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By

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Abstract

Essay on Financial Risk Taking and Embedded Heuristics

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This dissertation investigates the relationship between the use of financial risk taking and the complex mathematical models used to quantify risks. In the first essay, laboratory experiments demonstrate that students who have taken courses in finance and economics take more risk when they are exposed to complex mathematical models, even when these models do not provide more information. Furthermore, students who have a strong belief in the power of risk quantification to produce accurate assessments of future events are more likely to take more risk when it is accompanies by complex quantitative models. The second essay uses data on U.S. banks from 1994-2007 and investigates popular claims that innovative risk measures, such as value at risk (VAR) resulted in greater risk seeking by banks prior to the financial crisis. It theorizes that as formal risk assessment models, such as the risk models used by banks, become institutionalized within organizations, a model's abstract representation of reality becomes reified and treated as though it is real and complete. This results in organizationally-embedded decision-making heuristics that shape how choices are made within the firm. For risk models, this meant that when banks encouraged the use of risk models, they generated an implicit belief that these models represented accurate assessments of future outcomes. This reduced uncertainty about future outcomes and led to greater risk taking.

Safety in Numbers:

Individual risk taking and embedded heuristics

Beware of geeks bearing formulas

—Warren Buffett (2009)

In his seminal work, *Risk, Uncertainty, and Profit*, Frank Knight (1921) provides a classic explanation of how the ability to measure risk might lead to greater profit making. He uses the example of champagne bottlers. The bottler who is unaware of the rate at which accidentally bottles pop before they are sold must work with uncertainty and absorb the loss each time a bottle prematurely losses its top. The bottler's success is dependent on the number of popped bottles, over which he has little control. On the other hand, the savvy bottler, who knows how often the champagne bursts before leaving the shop, can adjust prices accordingly, passing the cost on to the consumer. By being able to measure the risk of explosive bubbly, the knowledgeable bottler is able to control his losses in a way the uncertain bottler cannot. Hence, Knight explains, "a measureable uncertainty…is so far different from an unmeasurable one that it is not in effect an uncertainty at all" (1921: 19).

Like the savvy champagne bottler, the finance industry had excelled at finding ways to measure its risks in the past 20 years. New forms of risk measurement, such as Value-at-Risk, helped finance experts to keep tabs on the risks banks were taking. Innovative financial instruments, like credit default swaps, enabled more risks to be priced and sold. Powerful computing technologies crunched enormous amounts of data to create risk estimates. In board rooms, Chief Risk Officers were added to banks' C-suites to oversee risk management. And, at the top of the financial food chain, Alan Greenspan adopted what he called a "risk management approach" to managing the US banking system. By most accounts, the financial industry had been like the savvy champagne bottler, able to account for risks and operate more profitably.

The financial industry's innovations had, in part, drawn their inspiration from physics. In devising the partial differential equation that describes the value of a stock option, Fischer Black and Martin Scholes relied on the heat diffusion equation from thermodynamics (1970). A decade before, Osborne (1959: 145) noted that "a statistician, trained perhaps in astronomy and totally unfamiliar with finance" who observed that stock market would realize percentage changes in stock prices had "a close analogy with the ensemble of coordinates of a large number of molecules." He demonstrated that the statistical analysis normally applied to the study of an ensemble of molecules will be equally effective when applied to stock prices. Indeed, several of the pioneers of modern finance came from science disciplines. In more recent years, banks and hedge funds began recruiting directly from physics programs. In 2012, Princeton's physics departments' web page recruited students by noting the applicability of physics to finance:

> The need for quantitative methods in the financial world has led an increasing number of physicists to join finance and investment banking. This is because a physics education is a very quantitative and rigorous education... Most large and small financial institutions now employ physicists, either with a graduate or an undergraduate degree (Princeton University, 2013).

The melding of economics and physics was reflected in the birth of the term "econophysics" to describe the academic field in which economists and physicists combined concepts to explore the movement of prices and markets. Some insiders began to wonder, "Is economics the next physical science?" (Farmer, Doyne, Smith, 2005, pg.37)

One important consequence of the close academic and professional ties between physics and finance (for more examples, see Bernstien, 1996) is that the industry began to treat markets more like physical phenomena. As a consequence, the trajectories of financial markets were treated like the predictable the paths of moving objects rather than unforeseeable social behavior. In somewhat hyperbolic language, Scott Peterson, Wall Street Journal reporter, describes the mindset of a financial "quant" like this:

> [T]hey had something far more powerful in common: an epic quest for an elusive, ethereal quality the quants sometimes referred to in hushed, reverent tones as the Truth [sic]. The Truth was a universal secret about the way the market worked that could only be discovered through mathematics…. (2011, pg. 8).

