies have. We're not there yet. We're getting pretty close. We have quite a bit of data and results on the incidence side. We still have a long way to go on the continuance side.

Among the first steps we took, we wanted to follow the Experience Committee's lead and extend these to create smoothed and consolidated tables. Early on, though, we realized we would need the original data files so that we understood whether we were getting credible results or not. Mark alluded to quite a bit of scrubbing that the Experience Committee did. We found that there was still more that we needed to go back to and clean up and understand better. We identified all the variables that we could look at, limited these to key variables, grouped the variables and then tried to build a limited set of tables. One limitation of the data is that only MIB has access to the company codes, so with our data set, we couldn't look at any differentials by company. That will turn out to be important later on.

We thought that we could group the data and maybe boil it down to about 20 tables, all varying by age and earned premium. However, taking this approach ignores trends in the data and interactions of other variables, which turned out to be critical.

Chart 2 shows the first-year LTC incidence rates by calendar year of issue. Not knowing anything else, you might say, "Well, it looks like morbidity has been improving dramatically by year of issue," and "Well, we're doing a much better job underwriting for calendar year of issue. It solved morbidity improvements. There's

some validity on the underlying population statistics." However, as Mark alluded to, the average elimination period has been going up steadily by calendar year of issue, as shown in Chart 3, and this is important in the incidence rate because, in this study, the incurral date is defined as the first paid service after the elimination period. It's not the incurral date that's the date for service eligible for benefits, so the longer the elimination period, the less probability that somebody will claim.

He also alluded to the fact that the average issue age has been coming down quite dramatically. The average issue age back in 1985 was about 67 years. It's come down to about 50 years by 1999. Again, I think by 1999 about 30 percent of the business is group business. That's in the example. You can take those two pieces of information and adjust the data for those. You can see in Chart 4 that most of that improvement disappears.

However, how do you get to those improvements? I assumed there was a relationship of about a 16-percent increase per year for year of issue, and I also made a similar adjustment for the elimination period. However, that's not a particularly good approach. We're supposed to be using the data to suggest the relationships, not to make assumptions. If we had to, we could do that. We could bring in our external data to try to smooth the data, but assumptions should really be avoided.

We needed to consider the variables and their interactions to build a model for LTC usage. We looked at what tools were available to do that, and we settled on regression models. We started with least squares and ended up with maximum likelihood, and also considered additive and multiplicative models.

First, I'll go through an example of one the early models we looked at very briefly. Table 1 shows a model where the least squares model is setting your incidence equal to a function of product characteristics and demographics. For instance, incidence might be an additive model where the  $X$  divides the product characteristics. This model is a poor choice. If you have 100 units of exposure in one claim, it's treated exactly the same as 10,000 units of exposure in 100 claims. That can be overcome using weighted least squares, but we went in a different direction.

Table 1

### **Least Squares Model #1**

- Incidence = F(product characteristics, demographics)
- Say Incidence =  $B_0 + S_{Bi} * X_i$  where  $X_i$ 's are product characteristics
- Not a good choice.  $1/100 = 100/10000$ . I.e., all incidences are treated equally
- Can be overcome with weighted least squares methods, but chose not to use this.

The next model we considered was a function of exposure (Table 2). Even product characteristics and demographics fit the claims. It has the advantages that it naturally weights on exposure volume, and you can group the data or leave it alone as far as for other tools that can be used later on. As far as what function we use, a multiplicative model seemed best. For instance, the preferred is probably best treated as 0.8 times your standard category, that sort of a relationship. Here's the model that we started with: the exposure times the constant, times one plus an indicator. We're trying to solve for the betas here, and the  $x_i$ 's are all product characteristics.

Table 2

**Least Squares Model #2**

- $F(\text{Exposure}(\text{product characteristics, demographics})) = \text{Claims}$
- Naturally weights on exposure volume
- Data can be grouped or left on a per-policyholder basis
- Multiplicative model seems best

One very powerful tool in regression is the use of dummy variables. For instance, if we had preferred standard and substandard in these categories, if we picked standard as a baseline and then had movements away from that baseline, the preferred would be treated as movement away from it, so we would get an indicator of one. Then the second variable substandard would be created, which would be a movement away from the baseline of the standard, and then it would get a one.

As a multiplicative model, this is not easy to solve. The usual practice is to take the log of both sides, and then you can use linear algebra, and it becomes fairly simple, as shown in Table 3. The problem with that is that the claims bucket is often zero, so we were forced to use nonlinear numerical methods to solve this.

Table 3

**Least Squares Model #2**

- $\text{Exposure (i)} * b_0 * (1 + b_1 x_1) * (1 + b_2 x_2) * \dots = \text{Claims(i)}$ . Solve for  $b_i$ 's, where  $x_i$ 's are the product characteristics
- Product characteristics were converted into indicator variables (0s are 1s) with one characteristic treated as the baseline
- Usual transformation is to take Ln of both sides and use linear regression. Claims(i) is often zero, so non-linear numerical methods were required to solve.
- Finding  $b$ 's is somewhat complex, finding std errors of  $b$ 's is very complex

To make this a little clearer, I'll go through the example. Here we have two variables: age and risk class. The age buckets are 60, 70 and 80 years; the risk classes are preferred, standard and substandard. We have an underlying population base for which we know that the standard incidence rate is 0.40 percent for the population aged 60 years; preferred is 80 percent of standard; and substandard is 200 percent of standard. Say that we have a relationship by age that each age is 16 percent greater than the last age, so that age 70 years is 4.41 times age 60 years, and age 80 years is 19.46 times age 60 years. I then created some reasonable exposure for these variables and groupings and created claims stochastic or even used the regression models to try to solve for this.

