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Emerging Technologies:
Insuring what has not been insured before

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Summary

The paper describes and illustrates some tools that are useful in meeting the challenge of insuring new technologies. Risk models can be used to guide pricing and quantify portfolio risk, in particular information risk and technology risk, so important in the case of insuring new technology. It is shown how to quantify the value of information. The use of expert opinion to develop risk models is discussed and Bayesian updating is suggested as the best way of updating risk models with data as claims data becomes available for new covers.

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1 Issues in Insuring Emerging Technologies

How does the task of insuring emerging technologies differ from the task of insuring established technologies? For one thing, the insurer knows less: it does not have much or any data on past exposures and claims. Engineering and underwriting experts who work or consult for the insurer may be more uncertain about the performance of the new technology and the frequency and severity of breakdown of the new equipment. In addition to lack of knowledge, there are certain enterprise-level risks that make insuring new technology especially challenging. For example, there is a chance that all the insured equipment of a new design will fail prematurely, or that a new technology will be made obsolete by a newer technology, or made uneconomical by a change in government subsidies. This paper contains no real loss data. Instead, some of the general points are illustrated by more or less realistic examples, along with artificial numbers used to demonstrate some of the calculations that might be helpful. Four examples that are used several times are (1) all-risk insurance of wind turbines, (2) insurance for power outage, (3) insurance for loss of internet access, (4) systems performance insurance for cellulosic ethanol production. Many of the issues in insuring new technologies also arise in insuring existing technology that is changing, and the examples cover both situations.

1.1 Lack of relevant loss experience

Setting terms and conditions and especially setting rates is difficult when insuring something that is new to the insurer. For example, an insurer may have one year's worth of experience with 100 insured wind turbines and may be considering an expansion of the wind turbine program. Suppose the program has generated no claims so far. Then, for this insurer at least, there is no empirical data on frequency and severity of failure modes, except that the frequency of claims from all failure modes combined is probably not higher than several percent per year (a mathematical model for this is discussed later in the paper). An insurer considering expanded power outage coverage may have good data on past power outages but may be concerned about higher future grid instability due to heavier loading of the transmission system. An insurer will have access to data on past internet threats, but there may be future threats that have not even been visualized, let alone quantified. An insurer may have a good general understanding of existing cellulosic ethanol production but will not know how vulnerable new genetically-modified microorganisms will be to toxins in their feedstock.

- **Lack of data**
  The most directly useful data for insurance purposes are claims and exposure data, including any pooled data. Lacking this, there is other possible data that could be useful but may not exist. If it does exist it may be unavailable to the insurer, being in the possession of other insurers, operating units, or equipment vendors. For example, wind-farm operators using a new type of wind turbine may have limited data on historical failures, although this may be more data than the insurer has. Wind-turbine manufacturers may have reliability test data or modeling results that they may not be willing to share.

- **Lack of expertise**
  The insurer may have underwriting or engineering expertise that is geared to insuring existing technology; expertise that allows the insurer to distinguish a good risk from a bad risk and to recognize when a risk is outside the normal parameters. The experts may be able to identify where the use of new technology increases the risk profile. The underwriting and pricing for risks "inside the box" is based on historical loss and exposure data and general experience. In contrast, for new technologies, the experts must be able to identify failure modes and their frequencies and severities without benefit of the usual data.

- **Rapid change**
  Whenever there is rapid change, insurers are dealing with the same issues of lack of data and lack of expertise. Change can be in technology, but also in where and how technology is being deployed. For example, there may be data on failure rates for a new technology, but what if the new technology is then deployed to countries where maintenance practices are poorer, or operating demands higher, or environmental conditions more severe?

1.2 Systems risks

New technologies may confront the insurer with having to price and underwrite when data and expertise may be an issue. Another difference is that the risks of insuring new technology have a different profile than the risks of insuring established technology, and insuring new technology has a different impact on overall enterprise risk. One way of thinking of this is that a new technology portfolio is non-diversified in comparison with an established technology portfolio. That is, the losses from the insurance policies that make up the portfolio are positively correlated. The simplest example of this is a portfolio of policies insuring a new piece of equipment for breakdown. If the design is poor, the portfolio may generate a large loss, while if the design is good, it may generate a large profit. This portfolio contributes more to the overall enterprise risk than a similarly-sized portfolio of policies insuring some established technology, even if the new technology portfolio has a higher profit expectation.