Mathematical sophistication came to represent the ability to change an uncertainty—future performance of the market—into profits. Steeped in theories from the natural sciences where "laws of nature" are valid everywhere and can be used to precisely predict physical phenomena, finance professionals took a Knightian approach to uncertainty: quantify, quantify, quantify.

Yet, despite the onslaught of quantitative methods and mathematical expertise, finance did not fare as well as Knight's happy champagne bottler. Instead, as Greenspan admitted, "In August 2007, the risk-management structure cracked" (2009). He noted that the "sophisticated mathematics" and "computer wizardry" had not prevented banks from taking on too much risk. Why? Some commentators, including Nobel Prize winner Paul Krugman (2009) and legendary investor Warren Buffet (2009), pointed their fingers at the very risk management systems that were aimed at making uncertainty more measurable. One of the risk management's most vocal critics, Nassim Taleb told Congress that advancements in risk management were actually the very reason for increased risk taking: "We increased our leverage in society as we thought we could measure risk**.** If you think you can measure it you blow-up risk, you are going to borrow, you know. You have more overconfidence, also, as a side effect of measurement" (2009). This paper explores these unintended consequences of risk quantification.

If decision makers can accurately calculate future probabilities, like Knight's shrewd champagne bottler, then the future holds few surprises and individuals can make plans that account for various contingencies. But what if risk quantification isn't accurate and the probabilities will not map accurately onto the future-- what is the value of quantification then? Social phenomena, like financial markets, can never be predicted as easily as physical ones, like the pressure inside a champagne bottle.

Instead of relying on foresight of a prediction's accuracy, decision makers must evaluate the means of prediction. Does this risk calculation seem like one that can be trusted? Does it use the proper form of prediction? Take into account the right contingencies? Use the latest technology? To answer these questions, decision makers rely on their own cognitive processes and social norms. In this paper, I investigate one way people evaluate the way a prediction is generated—the use of sophisticated mathematics. In the world of risk management and econophysics, the use of complex mathematical methods came to represent the validity of a prediction. Thus, one way decision makers can tell whether a financial prediction conforms to the social norms is whether it employs the kinds of sophisticated mathematical models that have become the playthings of financial quants. This kind of mathematical complexity acts as a signal to decision makers that the predictions are reasonable and that the unmeasured uncertainties have been transformed into manageable probabilities. This signal may or not be validated in the future, when retrospection will enable decision makers to assess the validity of the prediction by comparing it to the outcome.

In the mean time, however, complex quantification may have some serious behavioral consequences. At the moment when investment decisions are made, the sophisticated quantification may make uncertainities seem more thoroughly understood—more like the quantified champagne popping probabilities—and therefore less "risky" and more valuable. "Constructed by a nerdy-sounding priesthood using esoteric terms such as beta, gamma, sigma and the like, these models tend to look impressive," warns Warren Buffett, "Too often, though, investors forget to examine the assumptions behind the symbols" (2009, pg. 15).Complex mathematical methods suggest to decision makers that financial risks, like the shrewd champagne producer's bottles of bubbly, are well-understood—that the predicted probabilities will map onto the frequency of future events. There is nothing about complexity, however, that is inherently more valuable for enabling this kind of risk management. The champagne bottler does not necessarily do any better with a probability of popping formulated with Greek symbols and partial differential equations, nor does a financial decision maker. What matters ultimately is whether the predictions are right, not whether they are complex. Yet, the complex mathematics hides the uncertainty inherent in predicting human behavior by making the science behind them seem more authoritative. Previous research has shown that individuals reading text often feel they have greater comprehension of the content than they in fact do—that people can suffer from the illusion of knowledge (Glenberg et al., 1982). Complex risk models take this illusion to the next level, creating an illusion of knowledge not just about the content of the models, but about the very future they predict.