Table 4 shows the example data that I created. I'll spend a quick second on that. If we took that data and just said, "We're just going to group the data together and see what comes out," the top three lines in Chart 5 are the groupings by age, and the bottom three lines are the groupings by risk class. You can see over to the far right that the age results relative to the underlying population statistics come out not too bad, but when you look at the preferred, standard and substandard, they are very far off, and that is due to the mix of age and substandard. Where there's a shift in the mix of business, there is more substandard at the oldest ages. We're trying to sort out that interaction, so grouping the data directly is not a recommended way to go.

Table 4

Example Data

Population Incidence	Age	Risk Class 1=P, 2=std, 3=substd	Exposure	Stochastic Sample Claims	Sample Incidence
0.32%	60	1	36,000	104	0.29%
1.41%	70	1	30,000	446	1.49%
6.23%	80	1	3,000	188	6.27%
0.40%	60	2	60,000	237	0.40%
1.76%	70	2	100,000	2,339	7.80%
7.78%	80	2	30,000	2,339	7.80%
0.80%	60	3	2,000	66	0.00%
3.53%	70	3	2,000	66	3.30%
15.57%	80	3	1,500	246	16.40%

Let's turn to Least Squares Model 1 and see how that model does. Here we have an additive model of age and risk class and sets to solve for the incidence, and does it work? Well, the  $R^2$  measures how much of the variability has been explained. It's 75 percent. That might seem not too bad. The  $t$  statistics are marginally significant, but when you look at the actual fit at the far right of Table 5, you can see that sample incidence rate at the far left shows a population incidence rate, and then the regression-fitted values. They are quite far off and, in fact, produce negative probabilities, so that is not a good fit.

Table 5

**Fitted Regression Based on Model 1**

Population Incidence	Age	Risk Class 1=P, 2=std, 3=substd	Exposure	Stochastic Sample Claims	Sample Incidence	Regression Fitted Values
0.32%	60	1	36,000	104	0.29%	-2.72%
1.41%	70	1	30,000	446	1.49%	2.24%
6.23%	80	1	3,000	188	6.27%	7.21%
0.40%	60	2	60,000	237	0.40%	-0.78%
1.76%	70	2	100,000	1,750	1.75%	4.19%
7.78%	80	2	30,000	2,339	7.80%	9.15%
0.80%	60	3	100	0	0.00%	1.17%
3.53%	70	3	2,000	66	3.30%	6.13%
15.57%	80	3	1,500	246	16.40%	11.09%

What went wrong? First of all, the linear model was used when a multiplicative model was more appropriate. This model doesn't confine values between zero and one for probabilities, and it was a nonweighted regression.

Moving on to Model 2 in Table 6, I took a further step and converted everything to dummy variables. I chose age 60 years and standard to be the baseline values. Any characteristic is moving away from those baseline values. The X1, X2, X3 and X4 indicate a movement away from that baseline, so they are all zeroes. That says that you have an age 60 years, standard life. Here's the fit of the model.

Table 6

**Least Squares Model 2**

- Let age 60 and Standard be the baseline (0 values)
- Let each characteristic be a movement away from the baseline (1 values)
- Model is  $claims(i) = Exposure(i) * B0 * (1 + B1 * X1) * (1 + B2 * X2) * (1 + B3 * X3) * (1 + B4 * X4)$   
 where  
 X1 = 1 if Age 70, else is 0;  
 X2 = 1 if Age 80, else is 0;  
 X3 is 1 if preferred, else is 0; and  
 X4 is 1 if substd, else is 0

In the nonlinear regression model, you can see that it produces a baseline incidence of 0.38 versus 0.4 percent for the base. The preferred and substandard relationships are pretty good, and the age relationships are pretty good. The  $R^2$  value is almost 100 percent, so it does a very good job of explaining the data.

How does it fit to the actual data? At the far right in Table 7, you can see the fitted values compared to the far left with the population incidence rates. At the very far right is the ratio of the underlying population incidence, or the fitted values divided by the underlying population value. Therefore, you can see that the fit is quite good.

Table 7

**More Model 2 Results**

Pop'n Incidence	Age	Risk Class	Exposure	Sample Incidence	Model 1 Fitted Values	Model 2 Fitted Values	Model 2/ Population
0.32%	60	Preferred	36,000	0.29%	-2.72%	0.32%	98.9%
1.41%	70	Preferred	30,000	1.49%	2.24%	1.45%	103.2%
6.23%	80	Preferred	3,000	6.27%	7.21%	6.48%	104.0%
0.40%	60	Std	60,000	0.40%	-0.78%	0.38%	95.1%
1.76%	70	Std	100,000	1.75%	4.19%	1.75%	99.4%
7.78%	80	Std	30,000	7.80%	9.15%	7.79%	100.1%
0.80%	60	Substd	100	0.00%	1.17%	0.78%	98.1%
3.53%	70	Substd	2,000	3.30%	6.13%	3.61%	102.2%
15.57%	80	Substd	1,500	16.40%	11.09%	16.06%	103.1%

What else is there to look at? One thing that I should say is that the model is not particularly sensitive to shifts or the mix across different variables. In other words, if we tripled the amount of preferred business, you would still largely get the same answers, whereas if you did the original groupings of the data, it would cause quite a shift in your answers. This model can also handle interactions quite well. In other words, if we felt that high ages of substandard wasn't just a product of the two factors but instead was maybe much more or much less, you could handle that through interaction terms. You could just multiply the two indicator variables together.