1.2.1 Technological risk

- **Quality, Reliability, Cost**
  From the point of view of the operating unit, and from the point of view of an insurer providing systems performance insurance, the quality (and quantity) of output is critical as is the cost of production. From the point of view of an insurer providing equipment breakdown insurance, reliability of equipment is the only relevant issue, and only certain types of failures are relevant. In all cases, though, there is the same non-diversified risk to the insurer. For example, if a systems performance insurer insures cellulosic ethanol production using genetically-engineered microbes, it may find itself facing losses from multiple insured enterprises using that technology. When using acid hydrolysis, an older technology, the insurer's results would depend more on whether the individual insured was proficient in operations and

maintenance. From the insurer’s point of view, the first case is a big bet on technology while the second case is a series of small bets on individual operations.

- **Competing technologies**
  The largest risk facing a new technology is that it will be made obsolete by a yet newer technology. Before gasoline engines became dominant, steam engines for cars was a promising technology. For an operating enterprise, this is a critical concern, obviously. It is also important for the insurer, not so much because of its effect on profitability of individual insurance policies, but on premium volume and expense loadings. If a large investment is made by the insurer in understanding a new technology that then becomes superseded, the insurer’s bottom line is hurt.

1.2.2 Regulatory & political risk

A new technology can be made obsolete through market forces, but it can also be affected by government actions. One risk to the insurer is that a new technology in which it is involved is banned, regulated or taxed out of existence. Another risk is that a competing technology (in which the insurer is not involved) becomes more favored. Another risk, which is substantial, is that government regulations and subsidies favoring the new technology are reduced or removed. For example, the risk to the insurer with a portfolio of wind turbines may be that the future revenue from that portfolio may be less due to loss of government subsidies. The loss ratio from the portfolio may still be good, but the opportunity costs to the insurer may outweigh the revenue benefit.

2 Some Relevant Tools

Given all the risks that an insurer seems to be facing in insuring emerging technologies, what are some tools that can help the insurer understand the risks and perhaps mitigate them?

2.1 Risk models

Quantitative risk models are any mathematical structures that allow us to obtain the probabilities of something of interest. For insurance applications, the thing of interest is usually some event, such as an insured submitting a claim of a certain type and amount or a portfolio generating a certain aggregate amount of claims over a given future period. The probability distributions depend on inputs or variables, whose probability distributions themselves depend on other factors. Risk models in insurance and failure analysis (but not in general) can often be factored into frequency and severity parts.

- **For pricing insurance**
  Average annual loss for an insurance contract is given by average annual loss

frequency times average severity, both of which can be obtained from a suitable risk model. This amount, along with expenses, risk load and profit, can be used in pricing.

- **For modeling portfolio risk**
  While some pricing may be done without using an explicit risk model, when it comes to quantifying portfolio risk, a fully probabilistic risk model is essential. Often, the critical issue in modeling portfolio risk is the correlation between losses. For example, consider modeling power outage risk. If the only causes of power outage were electrical breakdowns of the local distribution transformers, then we would expect losses to be relatively independent and localized and the portfolio risk low (in the sense that the annual aggregate losses would probably be stable from year to year, over the short term). If the number of insureds were low or the portfolio were dominated by a few large risks, the portfolio risk would be higher. In reality, power outage can be caused by widespread grid failure in which multiple risks suffer losses from the same occurrence. This phenomenon causes positive correlation between losses and inflates the portfolio risk. Of course the risk (as seen by the insurance company) depends only on the uncertainty of the portfolio's future results. If we are certain about the results, there is no risk, from our perspective.

  Several techniques are available to model correlations between losses. One way is to estimate the correlations from data. Since this approach requires a lot of historical data and a stable system, it is not useful for modeling risk associated with new technology or new coverages. Another more promising way is to model the causal factors which produce the correlations. In the power outage case, this involves modeling the probability of grid failures of various types and geographical range.

2.2 Models that combine data and expert opinion

Quantitative risk models are based on probability distributions. When we have data, there are many statistical tools and techniques we can use to fit models to our data and to examine how well these models fit the data. In insuring new technology, data is often limited. Our expertise may also be limited, but combining expertise with data may produce better results than using data alone. If we have no data, we have no choice but to use expert opinion.

