Inconsistent Inference in Qualitative Risk Assessment

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EXECUTIVE SUMMARY

The variety of risks that the financial industry faces nowadays requires different approaches to risk assessment. If enough experience data exists, quantitative risk assessment using statistical inference is normally chosen. For risks with insufficient data, qualitative risk assessment using human inference is used. While standard rules are used in statistical inference in most cases, human inference is subject to cognitive biases. Biases can be caused by loss aversion, overconfidence, anchoring, representativeness, and the incapability of processing too much information.

Biases likely affect our risk assessment and decision-making. As a result, exposure levels to different risk types may be inconsistently estimated; they may be overestimated, underestimated or even ignored. Suboptimal and inferior decisions may be made. It is difficult to eliminate biases but some strategies can be used to reduce their negative impact.

1. A model-based standard and consistent inference framework can replace human inference to minimize the impact of biases. Subject-matter experts will not be asked to provide the risk assessment result. Instead, they will be consulted on things such as the underlying risk factors and the cause-and-effect relationships. The model will then draw inference from the information in a consistent way. By relying on the model-based inference, some biases arising from the human inference process can be avoided.

2. Subject-matter experts from a variety of backgrounds with different emotional and moral motivations can have different types, magnitudes, and directions of bias. When aggregating their opinions, the total impact of bias may be mild because of the offsetting effect of the biases.

3. As an on-going process, back testing is another way to improve the inference. Comparing previous predictions with the actual experience will not only help improve the future risk assessment but also provide useful information to subject-matter experts. If the experience is out of their expectation, they may adjust their inference processes and provide more valid inputs in the future.

4. The last but probably most important strategy is to build a healthy risk culture. People need to be aware of their cognitive biases and encouraged to improve their inferences instead of defending their biased opinions.

1. INTRODUCTION

Many risks, such as emerging risks and some operational risks, do not have enough experience data upon which to apply statistical inference. Qualitative approaches need to be used to assess the level of exposure to them, using limited data, knowledge, and experience with human inference.

Human inference is not only about rational behaviors. Irrational behaviors caused by heuristics, emotions, moral motivations, risk aversion, and many other factors influence our inference and decision-making. They may not make sense from a pure economic perspective, but they normally have reasonable psychological reasons. For example, to reduce the chance of outliving retirement assets, some retirees invest heavily in stocks with high dividend yields. By only using the dividend payments to cover their living expenses, the retirees want to have a self-control mechanism in place to limit their longevity risk. This may introduce a higher level of concentration risk on high-dividend-yield stocks and maybe not the best solution for the retirees. They could buy life annuity products, or they could also invest in stocks with low dividend yields as well, as long as they do not overspend. The economic outcomes of other alternatives may be better, but the retirees may still prefer to invest in high-dividend-yield stocks as it meets their psychological need of self-control. Qualitative risk assessment is based on human inference and the assessors also have psychological needs. Undesired impacts of biases on the assessment may need to be addressed.

The remainder of the paper proceeds as follows:

- Section 2 (Inconsistent Inference in Risk Assessment) discusses some typical biases in qualitative risk assessment.
- Section 3 (Mitigating the Impact of Biases) discusses four strategies to increase the awareness and reduce the impact of some biases.
- Section 4 summarizes the key points of and concludes this paper.

2. INCONSISTENT INFERENCE IN RISK ASSESSMENT

Qualitative risk assessment relies heavily on inputs from subject-matter experts and is full of uncertainties because the experts' opinions are inferred from their knowledge and experiences. General human inference rules apply to everyone, but to different degrees. Shefrin (2002) summarized the common biases witnessed in investment decisions. Many of those biases are applicable to qualitative risk assessment and decision-making as well. Biases may be heuristic-driven; due to the lack of data and experience, people develop general principles by themselves and draw conclusions from limited information using untested rules of thumb. Biases may also be caused by frame dependence. People's emotions, social-economic statuses, and degrees of risk aversion may affect the inference as well. Some typical biases are discussed below.