The model fit looks pretty good, but how reasonable are the betas? To be able to answer that question, you need the standard areas of those betas. To do this, I talked to a friend of mine that knows quite a bit about it. He said that you need to form localized quadratics on the model surface itself, and don't even bother trying.

The hazard rate is the key thing that needs to be focused on here. It's the conditional density of failure at time T and survival to time T. This model is going to

solve for hazard rates rather than probability, so we need to take an additional step of converting the hazard rates to probabilities. If you pick a baseline form for that hazard rate, say, a constant lambda, then you find your probabilities as one minus Z to the minus lambda T.

Table 8 shows the proportional hazard rate regression. This tool is used very extensively in medical research where they're trying to test a control group versus some test group with a particular disease or a treatment and so on. I'm using it here as a one-year survivorship against the risk of a nursing home claim. For the function that we're maximizing, the first part of the function is the probability of someone surviving to time t times the probability of the hazard of an event occurring. That's the first part of that.

Table 8

**Proportional Hazard Rate Regression**

- Commonly used in medical research for testing survivorship of controls vs. some test group
- Used here as one-year survivorship against risk of NH claim
- Maximize  $L = \prod_{i=1}^n h(t_i) S(t_i)^{d_i} * S(t_i)^{(1-d_i)}$ ,  
 where  $d_i = 1$  if claim,  $0$  if not  
 (note  $S(t_i) * h(t_i) = t p_x * \mu_{x+t}$  in actuarial notation) L  
 $= \prod_{i=1}^n h(t_i)^{d_i} * S(t_i)$

Let  $h(t_i) = h_0(t) * F$  and  $F = e^{(B_1 * X_1 + B_2 * X_2 + \dots)}$   
 $L = \prod_{i=1}^n (h_0(t_i) * F)^{d_i} * S(t_i)^{1-d_i}$  Solve for the values of  $h_0(t)$  and B's such that L is maximized  
 Note that F functions like the  $(1 + b_i x_i)$ s in regression model 2

The second part is if you don't get a claim, then it's just the survivorship. That simplifies down to the hazard rate times your raise to your indicator of zero or one times the survivorship function. The important thing on this tool is that the hazard rate can be separated into a baseline hazard rate  $H_0(t)$  times a function. That function is e to the beta1 times X1. Now we're back to the model that we had before where the beta1 is what you're trying to solve for and the X1 is an indicator for your particular characteristic. We want to solve for the  $h_0(t)$  and the betas.

I would have liked to stop here, but the SAS tool doesn't seem to work very well with this, so we had to go on to a Cox regression. This takes us one step further and takes a ratio of a likelihood function and is then able to eliminate the  $h_0(t)$  from this equation. It's called a semi-parametric method, because the baseline has a rate that's unspecified, which meant we had to go back. We wanted that. We really need that baseline hazard rate function, so we had to go back and solve for it, but that's not a big deal; it just added an extra step.



Now, under the intercompany data, there are actually about 40 different variables that we could look at. Many of them have problems in that, as Mark alluded to, companies didn't fill out a lot of their fields. Many of them were just optional fields that companies didn't have to fill out, so the data quality is not very good. You could eliminate a lot of variables just because there wasn't meaningful data to look at.

We also had problems with hardware limitations. Both our company and MIB have SAS only available on a PC level, but we did consider attained age, underwriting type, risk class and a whole slew of other things you can see there.

We next took each variable and grouped them to simplify the analysis and increase the statistical credibility. We had attained ages within the sample ranging from zero to 106 years. I'm not sure what's going on with LTC policies under age 14 years, but there are only about 20 of them. Where there were very small amounts of data, we didn't worry about it too much and just included it. We found that, through some preliminary work, incidence rates don't change very much below age 60 years, so we grouped everything below age 60 together, and then used five-year bandings up to age 91 years plus. We also needed to choose a baseline to be able to use the Cox regression tool, and that baseline function was ages 71 to 75 years for underwriting, duration 1. The middle-issue year grouping was females, benefit periods 1 through 7. I think that actually should be 60-day plus, a greater than 60-day elimination period, \$1 through \$150 of daily coverage, LTC type of coverage as opposed to nursing-home care only and home health care only, the standard risk class and the unknown marital status. That was because that was the biggest grouping. About 85 percent of the policies in the sample do not have marital status coded. It was only recently that that people have been coding marital status. Finally there is company T.

Table 9 shows the results coming out of the model. The guaranteed issue business is coming out. The important thing here is the hazard ratio. That indicates that guaranteed issue business is coming out about 39 percent, the 1.387. That's the multiplier times the baseline hazard, which is fully underwritten. It appears that guaranteed issue has a slightly worse experience than other business.

Table 9

### **Intercompany Data Groupings and Baseline**

- Each variable was grouped to simplify analysis and increase statistical credibility.
- For example, attained age ranges from 0 to age 106. These were grouped as  $\leq$ age 60, 61-65, 66-70, 71-75, 76-80, 81-85, 86-90, and 91+
- Baseline chosen was: Age 71-75, full underwriting, duration 1, Issue yrs 90-93, Female, 1-7 year Benefit Period, 100 day+ Elimination Period, \$1-150

daily coverage, LTC type of coverage, standard risk, unknown marital status, and company T.

The other underwriting category is just the other grouping we did. It includes simplified underwriting, unknown underwriting and other. Simplified underwriting we chose to include here, as 97 percent of the simplified underwriting group was before 1993. There's very little coding after 1993 or 1994, so we felt it wasn't a critical thing to look at.