For example, suppose an insurance company insures a fleet of wind turbines in Europe, and wishes to extend its target market to another region where maintenance is typically poorer. There may be enough historical loss data to obtain frequency and severity probabilities for Europe, while a panel of experts may feel it can quantify the increase in failure frequency associated with the poorer maintenance in the new region. The panel may feel that the multiplier is between 1.3 and 2.5 with a 90% certainty, which may be the basis for a probability distribution on the maintenance frequency multiplier. In this case expert opinion is used to establish probability distributions for model elements for which no data is available. More generally, each probability distribution can be based on a mixture of data and expert opinion, depending on the credibility of each.

2.3 Procedures for efficiently updating models as new data becomes available

If an insurance company offers coverage on a new technology, frequency and severity data will begin to accumulate. It is critical to be able to incorporate this new data into the model as efficiently as possible. A well-known way to do this is using Bayesian updating. This technique allows the risk model to change whenever new data become available. In fact, the procedure can be automated, provided the results are scrutinized carefully. The ad-hoc alternative is to wait until sufficient data has accumulated to fit a completely data-based model. The problem with this is that the data is not used as soon as it becomes available.

2.4 Techniques for incorporating systems risk into models

As mentioned above, correlations between losses should be built into the risk models, which is another way of saying that models should reflect all of the uncertainties and risks including the system-level or enterprise-level risks. For loss models, all risk sources including uncertainty about the reliability of new technology and uncertainty about its operational and maintenance environment should be modeled. Profitability models require more types of risk to be considered. As a very simple artificial example, suppose there is a new wind turbine model whose annual failure probability is uncertain, but is believed to be 1% (if a good design) or 25% (if a bad design), considered equally likely. Then choosing 13% to represent the failure probability would be reasonable to guide initial pricing but would underestimate the portfolio risk. In another case, more data-based, the failure rate of an item might be based on the results of a manufacturer's accelerated life test. The test might produce a confidence interval or probability distribution for the failure rate, and it would be understating the portfolio risk to choose a single estimate of the failure rate and use that estimate in a portfolio risk model.

3 Some Potentially Insurable Losses

In insuring new technologies, it is important to relate the losses as categorized by the insurer to characteristics for which data and expertise may be available from non-claims sources. For example, data may be available from manufacturer's reliability testing. Failure modes may be available from the reliability data. Frequency of failure can be related to MTTF (mean time to failure) or MTBF (mean time between failures). For the case of aging systems, or systems with infant mortality, hazard / failure rate curves depending on age or time since installation are more useful. For systems in which the hazard curves depend on environmental factors, a popular model in survival and failure analysis is the Cox proportional hazards model, which can be used directly in risk modeling. For repairable systems, hazard curves that depend on the time since repair can be used to model failure frequency if one can assume that the system is "good as new" after a repair (renewal models). There are a multitude of other failure models that can be applied directly to insurance risk modeling.

- **Property damage**
  Property damage relates to the cost of repair or replacement of components, including labor, equipment and materials, demolition, increased construction cost, ordinance or law, and other elements. Some of these cost elements may be available from insurance company experience but not from a traditional reliability database.

- **Business interruption & extra expense**
  Business interruption cost can be related to MTTR (mean time to repair). Information on extra expense costs is unlikely to be available from reliability databases.

- **Products & Operations liability**
  Risk analysis may be possible by examining litigation for technologies that serve the same market needs as the new technologies under consideration.

- **Systems performance shortfall**
  Systems performance insurance requires a full economic analysis. Since the focus of this paper is on equipment breakdown risk, this will not be discussed further.

- **Other revenue losses & cost increases**
  Other insurance coverages can be relevant to new technology, such as insurance against supplier disruptions or market disruptions caused by unfavorable economic, political and environmental effects. These will not be discussed further except to say that hedging via derivatives may also be a way of addressing these sources of risk.

- **Equipment Breakdown: PD and resulting BI & EE**
  The focus from this point will be on equipment breakdown insurance rather than systems performance or insurance against traditional property perils. For all-risk insurance of new technologies, vulnerability to property perils may be important. For example, solar arrays may have a vulnerability to hail and wind that may not be fully characterized, and likewise wind turbines to earthquake.

4 Equipment Breakdown - Basic Model Elements

- **External hazards & environmental influences**
  Even excluding traditional property perils, all equipment may have significant exposure to weather, power disturbances, and other effects that may cause correlated losses and inflate portfolio risk.