Research on decision making has demonstrated that how uncertainties are expressed shapes how risk is perceived. One area of research has looked at the difference between verbal (e.g. very likely) and numerical (e.g. 90 percent) expressions of chance (von Winterfeldt and Edwards 1986; Budescu & Wallsten, 1995). However, the overwhelming majority of this research distinction has been dedicated to demonstrating that interpretations of verbal expressions of uncertainty (e.g. "small chance," "highly probable," ect.) vary inter- and intra-personally; little consideration has been given to differences in the interpretation of quantitative expression of probabilities. It is common in this literature to find references to the supposed superiority of numerical probability; for example, Wallsten, Budescu, and Zwick (1993, pg.177) write, "[N]umerical expressions are precise, unambiguous communications that allow expected value or expected utility calculations." Bedescu and Wallsten, however, have argued elsewhere that the "meanings of numbers should also show imprecision" (1995, pg. 276). That is, the meanings of numbers vary by individual and by context. In fact, they argue that people both use the same numbers to convey different meanings and interpret numbers to have different meanings. For example, if irresponsible friends tell you that there is a 50 percent chance that they will show up at your party, you probably won't expect them to show up. If, on the other hand, a highly critical colleague informs you that your odds of getting a paper published are 50-50, you may rejoice since this is significantly higher than typical odds of publication. In both these examples, however, numerical probabilities are just another way to express highly subjective judgments. Bedescu and Wallesten, speculate that people "would believe numbers to be relatively more precise if they knew the values represented extensive relative frequency data rather than other individuals' judgments. But, to our knowledge, this fact has not been established" (1995, pg. 287). They contend that people differentiate casual uses of probabilities to express subjective estimates and mathematically derived probabilities based on frequency information. One of the effects of quantitative models may be exactly that it promotes the belief that predictions are more accurate because they are generated through the use of extensive frequency data. The complexity of mathematics can be a symbol of the ability to predict the future using large amounts of data on the past; therefore, predictions made with complex mathematical formulas may be assumed to tell the future more accurately than ones that do not. Hence, a bias may exist toward taking risks that are explained using complex mathematics—a *risk quantification bias*.

The risk quantification bias is the result of both cognitive processes and social ones. The idea that how decisions are framed influences how they are made is one of the central tenets of the research on decision making. For example, Tversky and Kahneman (1971) have demonstrated that framing choices in terms of losses increases individuals' willingness to take risks, while framing choices in terms of gains creates risk aversion. The effects of frames seem to stem less from a shift in decision maker's actual risk tolerance than from a change in focus among a set of inconsistent, ambiguous preferences (March, 1978; March and Shapira, 1987; Nisbett and Ross, 1980; Tversky, 1972, Tversky and Kahneman, 1971; Fiske and Taylor, 1991).

Similarly, mathematical models may act as frames for risk takers and draw attention to the measurable aspects of a risk, making the risk seem less risky—better understood and therefore more easily hedged.

Furthermore risk models shift attention away from the many contingencies that are not included in the quantitative model. Organizational routines for measuring and evaluating choices shift attention to areas decision makers are able to measure (Greve, 2003; Cyert & March, 1963). Consider the champagne bottler who may have an equation for the ways a rise in room temperature (easily measured) will increase popped bottles; the uncertainties regarding the (possibly even more important but more difficult to measure) inconsistencies in cork manufacturing may be ignored as attention is given to the quantified aspects of the model. Similarly, complex mathematical equations may drive attention toward the quantified risks and away from other potentialities. In this way, quantitative models boil down information relevant to a decision to only that included in the model. Previous research has shown that decision makers with only relevant information, rather than a whole mix of relevant and irrelevant information, tend to make more extreme judgments (Nisbett, Zukier, and Lemley, 1981; Zukier, 1982). Mathematical equations work to frame as relevant the information in the model and enable the excluded information to be easily discarded, resulting in more extreme risk taking.

The effects of complex models are not merely cognitive, but also dependent on social norms that emphasize the importance of quantification of risk. Before mathematical models can work as frames, they must be considered relevant and authoritative to decision makers—individuals must be influenced by social norms that emphasize the importance of mathematical models. This bias toward risk taking under complexity diverges from those typically studied within judgment and decision making research because it is embedded in a particular style of thought, one associated with education in economics and finance.

Because the risk quantification bias is embedded within a particular cultural norm, it diverges significantly from most biases described by judgment and decision making literature. This work typically operates on the premise that baises and heuristics are hard-wired, inherent processes of the mind. The research is generally conducted on undergraduate students with the assumption that whatever biases and heuristics they demonstrate are externally valid for decision makers in all contexts (for discussion see Staw, 2010). This theoretical leap is acceptable because heuristics and biases are not considered context specific, but rather universal.