For the durational results, the baseline again is duration 1, so these are movements away from the baseline. Durations 2 and 3 are about 42 percent higher than duration 1. From this information, durations 2 and 3, 4 and 5, 6, 7 and 8 and 9 plus, you can get an idea of the selection factors for the overall sample. You can see that with durations 6, 7 and 8 going to 9 plus, the selection appears to be wearing off, but based on this data, it may be peaking out at 1.8 times the duration 1 experience. By age, the baseline here is, again, age 71 to 75 years. You can see that there is an exponential form for the by-age results, and it gives a pretty good indication that, as we expected, LTC has a very steep slope upwards for nursing-home incidence.

Things get a little stranger. Baseline year of issue was 1990 through 1993. Years 1984 through 1989 were about 5 percent higher, but years 1994 plus were only 22 percent of the baseline. We have spent quite a bit of time talking about this, and we will continue to talk about what to do with this. My best guess on this one is that we've done, as an industry, a much better job underwriting in more current years, so that is probably an indication of an effect of selection more than anything else. We may need to consider deeper selection factors, but it's not clear exactly what this means.

I think male versus female has been alluded to in the Experience Committee's work, but basically we're finding no difference whatsoever between male and female morbidity. By benefit period, again, the grouping is one through seven years, so a benefit period of less than one year is actually a strange grouping of zero if the benefit period wasn't coded. It's not clear what that means; maybe it's medical necessity policies. The data on that one appears to be pretty old data, but it's not very many policies. I think it's about 100,000 policies.

The results for benefit periods of greater than seven years, which is essentially lifetime coverage, came out a little bit lower than the baseline, which was also another puzzling result. We expected that lifetime coverage would have worse results than years 1 through 7; however, it may just be that companies are doing a better job underwriting as a whole on the lifetime coverage, and maybe that is real. It is something we're probably going to need to go back to the data and look at. This also doesn't apply, just because the benefit period incidence rate looks good on lifetime, but there is the continuance. Certainly, we could see very closely also in the continuance by benefit period, but that remains to be determined. We haven't

looked at continuance at all. Mark, have you or the Experience Committee ever looked at the continuance by benefit period?

**MR. NEWTON:** No.

**MR. DENERING:** Moving on to the elimination periods, the baseline elimination period was 60 days plus, or greater than 60 days. These results are actually pretty reasonable. We have less than 20-day elimination period, actually mostly zero and seven days, and I think the average comes out at about three days. Net experience is roughly 2.3 times the baseline; 60 days plus really averages out to about a 90-day elimination period. This doesn't mean that rates should be 2.3 times higher. This just says that the attachment point on the continuance curve is 2.3 compared down to, say, a 90-day elimination period, so it's just that area under that curve that you would be looking at.

Coverage equals zero. That was another strange category. I think there were about 100,000 policies. You can see from the *P* value that it's not statistically significant, and I think it was so we just have an issue of what to do with that. Most likely, I think we can roll it in with everything else, since it's not a lot of coverage. You either need to throw it out or roll it in with other data, but every time we throw out 100,000 here, 100,000 there, we're down to a pretty small sample, so we need to keep as much in as we can.

The next category is coverage created on \$150 a day. We have to go back and look at that, but a factor of 0.082 is not clear. There isn't a whole lot of data over \$150 a day in the intercompany sample, so it may be just the results of one company that sold a lot of coverage. I'm not sure what's going on there.

Nursing-home-only coverage also is another one we're going to have to go back and look at. It doesn't make any sense to me that the nursing-home-only coverage is only 27 percent of LTC coverage.

The reason why we went back to MIB is because we wanted to be able to look at things by company to the extent that we could be allowed to have that data. Secondly, we found that some of the results were coming out very strangely the first time around. Preferred risk came out 154 percent of standard the first time we ran the models, and there was speculation that maybe the reason was because we had some companies in the study that sold a lot of preferred business and didn't do a very good job underwriting that preferred business. If you don't have the company indicator in there, in the study, then it's going to show up in the preferred risk class. It appears that may have been the right answer because once we added company code to the study, the preferred and the substandard classes came out very good, with preferred coming out at 57 percent of standard and substandard coming out at 192 percent of standard.

The next categories, married and not married, also came out rather oddly. The married category was no surprise. Again, the baseline here is unknown class, and having the married indicator of 47 percent of unknown seems a little too good. Other information that I've seen is it's usually maybe 50 to 60 percent of unmarried, and the unknown category is going to be a mix of married and unmarried. That is probably not believable, but the really big surprise was that the not-married group is better than the mix of married and unmarried. I think what's going on here is we have 85 percent that are unknown, 14 percent that are married and 1 percent that are coded as not married in the sample. So if we have 14:1 as the ratio of coded married to not married, that would seem to indicate that companies are selling 14 policies to married people for every one that's not married, and I don't believe that. I think that's another area that we have data cleanup issues there that we have to go forward with.

Regarding the hazard rates by company, there are 20 companies in the sample and, by luck, the baseline company turned out to be right at the median. The baseline company and company J formed a median, and this gives, I think, very valuable information for determining what kind of loads we might need for a valuation table. We're still trying to sort out exactly how we can use this information. Certainly, just taking an average of all these hazard ratios, which comes out to about 1.2, and then taking the standard deviation around that, which if we say that we want to capture one standard deviation of risk for a valuation table, would put the table at about 2.0. I think that's way too high and that we have some more work to do. I think, for one thing, if you have problems with statistical credibility with any of these company results, then we definitely have to take that into consideration and sort that out.