- **Vulnerabilities and failure modes**
  If enough loss and exposure data is available, a basic frequency and severity

risk model can be constructed which combines all failure modes and can be used for top-level risk modeling. When this sort of data is not available and expertise needs to be drawn upon, then analysis by failure modes is essential. Using failure modes also allows insights from the analysis to be incorporated into the crafting of the policy language (exclusions, sub-limits by failure mode) and into underwriting criteria (risk characteristics that drive frequency and severity by failure mode).

- **Loss frequency distributions**
  Each failure mode will have a frequency of loss per exposure unit (such as a machine-year or a location-year). For new technology, there is likely to be uncertainty about these frequencies because of limited data and uncertainty among and within experts, so there should be a probability distribution for each frequency that reflects this uncertainty and could be updated as new data becomes available. The frequency distribution should depend on the characteristics of the risk.

- **Loss severity distributions**
  Each failure mode will have a severity. This may be a single cost, such as the cost to make a certain type of repair associated with the particular failure mode. In this case the severity should be treated in the same way as a frequency, having a probability distribution based on the limited data and expertise when dealing with new technology. This distribution again should depend on the characteristics of the risk. Instead of a single cost, it may instead have to be a probability distribution of cost, because a failure mode may produce a range of losses due to other variables not considered individually. Just as we could be uncertain about the frequency, we could also be uncertain about the severity distribution, and would quantify our uncertainty with a probability distribution. When analyzing historical claims data, it is always necessary to work with severity distributions, but with an initial expert-only risk model, it may be sufficient to work with a single cost for each failure mode.

5 External Hazards for EB

- **May cause losses or may simply increase the probability of losses**
  For all-risk coverage, a natural peril may be a covered cause of loss. For equipment breakdown only, this may be excluded as a property peril if it directly causes a loss but not if it indirectly causes a loss or increases the probability of a loss. This may be a particular issue with new technology that has not been designed to be environmentally rugged. For example, earthquake or flood may appear to leave a piece of equipment undamaged but vibration or hidden water penetration may cause subtle damage that increases the probability of later failure.

- **Weather: temperature, humidity, dust**
  Again, new technology may be more susceptible to the environment than established technology. The new technology may have recently migrated from a laboratory or pilot plant environment in which the environment is well

controlled. Research and development may have focused on getting a complicated new technology to work rather than to make it rugged. An example would be the extreme sensitivity of early disk drives to vibration, shock and dust, compared to later, more mature, disk drive technology.

- **Power outage & power quality disturbances**
  New technology may be more sensitive to power quality disturbances. For example, newer electronics tends to use smaller geometries and smaller energies to store and manipulate each unit of information which may make equipment using newer electronics more sensitive to voltage spikes and surges, harmonics, and external electromagnetic fields. A wide variety of equipment that uses existing technology is known through experience to be vulnerable to disturbances in power quality.

- **Computer & communications network disturbances**
  As equipment is networked, the potential for correlated losses increases since disturbances such as computer worms and viruses can be broadcast from a central point (which may be a network of infected computers) to multiple hosts or can propagate from node to node as a contagion. In either case, this potential for correlated losses increases portfolio risk. In the case of internet access insurance, the portfolio risk is high but even for equipment breakdown there may be correlated failures due to computer network disturbances now or in the future. Protective systems like air conditioning may shut down, and even shutdown-restart cycles may increase failure probabilities by increasing thermal cycling stresses.

6 EB Failure Modes - New Technologies

- **First step: identify, don’t quantify**
  Even where data is available, identifying possible failure modes is a job of those with expertise in the technology. Where data is available, tools such as text mining of reports of investigation can be useful. Experts need to think broadly at this stage. In the case of the internet, for example, it may be impossible to imagine all of the failure modes.

- **Using components with known failure modes? Identify how component failures can interact to cause system failures**
  If the new technology consists of a system of known elements configured in a new way, it may be possible to identify failure modes through knowledge of the failure modes of the elements. For example, the electrical grid consists of transformers, transmission lines, turbines, generators, and so forth, with known failure modes. However, it may not be possible to identify all the failure modes of the system in this way. For the electrical grid, loss of synchronization of the generators on the grid can cause voltage and angle instability and can cause the grid to collapse or break into islands. This phenomenon can only be understood at the system level, as emerging from the interaction of the elements.