1. Representativeness

   Representativeness occurs when expectation for the future is largely based on past experience, especially recent experience. The 2008 financial crisis is a good example of the negative impact of representativeness. Because there had been a long time since Black Monday in 1987, many financial institutions were not expecting such an extreme event. The 2008 financial crisis is more severe than a 1-in-100 or 1-in-200-year event represented in risk models.

2. Overconfidence

   Overconfidence occurs when people place too much confidence in their own opinions. Overconfidence will likely cause underestimating uncertainty. People may predict a narrow confidence interval of a potential loss, leading to a riskier business profile above the company's true risk tolerance.

3. Anchoring and Adjustment

   Anchoring occurs when people start from an initial value and are unable to incorporate the full impact of new information on prediction. When new information is received, updated estimates may be different only because the starting points are different.

4. Herding

   Herding occurs when people share similar opinions on an issue. When people share the same views on risks that are new and have not been studied thoroughly, herding can be quite dangerous. Having different opinions is good for improving our understanding as it will lead to more discussions and thinking.

5. Regret minimization

   Some people tend to avoid regret of making a bad decision or providing a wrong opinion and may be reluctant to comment on topics for which they are uncertain, although they may have the most knowledge. They are likely to overestimate exposure to risk types that are new and evolving.

3. MITIGATING THE IMPACT OF BIASES

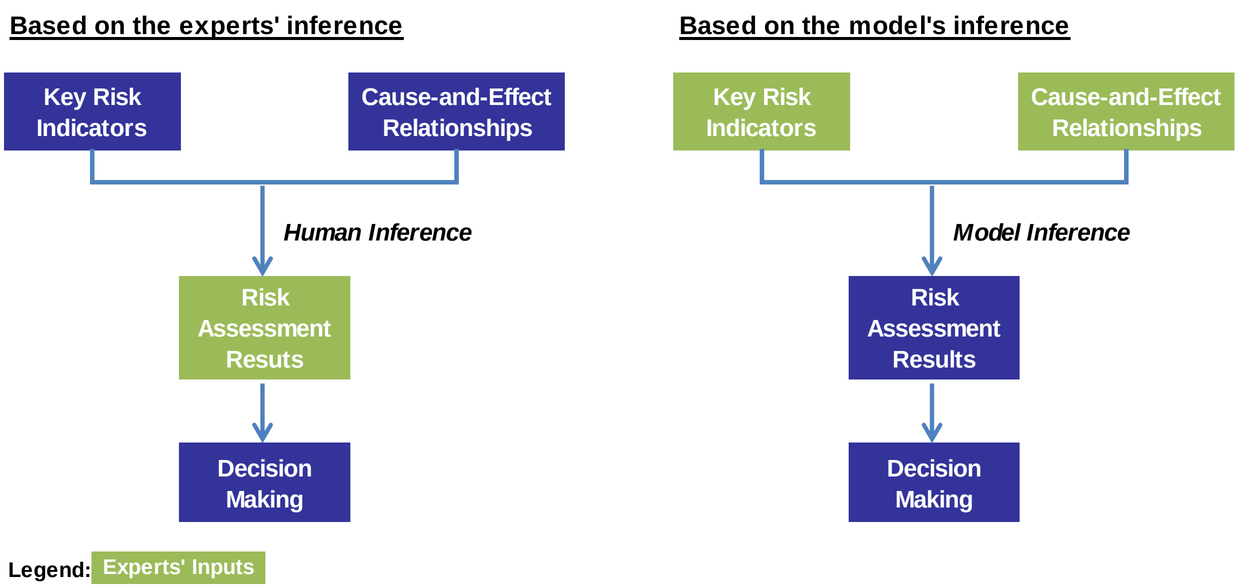
Being part of human nature, biases may be reduced but not eliminated. Several strategies are proposed below to reduce biases and promote consistency in inference.