From here, we have a lot of data. In terms of movements away from baseline hazard, how do we take that and turn that into a table? The first step I would take is to take our hazard ratios that we have by duration and renormalize those so that we're looking at an ultimate point in time. I divided everything by 1.764, so we have a first-year selection factor of 0.57 for all of the intercompany data. Again, with that calendar year of duration, one of the first things we're going to do is take this data back apart and add in interactive terms by calendar year and by duration so that we can directly address whether or not the selection varies by more current business. Of course, the problem with that is that if you have a policy that was issued two years ago, you're not going to have any comparison for what the ultimate level is, so I think it's going to be difficult to sort that out.

This gives us selection factors. Chart 6 shows the by-age hazard ratios. One thing we did also get is the baseline hazard, which is 0.44 percent, and we can multiply the hazard ratio times the baseline hazard, but these are all, again, relative to a baseline function. The baseline function, again, is duration 1. If we multiply the first two columns, everything is expressed in terms of the first duration. If we consider duration 9 plus the ultimate level, then multiply that, and the very last column would give us the hazard rates by age and at the ultimate duration. From there, we

need to fit a curve to this and we'd have all the ages in between. We'd also have to extrapolate beyond age 91 years and for ages younger than 60 years.

Again, I should stress that this is relative to a baseline, so again, this is still only in terms of the baseline company. If it happens that that falls out of median, we have to have some further discussions on exactly where we think this should be for just a base table, whether it should be at the median or mean. If we use the mean, for any company that tended to dominate the study, if they had a lot of exposure, we're going to wind up with overweighing toward that company. It may actually make sense to use the median.

For some of the next steps, we'd like to split off the guaranteed issue business. It could very well have been that the selection factors were too small because we included guaranteed issue in that first cut. We have already completed all of that work. When we split up the guaranteed issue business, it wasn't surprising that the selection factors, when looking at guaranteed issue business, disappeared. None of them were statistically significant, and so they're all really around one. What was surprising was when you look at what was left, the fully underwritten and the other business, the selection factors didn't really change. I think we're getting a fairly good handle on what the selection factors should be.

There are areas of interactions that we would like to test. For instance, we found that male versus female had no significant difference. That may be just because it's a one-factor approach and, in reality, if you look at the National Nursing Home Survey data, the males have worse experience at the young ages, but better experience at the oldest ages relative to females. We probably needed to test interactions of age and sex. We did that and it still came out the same. There are no significant results for the combination of age and sex.

I think I've already mentioned that we would like to test the calendar year. One of the others that we would like to test is duration and age. I didn't mention this one. That has to do with the selection factors. Does it really make sense that the selection factors are level, or are the same for all ages? I suspect that selection factors probably should be deeper at the oldest ages.

I think I've already mentioned that we have to apply those hazard rates to the baseline hazard and then interpolate and extrapolate the complete table. Then we would have a lot of factors that are just movements away from the table. Of course, for the big step beyond this of fitting this data to the population data, or integrating the two, we certainly would not recommend this data as a valuation table by itself. It is very likely still in the select period. There are just too many moving parts, for instance, the improvement by calendar year of issue. I think the very last step we would do is to go back and check just to make sure that the model fits well against the actual claims.

**MR. NEWTON:** In a few minutes, we're going to go into a question-and-answer session. During that transition, I want to mention a few things. One of the ways to tell about the personality of a group is by the questions they ask and, in my mind, there were actually two presentations today or two presentation styles. Kim's and my presentations were in English, and Wes' was in statistics. When I started working with Wes, I needed to dust off my old statistics books. It was a small miracle that I actually found them. If you're interested and you want to take the time to go into this stuff further, all of us did learn this at one point, and you can look it up and try to understand some of the slides. I'm a little reticent to think about a slide on proportional hazard, regression and simplified down in the same sentence that Wes mentioned. In any case, this presentation will be available in English on the Web site when all the groups' presentations are finally up on that.

If you have any questions about what the Valuation Task Force is doing, particularly the statistics, but even some of the baseline assumptions they're making, or if you want to get involved or ask questions, or do anything like that, the committee absolutely welcomes questions and volunteers and anything you want to give at any time. It's a terrific thing to have feedback from people who are going to use the tables eventually, and feedback, quite frankly, from people who will be affected by the work at some point in time when this is all done. Mark Litow is the chairperson of the committee, so you can always ask Mark at Milliman. I see some folks in the audience who are also on the task force. All of us would welcome your input, questions, comments or complaints at any point in this process.

It would be unfair of me not to put a plug in for submitting data to the Experience Committee. If we didn't have any other data from the companies who were good enough to submit it to us, none of this would ever be happening, and we would be working somewhat in the dark, or at least more in the dark, in my opinion. All of the committees take extreme care with the data that companies submit. The people on the committees know which companies are there. It would be somewhat difficult to figure out which companies were which, but we have absolutely no access to the codes that are given and the names of the companies. Because the larger companies are asked to submit much smaller sets of data than they actually have so that the data fits into the sizes and match the other companies' contributions very well, it is difficult to figure out, even if I cared to, and I don't, which companies are which. The very large companies submit one out of five or one out of 10 of their policyholders so that their size doesn't unduly weight the results that are given.

I'm coming to the end of another data collection period, but if you're interested in submitting data in the future, see me or Gary Corliss in the back of the room, and we'll tell you what you need to do to put some data into the study.

