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How Risky is that Risk? Measuring Likelihood of Risks

Easwar Nyshadham
Nova Southeastern University

Amon Seagull
Nova Southeastern University

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Easwar A. Nyshadham
Nova Southeastern University
easwar@nova.edu

Amon Seagull
Nova Southeastern University
amons@nova.edu

ABSTRACT

Many risks are well documented in academic and trade publications, even though attempts to estimate the likelihood of such risks have not received much attention. Quantitative measures of risk, even approximate measures, can help consumers take rational decisions, help security professionals prioritize their countermeasures, and enable ecommerce by helping insurers price risks accurately. In this research, we survey research from reference disciplines and suggest several research methods that could help approximate the magnitude of risks. These are: a) psychometric methods, b) lotteries with induced values (BDM Procedure), and c) using prediction markets. We suggest that using multiple methods can help triangulate estimates so as to arrive at better risk estimates.

Keywords

Online risks, quantifying risks, psychometric paradigm, prediction markets

INTRODUCTION

The ecommerce environment presents several new risks for various stakeholders (Rose et. al. 2005, 2001). Many of the risks engendered by ecommerce are relatively new and even approximate estimates of the likelihood of risks are not available. This has consequences for the different stakeholders in ecommerce such as consumers, security professionals, and insurance companies. Consumers do not have enough information to judge the riskiness of ecommerce transactions. Security professionals, in the absence of quantitative data on risk magnitudes, may not be able to rank order risks and allocate their efforts optimally to prevent attacks. Finally, insurers cannot underwrite contracts when risk likelihood is unknown.

However, no existing studies actually ask the question: how risky is that risk? For example, what are the odds of a credit card number being stolen while transacting with a B2C web site – 1/1000, 1/1,000,000 or 1/1,000,000,000? Surprisingly, while opinions abound, there is no agreement on the magnitude of these risks, even among experts.

The more important question for a researcher is: are there any theory-based measurement approaches for estimating risk likelihoods? In this research, we review three interesting approaches, each coming out of a reference discipline. The first method uses psychometric methods and comes from psychology. The second method uses incentive-compatible elicitation techniques and comes from the area of behavioral decision theory (BDT). The third method, prediction markets, comes from economics. We compare and contrast the underlying theories, discuss the measurement methods that could be derived from the theories and illustrate using examples.

LITERATURE REVIEW

General Notions of Risk

Risk is generally considered undesirable and usually understood in terms of a likelihood of an undesirable event (p) and its consequences/losses (L). Therefore, risk can be written as Risk = f(p, L). Standard theories in decision sciences and economics, which are extensively used by IS researchers, generally adopt utility theory as a basis.

In utility theory, it is assumed that a rational decision maker, with consistent preferences over alternatives, makes choices among alternatives. Based on the choices, one could infer a function, called a utility function. Rationality is specified using restrictions on preferences (e.g., preferences should be transitive, independent from irrelevant alternatives, etc.). Under the assumptions on preferences, it is deduced that a rational decision maker would combine probabilities and values with a linear in probabilities function, i.e., Utility = p * f (L). The functional form of f(L) is interpreted as risk attitude, and its shape is used to model risk neutrality, risk aversion, or risk seeking tendencies.

A variant of expected utility theory, called subjective utility theory (SEU), is equally popular, especially in the field of decision analysis. Under SEU, a decision maker uses a Bayesian perspective and can use idiosyncratic beliefs (likelihoods) and values – a decision maker is considered rational if she displays consistent preferences as in the utility theory. One could therefore write: Subjective Utility = $p_s * f(L_s)$ where p_s and L_s represent subjective probability and value respectively. A rational decision maker, like in utility theory, is expected to maximize subjected expected utility.

Systematic deviations in decision maker behavior from predictions of utility theory led to several alternative formulations. The most famous of these theories is Prospect Theory (Kahneman and Tversky, 1979), which the authors call "unabashedly descriptive". In prospect theory, instead of imposing some "logical" assumptions on preferences, known violations are explicitly built in. As a result, in prospect theory, decision makers are assumed to overweight low probabilities and underweight high probabilities, therefore using a different weighting function for probability. Decision makers also use an S-shaped value function, which is convex for losses and concave for gains, thereby resulting in inconsistent preferences. Prospect theory is, therefore, more descriptive of human behavior rather than a normative theory like utility theory.