- **Using novel components? Look at basic failure mechanisms**
  If even the failure modes of the elements of the system are not known, then basic physical considerations may lead to candidate failure modes for consideration. This should have been done in the case of the Comet, the unsuccessful first commercial jetliner, which experienced crashes due to unrecognized metal fatigue, a failure mode that might have been anticipated if the failure mechanism had been envisioned.

7 Some Basic Failure Mechanisms

Here are some failure mechanisms, obviously not a complete list.

- Chemical
  Chemical mechanisms include oxidation-type reactions such as fire, some explosions, rusting, corrosion; other rapid exothermic reactions, cross-linking causing embrittlement, dissolution, precipitation, and many others.

- Mechanical
  Mechanical mechanisms include crack propagation, tearing, erosion, annealing, work-hardening, plastic deformation, contact welding, and many others.

- Biological
  For biotechnology specifically, there are a large number of unique failure mechanisms, including toxin generation and infection with unwanted organisms. More generally, there is attack by mold, rodents etc.

- Programming Error
  Usually excluded under equipment breakdown, programming errors may cause equipment breakdown losses indirectly, as in the case of grid or computer network failures.

8 Wind Turbine Example (Hypothetical Data)

The slides exhibited below illustrate the identification and quantification of frequency and severity and by failure node for a hypothetical new 1.5 MW wind turbine. They illustrate the treatment of portfolio risk and also how to quantify the value of information in reducing portfolio risk and improving profitability. This data is understood not to be especially realistic, but is used to illustrate some of the steps described previously.

Loss Frequency Distributions

- Frequencies of failure by component & failure mode
- Choice of exposure unit
- Hypothetical data for illustration only: new 1.5 MW wind turbine

Component	Failure Mode	Failure Rate per Unit per Year
gearbox	mechanical failure	.01
entire unit	lightning strike causing electrical fire	.002

Loss Frequency Model

- Depends on characteristics of the unit - a multivariate frequency model
- Hypothetical example: gearbox failure rate (model A2 is a new design with no gearbox)

Model	Maintenance	Failure Rate
A1	Good	0.01
A2	Good	0.00
B1	Good	0.02
A1	Poor	0.03
A2	Poor	0.00
B1	Poor	0.06

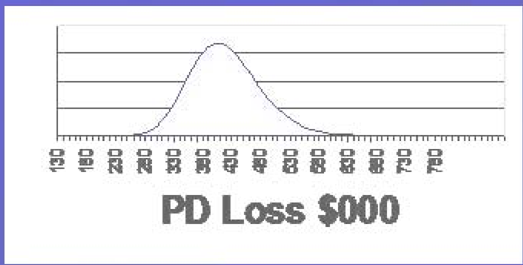
Loss Frequency Model (continued)

- Hypothetical example: electrical fire from lightning strike

Model	Lightning Strike Frequency at Location of Unit	Failure Rate
A1	High	0.020
A2	High	0.020
B1	High	0.030
A1	Medium	0.004
A2	Medium	0.004
B1	Medium	0.006
A1	Low	0.002
A2	Low	0.002
B1	Low	0.003

Loss Severity Distributions

- Severity distributions by component & failure mode
- Hypothetical example: gearbox failure, model A1:



Pure Premium

- Pure Premium = expected loss per exposure unit (such as a unit-year)
- May include certain allocated expenses
- Does not include unallocated expenses
- Does not include profit
- Does not incorporate risk loads

Pure Premium Calculation for a Specified Unit

- For each failure mode, multiply expected frequency and expected severity to obtain the pure premium for that failure mode
- Add up the pure premium for each failure mode to get the pure premium for the unit
- The pure premium for the unit depends on the unit's characteristics and exposures

Portfolio Risk for a Collection of Units

- Add up the pure premium for each exposure unit to get the pure premium for the portfolio
- Two portfolios may have the same pure premium but very different likelihoods of high portfolio losses
- Positive correlations increase the likelihood of high portfolio losses
  - Correlated failure modes within a unit
  - Correlated failure modes between units (more important)

Correlations for the Hypothetical Wind Turbine Example

- If we are fairly certain about the technology and its implementation then:
- Gearbox failures are statistically uncorrelated between units (approximately)
- Electrical failures due to lightning are correlated between units
  - A single thunderstorm at a wind farm may cause multiple failures
  - A year with a large number of thunderstorms will produce more portfolio failures, on average