**FROM THE FLOOR:** I should probably put someone else's name with this question, but I wouldn't do that to anyone I know. I'm with LTC Consulting in Nashville, Tenn. I had probably two weeks of statistics in college. Most of my math course was

around Babylonian and Egyptian numerals, which might have helped me today, but somehow, I couldn't pull that together. Now, I'm talking to people like those at Consumer Reports and some of these consumer organizations, and the biggest question I'm getting is, what percent of the people who bought LTC insurance have had a claim of any duration? What is that number projected to be, based on our current business environment, underwriting practices and so forth?

After hearing the presentation, I'm coming away with a figure of around 40 percent of the people, and that's probably not anything close to what you said, but why can't this be globalized? I know it varies by age, benefit duration, plan design and so forth. Is there a global statement that can be made to the industry, because consumers are trying to figure out if this is a good deal and, if it is, where they should be putting their premium dollars?

**MR. DENERING:** The statistic you're referring to is the two out of five people who used LTC on a lifetime basis and is quite different from what you were trying to do with the table. What we are doing here is trying to calculate the one-year probability of somebody claiming they're going into a nursing home in the next year.

**FROM THE FLOOR:** The number we've been using in the industry is there's a 50-percent chance people will need LTC of any type, staying away from the nursing home. I don't want people to be glued to the nursing home.

**MR. DENERING:** Sure.

**FROM THE FLOOR:** It could be three months of home care. It could be five years of nursing-home care. It could be two years of assisted living of any type. Is there an answer to that question? How many people who have bought LTC insurance have had a claim? Do we know?

**MR. DENERING:** I think it's a fairly early industry.

**FROM THE FLOOR:** I know.

**MR. DENERING:** We as an industry have not seen the bulk of our claims yet. I think, yes, you could probably calculate. You could add up all the claims. We know that, within this study, for instance, there are about 55,000 or 56,000 claims as an industry. This is only a piece of the industry. There may be samples or surveys out there that could answer how many people have had LTC claims.

**FROM THE FLOOR:** That would be versus the universe, and then that would be applied to some type of projection.

**MR. DENERING:** Yes, I think the answer to the question can be answered. I can't give you a number off the top of my head.

**MR. NEWTON:** If you haven't seen the study, I don't know if I would go to the appendices because they're really long, and there are tons of numbers in there. In the summary part of the report, there are boiled-down incidence rates or chances of using a claim at any particular age. Because LTC is a coverage that lasts a long time, the lapse rates are extremely low. You might be able to look at those incidence rates by age and see how quickly the incidence rates go up. People in our study are getting into their late 80s and maybe early 90s, and you can start to get a sense for how you might project the portion of people who eventually have claims. The incidence rates are extremely high. They are 25 or 30 percent, something like that.

**FROM THE FLOOR:** That's what we want to hear. We just need to put some muscle on it.

**MR. NEWTON:** Yes, it's not quite as simple as adding all the numbers up for all the ages that you have the policy, but you can see in there that there will be a lot of people with claims in this country and around the world.

**FROM THE FLOOR:** That's good to know.

**MR. NEWTON:** Yes.

**FROM THE FLOOR:** This question is to Wes. I was a little bit confused whether the results were considered to be between the different case characteristics. The one I was particularly interested in was the preferred, standard and substandard mix. Do the regression formulas assume a constancy by duration from the initial baseline duration? Are those expected to be acetotic to the baseline over time? Which variables are expected to go which way?

**MR. DENERING:** That's a good question. If we don't add interactive terms to the model, then it would assume constancy of cost alteration. When you look at preferred factor, I think 0.57, that is constant across all of the durations, and that would be something good to look at. Does the preferred factor tend to wear off with time? I think we probably don't have enough data at the out years to make that determination. I think we'd lose the credibility on that.

**MR. JAMES M. ROBINSON:** I'm with the University of Wisconsin, Madison. I want a little clarification on the definition of the claim incidence. You already said that it was after the elimination period that the count was triggered. What kinds of claims are you grouping together with regard to nursing home versus home care versus claims from comprehensive policies in the analysis that you just went through, Wes?

**MR. DENERING:** There are a number of different fields in the study. They code it for skilled nursing care, intermediate care and custodial care. Those three were



coded as nursing-home care, and then the fourth was coded as home health care; so nursing home and assisted living basically are the types of claims that are coded as a nursing home claim.

**MR. ROBINSON:** What was everything in your presentation?

**MR. DENERING:** That's nursing home. They don't show anything here about home health care.

**MR. ROBINSON:** I have another comment. In using Cox regression, you displayed some of the standard deviations associated with the beta parameters in your fit. In the background somewhere, there were also estimates of the correlations among these estimates.

**MR. DENERING:** Right.

**MR. ROBINSON:** With that information in theory at the end, not everybody needs to look at the guts of the calculation. At the end of the process, you should be able to come up with confidence intervals for the incidence rates for each combination of characteristics that you're publishing. I think that there would probably be a number of people interested in what the width of those confidence intervals are for certain combinations. I don't know if you're looking into that or not, but I think in theory you should be able to do that. It's a matter of who has the computer and the time to do it.

**FROM THE FLOOR:** I'm with Actuarial Services. I found the results of disabled life mortality being 16 or 17 times greater than the other mortality rates to be sort of a curious result. I'm wondering if the panelists think that that may be due to coding issues or otherwise due to the early duration of the claims in the study.

**MS. TILLMANN:** I think that very well may have something to do with lapse and death coding, because I would think that when people are on claim, companies would have a much better knowledge of whether it really is a death or not than they would for the active lives. I do suspect that we got a more accurate coding of the disabled lives and are missing some of those deaths in the active lives.

**FROM THE FLOOR:** When you're comparing the mortality, are you comparing the mortality within the study or an 83 gamma? What's the baseline?