Psychological risk, in general, moves away from the normative view common in economics research. There are many notions of risk in the psychology literature, and we focus our review on the subset that is relevant to this manuscript. One particular operationalization of risk, which is very popular in IS research on risk, embeds it in the attitudes research (Ajzen and Fishbein, 1980), which posits a process model of beliefs→attitudes→intentions→behavior. In such models, perceived risk is considered a subjective belief and is expected to affect other variables of interest (e.g., attitude, intention, behavior, norms etc.). Such a conceptualization helps embed perceived risk nicely into the TAM type of models. Studies in this tradition (e.g., Kim et. al., 2003) highlight the importance of conceptualizing and relating perceived risk to other constructs, but do not attempt to measure risk in an objective sense.

Three Perspectives on Risk:

We present our arguments using a simple framework consisting of three different perspectives: demand-side perception of risk, supply-side perception of risk, and market perception of risk. Demand-side risk perception deals with how consumers perceive risk. Since perceptions eventually drive behavior, theories and methods for assessing perceived risk from consumers can present one way to assess risks.

Supply-side perception (with a minor abuse of terminology) is defined as risk as perceived by an insurer. An insurer's business model depends critically on assessing and quantifying risks, so as to offer risk mitigation contracts to various B2C firms. One could of course include all parties responsible for production of risk, including security managers and hackers, but for this paper, we restrict attention to insurers. Finally, the market perspective focuses on equilibrium risk, which is arrived at when supply and demand interact in a hypothetical, perfect market.

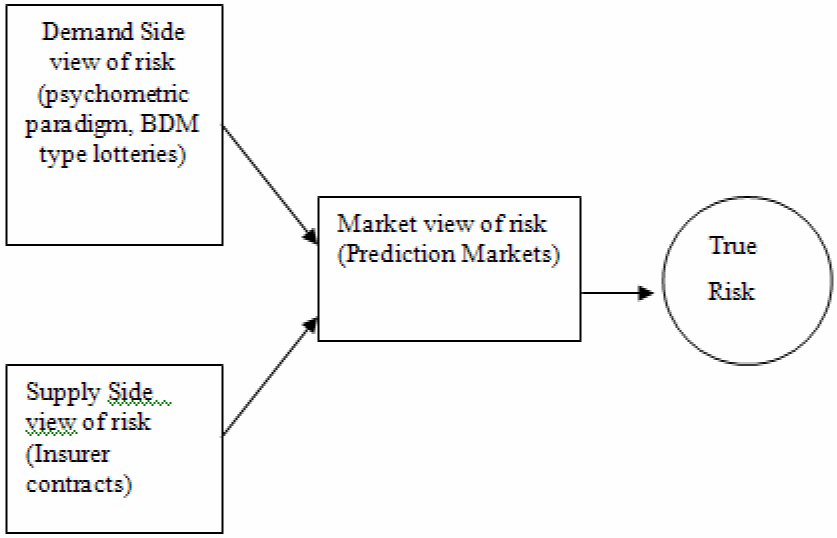

Figure 1. Three Views of Risk

Supply-Side View of Risk: Risk in general could be caused by vulnerabilities in technology as well as behaviors of various actors in a firm (users, developers etc.). Since our focus in this research is on risk probability and not its source, we use the insurance industry as a baseline for quantifying risk. Insurers' business models require that they create a variety of insurance policies (contracts), taking into account risk probability (p), potential loss (L) and consumers' risk attitude (assumptions on the shape of utility function). Insurers also need to offer a menu of contracts to address imperfect information in a market (e.g., screening, signaling, moral hazard, adverse selection etc.). For the purpose of this paper, we interpret insurer's contract offers (premium / coverage) as estimates of risk probabilities.

From a managerial perspective, to the extent that a "market knows best", risk estimates implicit in the contracts offered by insurers can suggest a baseline estimate or a starting point for measuring risk probabilities. However, some authors argue that when information about risks is unknown (e.g., when environment is characterized by ambiguity), insurers will display "ambiguity-aversion" and not offer contracts that they would otherwise offer (Kunrether et. al, 1995). Therefore, inferences regarding objective risks based on insurance contracts available in the market may be biased upwards. Despite this shortcoming, the information contained in the contracts can provide some useful information about risk probabilities.