A Hypothetical Portfolio of Identical Units

- The design may be robust or non-robust
- We don't know which is true
- If Design is Robust then Pure Premium = $10M, Profit = $2M
- If Design is Non-Robust then Pure Premium = $30M, Loss = $18M
- If our best estimate of the probability of a robust design is 95%, then the pure premium = .95*10 + .05*20 = $11M and expected profit = $1M

Hypothetical Portfolio (continued)

- The portfolio is profitable
- However, there is a 5% chance of an $18M loss
- The portfolio is not diversified due to the equipment design risk common to all units in the portfolio

Quantifying the Value of Information

- The quantified Value of Information is
  - the expected payoff using the best strategy with information
- Minus
  - the expected payoff using the best strategy without information

Value of Information Example

- For the hypothetical portfolio:
- Best strategy without knowing design robustness is to write the business (expected profit = $1M)
- Best strategy with knowledge of design robustness is
  - Write the business if the design is found to be robust (expected profit = $2M)
  - Don't write the business otherwise (expected profit = $0)
- There is a 95% probability that the design is robust, so the expected payoff with information is .95*2+.05*0 = $1.9M
- The difference, $1.9M - $1M = $0.9M, is the value in this context of finding out whether the design is robust

9 The Role of Expert Opinion

- **More important in the absence of physical models and data**
  Without physical models or data, we have to rely on expert opinion or not enter the market. Experts should be given progressively less weight as relevant data accumulates. Experts should be given less weight as accepted physical models become available.

- **The Importance of Quantifying Expert Uncertainty**
  There are two sorts of uncertainty: uncertainty in the mind of each expert and lack of agreement between experts. Quantifying both sorts of expert uncertainty helps us balance the value of more information-gathering against the value of immediate action. It helps us to determine the weight to be given to accumulating data. More expert uncertainty requires more sensitivity to incoming data signals but also more sensitivity to incoming data noise. If the experts are more sure, then it should require more evidence to change the insurance company's beliefs.

- **Tools for Quantifying Expert Uncertainty**
  Asking for confidence intervals from individual experts is important rather than simply asking for their best guess (in the case of the important parameters). The insurer may have to choose a single best course of action at the end of the day but uncertainties should be tracked and quantified up until that point. Using a betting framework (with notional money) may be helpful. There are tools to "fish out" the underlying mental structure used by an expert, such as the analytical hierarchy process which asks the expert to make a series of pair-wise comparisons.

- **Multiple Experts**
  It is risky to rely on a single expert. It is probably best to elicit separately at first to avoid an expert unduly influencing another, and to avoid groupthink and clashes of ego. However it may be useful to follow up with group discussions. Standard statistical tools can be used to quantify the disagreement between experts.

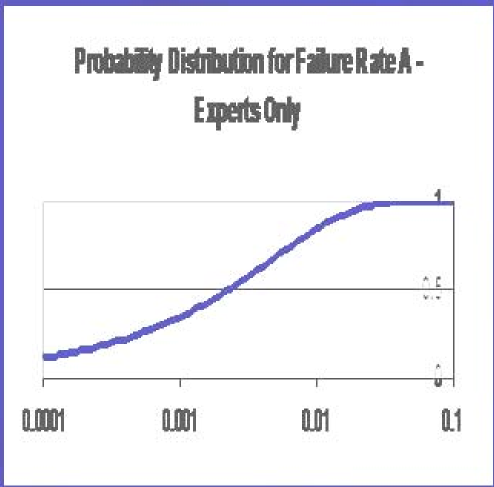
- **Why Might Experts Disagree**
  Experts might have different interpretations of the question. Questions need to be well-defined. Avoid vague or fuzzy concepts. Experts may lack of understanding of the probability framework of may reject it. Finally, the experts may have had different experiences or have different mental models of the same phenomenon. When the basis for the disagreement is different experiences, pooling those experiences may lead to the "wisdom of the market" effect.

- **Finding Hidden Data**
  A useful step is to try to identify some of the bases for the expert's opinion. Is it based on a formal or informal analysis of data? Can this data be obtained? If so, use this data directly to help build the risk model. Is it based on a document that can be obtained? If so, use the document. If the expert's

opinion is based on a wide variety of facts and experiences, use the expert's synthesis.