**MS. TILLMANN:** This is for the active versus disabled?

**FROM THE FLOOR:** Seventeen times, yes.

**MS. TILLMANN:** Yes, it was within the study active lives versus disabled lives.

**FROM THE FLOOR:** Okay, I understand that.

**MR. ROBINSON:** I have a thought. Do you have in the database that you've collected an indication of whether there were any ancillary death benefits attached to the policy like a return of premium on death, and if so, if you look at that population?

**MR. DENERING:** We haven't figured out what to do with riders.

**MR. ROBINSON:** Well, in particular, if you know that there is a death benefit available, maybe looking at the mortality rates on that subset might give you some view of all else being equal, what the mortality rates on that group are versus the other group. Then maybe you can infer what the underreporting is in some way.

**MR. MARK LITOW:** I'm with Milliman. I have one question and one comment on the last piece. I'll go to the comment first. It would strike me that the mortality disables would be hard because people on claim are much older due to the incidence rates, whereas the exposure base acted like mortality. So it's probably accelerated the gap.

My question is to Kim. You talked about the average length of stay. How is that calculated? Is that just on closed claims or is that on closed and open? I'm sure it's incomplete, but when we get into the continuance part, we're going to have to make some assumptions of either how the claim reserve works or open part and close some of those claims off because, otherwise, we're going to have an incomplete database, and we're going to get a continuance that may not be reflected in the total. How did you get your numbers?

**MS. TILLMANN:** I am not absolutely positive. I think those averages were calculated on all claims, so an open claim would just be the length that we see it.

**MR. LITOW:** So we haven't done anything yet to extend the open claims to an estimated closed basis.

**MS. TILLMANN:** No.

**MR. LITOW:** That would make that understandable; that's what I'm trying to get at.

**MR. NEWTON:** There are actually two. I'm not sure which section you're referring to, but it's probably claim characteristics. In the claim characteristics section, an open claim looks the same as a closed claim. If it happens to be open at the end of the valuation period, then that's the claim length that it gets.

**MR. LITOW:** Right.

**MR. NEWTON:** So there's nothing future about it. You can contrast that somewhat with the continuance table part of the report. There what happens is we use all claims as far as we know them, and if they're open on the last date that we're looking at, we dropped them out of the exposure and the continuance. We use everything we can possibly use of the data that we have, but then the rest of the claims that last longer just kind of keep going on and on. In a sense, although every one is not available from the beginning of the claim till the end of the claim, whenever that is, we're using every possible bit of data to build the continuance curves beyond some of the early duration claims that we have.

**MR. LITOW:** Right. In getting to the average claim, we need to take that continuance as calculated and recalculate the number to get to a new number because the average length of stay will be higher, I would assume, depending on how it's calculated.

**MR. NEWTON:** Right.

**MR. LITOW:** Or we can make an estimate of how long the claims that are still open will last based on the continuance you come up with and calculate the average length of stay that way.

**MR. NEWTON:** Exactly, and that's what those tables tried to do.

**FROM THE FLOOR:** I have a continuation of that question, and I guess it would relate mostly to the closed claims in considering some of the continuance. Did you notice much variability in the ranges of number of days of nursing-home care or home-care claims in taking into account the duration or lifetime maximum that the individual had purchased a two-year plan versus a five-year plan versus an unlimited? Did you really see much variation there?

**MS. TILLMANN:** I would have to say I don't know off the top of my head. I think there is some information about that in the report. I think you would be able to find some information about that. I just don't recall off the top of my head.

**FROM THE FLOOR:** In terms of interaction effects, did you look at gender and marital status combination? Because I remember John Timmerberg has come up through this group a couple of times and talked about how important that is.

**MR. NEWTON:** I don't think at this point we can look at that. I think that marital status data is just too scant to make that assumption.

**FROM THE FLOOR:** One of the biggest things that opened my eyes in terms of results would also be a daunting challenge for a uniform valuation table was the huge differential among companies in the company codes. I don't know that some of them are not credible, but there's a wide range even in the first quartile and the

third quartile. Is there any hope having a uniform valuation table independent of including company, credible company experience?

**MR. DENERING:** I think we clearly have to use population statistics in going with this information, and I think we're probably 10 to 20 years off before we could come up with tables that are just based on intercompany data.