Demand-Side View of Risk: Risks perceived by consumers and firms constitute the demand side of risks. Risk perceptions of consumers are relevant in a B2C context, and risk perceptions by firms in general may be relevant in a B2B context. Much of the research in IS, as argued before, uses a perceived risk construct in a TAM-type of model to explain variation in other variables. We could not find any published work that asked consumers' estimates of risk for individual risks (e.g., credit card fraud).

One theoretical argument for understanding risk perceptions can come from the psychometric paradigm, employed widely in psychology to study general risks. From a consumer's perspective, many risks are novel, and in the absence of knowledge of such risks, it is quite likely that consumers use their understanding of well known risks in the offline domain (e.g., hurricane landfall, automobile accident, etc.) and organize novel risks (e.g., loss of privacy) as similar or dissimilar to known risks in their memory. The cognitive structure, called the perceptual map, can be recovered using methods developed under the psychometric paradigm (e.g., Slovic et. al).

In a simple psychometric study, a subject is asked to compare several risk objects pair-wise on a Likert type scale indicating how similar or dissimilar two risks are on a dimension, such as overall riskiness. The pair-wise similarity matrix data can be analyzed using multivariate techniques (e.g., MDS, Factor Analysis, etc.). The risks are then related to one another using a distance measure in a derived, smaller dimensional space. One could then compare an unknown risk, like credit card fraud, by judging which other known risks (e.g., automobile accident, catching a flu) are closest to it in the perceptual map. An approximate estimate of riskiness of an unknown risk can be made by using risk estimates of known risks which are in the neighborhood of the unknown risk.

An advantage of psychometric methods (e.g., the non-metric MDS) is that the instrument used to gather data from subjects does not ask questions which a subject may not be able to answer. In a typical MDS type of study, a subject is asked to rate how dissimilar (say) privacy risk is compared to an automobile accident, which can be considered a very primitive form of comparison. With novel risks, however, that might be the best form of comparison a consumer can make. In general, psychometric studies are exploratory studies and are not used to estimate riskiness itself. Therefore, we do not see such methods as a unique or best method for estimating risks, but rather as one of the several methods a researcher could use to triangulate.

When a researcher is confident that subjects can make more precise judgments, one could use standard lotteries to judge risks. In a simple lottery, a subject is asked to bet a certain amount of money which could make him indifferent between facing a risk versus not facing one. If a researcher can assume that people are rational (i.e., expected utility maximizers), then a mechanism such as the Becker-Degroot-Marshack (BDM) procedure may be used to create an incentive for subjects to reveal their estimates truthfully. In general, depending on the context (and hence the assumptions a researcher could make), more powerful scoring rules may be used to uncover true estimates of risks from subjects.

The psychometric methods appear interesting because they make minimal assumptions on what is required from a subject (how similar/dissimilar is one risk compared to another). It also appeals to the notion that people use “schemas” (i.e., mental representations) for risks into which all new risks are embedded. Its weaknesses are that i) it is an exploratory technique developed to recover perceptual schemas and not estimate quantities, and ii) in judging how similar/dissimilar two risk objects are, a subject may use an idiosyncratic weighted average of both probability and loss information, which may be difficult to separate. Lottery-based procedures, under some conditions, can be tightened so as to make them truth-revealing and have been studied extensively in the BDT area. However, a weakness may be that, if a risk is unknown, on what basis does a subject make a choice in such a lottery task? Overall, the two methods discussed above, psychometric paradigm and lottery-based procedures, come from different disciplines and make different assumption on human behavior and therefore, may help triangulate to arrive at an estimate of risk.

Market View of Risk: In theory, markets are assumed to aggregate information available among several subjects efficiently. There is increasing evidence that suitably designed markets can be used to predict information and serve as decision support / forecasting tools. An excellent review of prediction markets is provided by Wolfers and Zitzewitz (2004).