3.1 Standard Inference Framework

Instead of relying on human inference for qualitative risk assessment, machine-learning models may be used to assist in the inference processes. Machine-learning models give computers the capability and methods to learn from experience like human beings. Those models replicate the human reasoning processes and have built-in learning algorithms to help themselves evolve based on newly received information. The experts are not required to provide the final risk assessment but rather they provide information used to make the assessment. The model can draw inference from the information in a consistent way. By relying on the model-based inference, the biases arising from the human inference process may be avoided.

Figure 1 illustrates risk assessment processes based on different approaches to inference. For the experts' inference, the key inputs are the results of risk assessment. For the model's standard inference, the key inputs are the risk indicators and cause-and-effect relationships.

Figure 1. Qualitative Risk Assessment Processes: Human Inference vs. Model Inference



The fuzzy logic model may be a good choice. Shang and Hossen (2013) studied fuzzy logic models which are useful for risk assessment with limited data. The inputs of fuzzy logic models include key risk indicators (KRIs) and relationships between KRIs and risk exposures. They use a standard and well-established set of inference methods based on the fuzzy set theory and fuzzy logic. The methods are similar to those used in human reasoning.

3.2 Diversification of Experts

Due to lack of data and possibly knowledge, qualitative risk assessment requires experts' subjective inputs be based on their own experience. Although one expert may have more experience than others, he/she may have biases in the inference process which can make the result less reliable. Experts may come from different social and educational backgrounds, work in different functions, and have different personalities. Therefore, they may have different emotional and moral motivations which may lead to opinions with different biases. One common example is the reluctance of people to identify and assess the risks of their own business. Bringing together people with different backgrounds can help solve this issue.

1. The biases they have may be of different types, degrees, and directions. In aggregate, the impact of bias can be small because of the offsetting effect.
2. Understanding other opinions is beneficial for people so that they may recognize their biases and make efforts to correct them.

In a risk assessment, it might be better if people from other functions join the discussion to provide comments from different perspectives. The owners can still make the decisions, but learning from different opinions may help improve their decision-making.

3.3 Back Testing

For most risk types dealt with using a qualitative approach, data is insufficient. Reasonableness of the analysis is primarily in the hands of the experts. However, back testing based on experience data, if available, may be used to validate or improve experts' opinions and knowledge. Comparing the actual experience with the experts' predictions is useful, even though the experience may be limited. When there is a significant difference between the experience and the prediction, the experts may recognize biases in their inference processes and take actions to correct them. Even though experts may not admit that their predictions were wrong, their understanding of the issue can be improved.

In addition, back testing may help us find consistent patterns of biases for some experts, which may be used to adjust experts' future inputs or the weight on each expert's opinion to remove the impact of the biases. An example follows.

Company ABC is planning to launch a new product. The company is seeking advice about the potential loss caused by a misleading advertisement. Two experts are asked to provide opinions about the range of future annual loss. Their opinions are given the same weight when the aggregated estimation is calculated.

Table 1. Annual Loss Estimation without Adjustments

	Expert A	Expert B
Annual Loss Estimation	[$1 million, $5 million]	[$3 million, $8 million]
Current Weight	50%	50%
Aggregated Estimation	[$2 million, $6.5 million]	

Expert B had a history of overestimating the cost of a misleading advertisement for similar products. His conservatism may be related to an extreme event he experienced ten years ago when a huge penalty resulted from an intentional misleading advertisement by an adviser. Recognizing this bias in expert B's estimation, the aggregated estimation can be adjusted by either changing the weights or lowering expert B's estimation.

Table 2. Annual Loss Estimation with Adjusted Weights

	Expert A	Expert B
Annual Loss Estimation	[$1 million, $5 million]	[$3 million, $8 million]
Current Weight	70%	30%
Aggregated Estimation	[$1.6 million, $5.9 million]	

Table 3. Annual Loss Estimation with Adjusted Experts' Input

	Expert A	Expert B
Annual Loss Estimation	[$1 million, $5 million]	[$2 million, $7 million]
Current Weight	50%	50%
Aggregated Estimation	[$1.5 million, $6 million]	

The magnitude of adjustments depends on the degree of conservatism. It is difficult to know the exact adjustment that is required to correct the bias; however, as long as the adjustments are consistent in all cases, the risk assessment results are comparable.