Chart 1

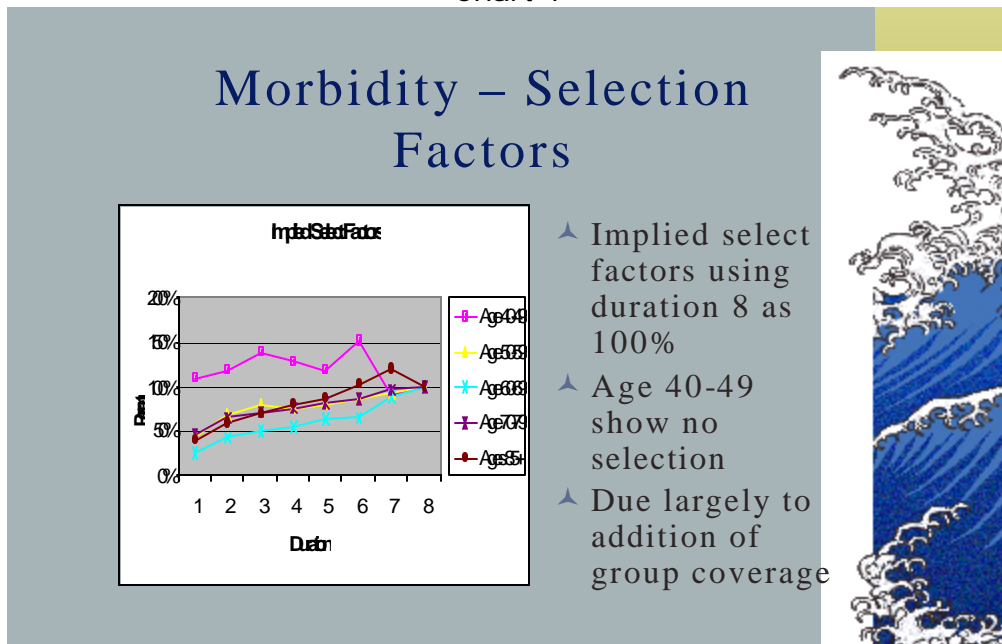


Chart 2

### Aggregate Intercompany Data: 1st yr LTC incidence rates

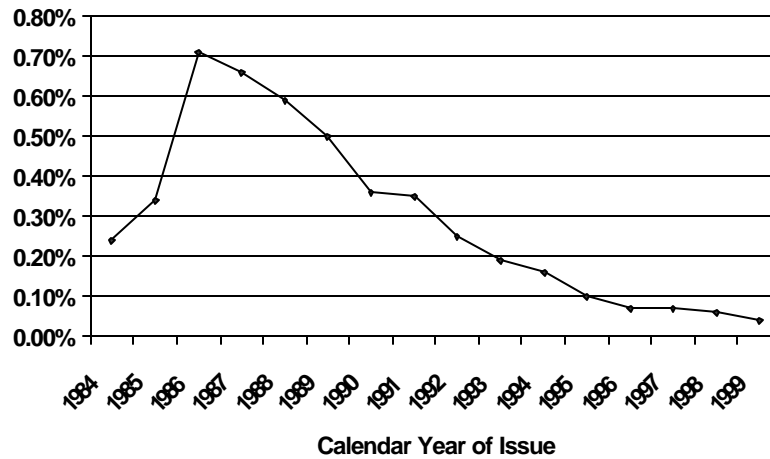


Chart 3

Aggregate Intercompany LTC Data:  
Avg EP days

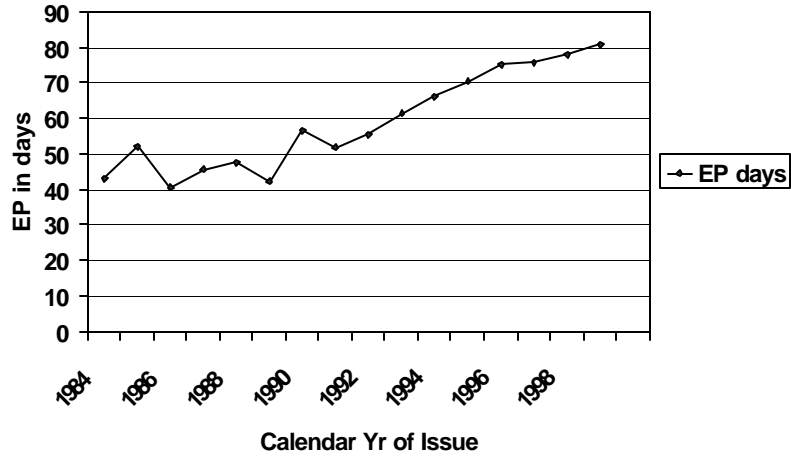


Chart 4

1st Year Incidence: Unadjusted and Adjusted (for EP and Avg Age differences)

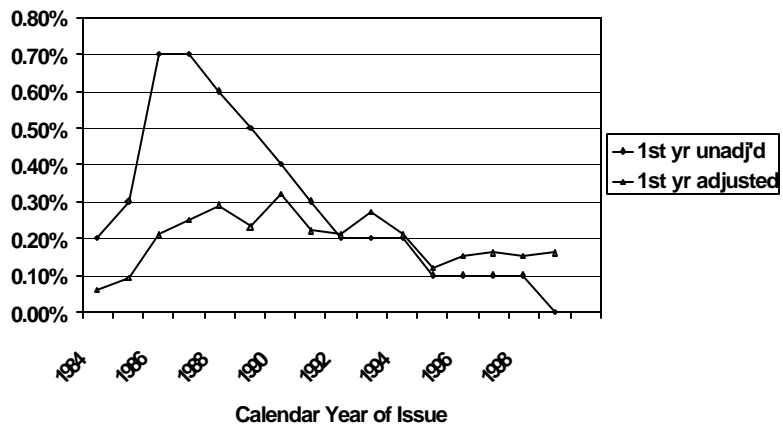


Chart 5

### Direct parameter Calculation

Age	Exposure	Claims	Incidence	Ratio to 60	Population Ratio to 60, std
60	96100	341	0.35%	1.00	1.00
70	132000	2262	1.71%	4.83	4.41
80	34500	2773	8.04%	22.65	19.46
Preferred	69000	738	1.07%	0.47	0.80
Standard	190000	4326	2.28%	1.00	1.00
Substandard	3600	312	8.67%	3.81	2.00

Chart 6

### Hazard Rates by Company

	hazard ratio		hazard ratio
Company A	0.322	Company J	1.006
Company B	0.358	Company K	1.052
Company C	0.388	Company L	1.177
Company D	0.643	Company M	1.204
Company E	0.649	Company N	1.248
Company F	0.746	Company O	1.26
Company G	0.804	Company P	1.446
Company H	0.822	Company Q	1.629
Company I	0.85	Company R	2.193
Baseline Company	1	Company S	6.565