Prediction markets (a.k.a. information markets, event markets, futures markets) can be designed to aggregate information available among a large group of people into a summary measure. In a simple prediction market, a market maker (e.g., experimenter) creates a contract (e.g., if a risk occurs, then subject is paid $1 otherwise $0). The contract is traded on the market, and the price is determined by the market participants. Under some conditions, the equilibrium price reflects the market estimate of the probability of risk. There is considerable evidence that well-designed prediction markets can generate better predictors than other methods.

Unlike the first two approaches, where either the supply side or the demand side is discussed, a prediction market can provide the market discipline required to estimate risk magnitudes accurately. It is possible to create a prediction market, for example, in which contracts are designed to measure risk probabilities or spreads. Agents from the demand side (e.g., consumers, firms using technology) and firms supplying risk reduction services (e.g., security services vendors, insurers) may use either real money or play money to trade the contracts in the prediction markets. Statistics derived from such markets can be used to predict risk magnitude.

A major difficulty with organizing such a market is to assemble the firms and convince them to trade in contracts related to risk – it may be very difficult to do so in practice. An alternative is to create a simple *information market* and ask the “experts” (e.g., members of well known security organizations, academics, etc.) to trade in similar contracts. In such a case, even though the parties do not represent the demand or supply side, the market can still be interpreted as aggregating dispersed and private information. Prediction markets may work very well in aggregating risk information in such markets. A well known organization (e.g., an association of security professionals, AIS, IEEE, or ACM) may have the ability to recruit subjects and run such markets, while researchers can address the market design and software implementation issues.

Summary: We summarize the discussion above into a table below for easy reference.

S. No	Measurement Approach	Method Characteristics	Comments
0	Baseline Model	• A simple heuristic is to collect insurance offers from industry and use it to estimate likelihood of risks (e.g., use premium, coverage, etc.) • Assuming that "market knows best", this method could be effective.	Provides a nice baseline model. If risk likelihood is ambiguous, then insurance market may fail to be efficient, thereby biasing likelihood estimates upward.
1	Psychometric Approaches	• One could assess how similar an online risk (e.g., credit card fraud) is to an offline risk (e.g., catching flu). Using available, objective data on flu incidence, one could then provide a range of values for the likelihood of an online risk. • This method assumes, implicitly, that consumers use a schema (a mental abstraction) for all risks. • Many biases may enter into judgments of risks.	Theory comes from psychology (e.g., Schema Theory). Multivariate statistical techniques such as (e.g., Multidimensional scaling) may be used.
2	Lottery procedures	• A researcher could create hypothetical lotteries and use choices made by subjects to estimate risks. • If subjects are expected utility maximizers, then a procedure like BDM can ensure truthful revelation. • In general, given the context, an appropriate scoring rule can be adopted or designed. • Many biases may enter into judgments.	Theory comes from rational choice models like Subjective Expected Utility Theory.
3	Prediction Markets	• Suitably designed contracts can be offered involving unknown, online risks and known, offline risks. • The equilibrium prices may be used as point estimates of risk likelihood. • Prediction markets have been shown to be effective in many domains.	Theory comes from the claim made in economics that equilibrium prices aggregate information accurately.

Table 1. Alternate Methods for Measuring/Estimating Online Risk Likelihood

Summary: In this article, we ask the question: how risky is that risk? Literature shows that quantitative estimates of risks, even approximate ones, are not available. We organize several methods available in a variety of reference disciplines and briefly discuss the underlying theory and implied measurement approaches. Each of the techniques rests on several assumptions and therefore, none of the methods may be able to individually provide an accurate estimate. However, using more than one method and triangulating the results, we hope that it might be possible to answer the question "how risky is that risk?" within a few orders of magnitude.

In this paper, we organize the several risk concepts and measurement approaches using a basic economic framework – using a supply-side, demand-side and an equilibrium notion of risk. Risk in general has also been studied under social sciences using cross-cultural notions as well as under social amplification notion of risk. The social notions of risk are not included in this review and future work could attempt to integrate those into this research.

Future Work: We believe that the question of quantifying risk probabilities, even approximately, is a difficult one. In a future version of this manuscript, we expect to elaborate on the theory, refine the measurement methods and provide some examples of experimental designs, lotteries, and market designs for prediction markets.

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