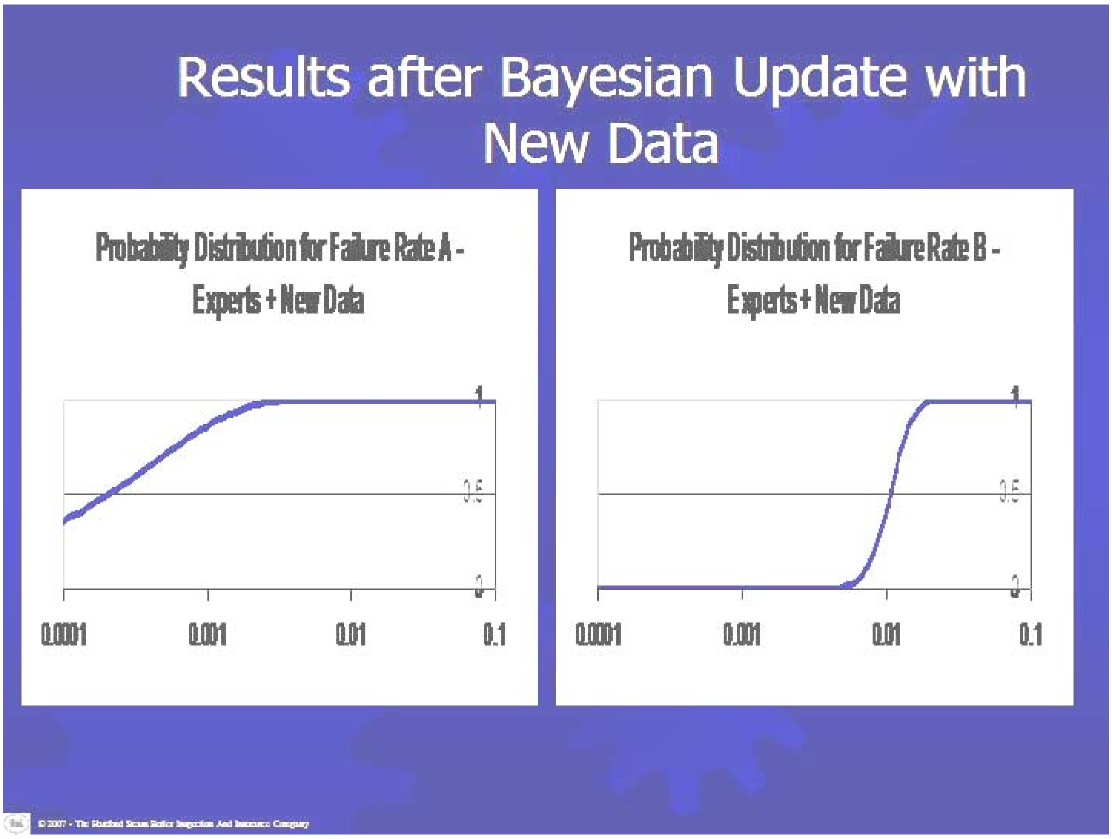
- **Combining Expert Opinion and Data**
  As more data becomes available, the data should have an increasing influence over the risk models. Of course the data should not be taken uncritically at face value. For example, in the case of claims data, the amount paid is unlikely to be in error, the date of loss is likely to be reasonably correct and the cause of loss may be somewhat unreliable, depending on the nature of the claim and the adjuster or investigator. The coded cause of loss represents data, in the sense that it is known, but it may equal the "true" cause of loss only some of the time.
  Bayesian updating, as mentioned previously, provides a logically sound method of updating risk models with new data. They can be built to incorporate phenomena such as measurement error as described in the previous paragraph. Some simple risk models produce a Bayesian update step that can be performed on a calculator, while with more complicated risk models the Bayesian update step may require extensive computing. The following shows the Bayesian updating of a very simple risk model without going through the mathematics.

Results from Expert Elicitation



New Data After 3 Months

- 1000 Exposure Units
- 0 losses for failure mode A
- 10 losses for failure mode B


Results after Bayesian Update with New Data
Probability Distribution for Failure Rate A - Experts + New Data
1
0.5
0
0.0001
0.001
0.01
0.1
Probability Distribution for Failure Rate B - Experts + New Data
1
0.5
0
0.0001
0.001
0.01
0.1