3.4 Risk Culture

Almost all aspects of risk management cannot be successful without a healthy risk culture. As Tavris and Aronson (2007) pointed out, it is difficult for people to admit that they made mistakes, even to themselves. Cognitive dissonance introduced by Festinger (1956) is a psychological explanation for this, occurring when a person holds two inconsistent cognitions that produce mental discomfort. The person has a psychological need to justify his/her mistakes to resolve the inconsistency. Montier (2007) listed the defense mechanisms that are used by forecasters to justify their wrong predictions.

1. If-only defense: If the conditions assumed in the analysis happened, then the prediction would be correct.
2. Ceteris-paribus defense: If the unconsidered factors remained unchanged, then the prediction would be correct.
3. Almost-right defense: The prediction is close to the actual experience.
4. It hasn't happened yet defense: The prediction could be correct. It just has not happened yet.
5. Single predictor defense: One wrong forecast does not mean all others are wrong as well.

Similar defenses are likely to be heard when experts are presented with actual experience that is different from their inputs. If not used wisely, the strategies suggested in Section 3 may not be able to reduce cognitive biases but cause fierce defenses that make the situation even worse. To mitigate the impact of cognitive dissonance and defenses for mistakes, a friendly and self-improving risk culture is essential. It may have the following features:

1. People are fully aware of cognitive biases in human inference, understand they are part of human nature, and do not feel ashamed about them.
2. People are encouraged to be open-minded and willing to recognize their biases in inference and adjust their understanding and opinions accordingly. Defenses based on weak arguments are discouraged.
3. Different opinions are welcomed and people need to understand arguments for opinions that are different from their own.
4. Mistakes are not avoidable. The focus of risk management is to improve the understanding and judgments instead of blaming people for mistakes.

4. CONCLUSION

Qualitative risk assessment is an important component of effective risk management. However, it is subject to cognitive biases in human inference. Recognizing the existence of biases and adjusting the inference process may help mitigate the impact of biased conclusions. Cognitive biases are part of human nature. A complete solution may not be available but certain strategies can be used to address them, at least to a certain extent.

1. Inputs about key risk indicators and the cause-and-effect relationships are more valuable than a possibly biased result of risk assessment.

2. Experts from a variety of backgrounds may lead to an aggregated result with small bias.
3. Back testing is an effective way to help us recognize our biases and adjust biased results.
4. A healthy risk culture is the key to encouraging people to recognize their biases.

There are many types of risk that exist with a lack of experience data. It is beneficial to have an increasing awareness of cognitive biases in the risk management area. In the end, more consistent and reliable qualitative risk assessment will improve our decision making.

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Biography of the Author

Kailan Shang works in the pricing area at Manulife Financial in Canada. Before that, he worked in the area of financial risk management and risk analytics in AIA. Years of actuarial and risk management experience has allowed him to get a broad exposure in the fields of day to day risk management, risk appetite and risk limit setting, risk quantification, asset liability management, variable annuity pricing, economic scenario generation, economic capital modeling, market consistent embedded value, strategic capital management, dynamic management option and policyholder behavior, and the like.

As an FSA, CFA, PRM, and SCJP, he is also an enthusiast of actuarial research through both volunteer works and funded research programs. He participated in the CAS LSMWP and was awarded the Emerging Issues Prize from the CAS in 2011 for the paper titled "Loss Simulation Model Testing and Enhancement". He co-authored the papers "Risk Appetite: Linkage with Strategic Planning" and "Applying Fuzzy Logic to Risk Assessment and Decision-Making" sponsored by the Joint Risk Management Section of the CAS, CIA, and the SOA in 2012. He was invited to speak on some research topics at several actuarial seminars.