Several previous studies, however, have demonstrated cultural differences in the use of decision making biases. For example, attribution errors have been shown to diverge between American and Chinese decision makers (Morris and Peng, 1994; Menon et al. 1999;) and several other studies have demonstrated cultural differences between the "West" and the "East" (Miyamoto et al. 2006; Nisbett and Miyamoto, 2005; Choi et al. 1999; Hsee and Weber, 1999). This divergence of "West" vs. "East" research has done an excellent job of invalidating the assumption that decision making processes are universal, by demonstrating that Western biases don't exist in Eastern cultures; however, they have stopped short of demonstrating how decision processes are embedded within cultural beliefs. Instead, they rely on the "culture" as the explanation for differences without directly connecting cultural beliefs with decision making processes (Brockner, 2003). Given the many differences between the Western and Eastern subjects in these studies-- geographies, levels of national wealth, predominant religions, age of civilizations, education, climate-- it is impossible to pin down what exactly about the cultures is accountable for the differences in decision making processes. In the final study of this paper, the risk quantification bias is investigated as the product of a particular set of beliefs about the value of quantification. It aims to more directly investigate whether a tendency to take risks when they are accompanied by complex equations is due to a Knightian belief in the value of risk quantification and whether such a belief is the result of education in economics and finance. By showing how a particular cultural belief become embedded within cognitive processes, this paper takes a cue from institutional theory, which has sought to explain the " interaction of shared cognitive structures and supra-individual cultural phenomena…that activate those structures to varying degrees" (DiMaggio, 1997, pg 264).

This paper aims to make preliminary inroads in understanding how a specific set of "supra-individual phenomena" shape decision making processes by showing how the risk quantification bias is embedded within a set of beliefs about risk management. Through three experimental studies, this paper aims to make two contributions to research on decision making. The first experiment demonstrates a bias toward risk taking when investment descriptions are accompanied by complex mathematical equations for individuals with finance education. The second experiment demonstrates a similar difference for economics majors and controls for two alternative explanations—that the bias is the result of greater trust of experts and that the bias is the result of greater mathematical literacy. Further tests find that neither of these mediate the risk enumeration bias and cannot account for it. The first two experiments aim to demonstrate the unintended consequences of complex mathematics on decision making processes of people with backgrounds in economics and finance. In the final experiment, a positive correlation is found between agreement with risk management philosophy and the risk quantification bias, suggesting that this decision making bias is embedded within a specific system of belief. This paper aims to make two contributions to research on decision making: first, by demonstrating that complex mathematics can act as frames for risky decision making and second, by providing an example of a decision making bias that is embedded within a particular belief system.

Experiment I: Preliminary evidence for the risk quantification bias within finance

If complex mathematics have come to represent in finance a heightened ability to profit in the future from risky investments, then individuals with backgrounds in finance should be more likely to take risks when they are accompanied by complex mathematics. The first experiment was designed to find out whether individuals with finance backgrounds, as compared to individuals without finance backgrounds, took greater risks when these risks were accompanied by highly quantitative models and whether this bias was specific to individuals with backgrounds in finance.

Because the risk enumeration bias is a cognitive institution (Scott, 1995, pg. 35-45) that is embedded within the particular subculture of finance, the effect of complexity on individuals with finance education is hypothesized to manifest as a positive interaction between complexity and finance, rather than as a main effect. The argument is not that individuals with finance backgrounds are more risk seeking in every situation, but rather that financially-trained persons will have a different reaction to complexity that those who are not educated in that way. They have adopted a cognitive schema that equates complexity with reduced uncertainty and this will shape their decision making when confronted with mathematical complexity.

Method

Participants. Participants were 59 individuals. Of this group, 26 were graduate students in a prestigious finance program and the others were MBA students at the same school. Participation was voluntary and not compensated.

Task. Participants were all given a scenario-style survey in which they were asked to make investment decisions in three hypothetical situations. For all the investments, the expected value was zero. For example, in one scenario, students were asked to imagine that they had a one-time opportunity to invest up to $10 million in a particular venture fund. The subjects were told that the risk department had analyzed the fund and determined that there was a 50 percent chance of doubling the investment and a 50 percent chance of losing the investment. They were told there was no cost to capital or alternative investments to consider. They were then asked how much of their $10 million they would like to invest. The amount invested indicated how much they were willing to risk.

There were two version of each scenario—one with a simple equation and one with a complex equation. In one example of the simple condition, subjects were told:

> *For your reference, you have been provided with the following formula for calculating the total amount of money [A_n] the investment will make three months after the initial investment [A_{n-1}] given the rate of return [r_n]:*

$$A_n = A_{n-1} * r_n$$

In the complex condition, subjects were told the same but the following equation was given:

$$A_n = A_{n-1} + (n+1)\sum_{j=i}^{n-1} [A_j r_j \frac{j}{n^2 - n + j} - jA_{j-1} r_{j-1} \frac{1}{j + (n-1)^2 + n - 2} + A_j r_{j-1} \frac{1}{j + (n-1)^2 + n - 2}$$

Importantly, the simple equation and the complex equations are identical in meaning. The complex equation can be reduced down to the simple equation in approximately 14 mathematical reductions. This means that the only difference between the two equations is their complexity; neither equation is more or less informative than the other. A post-hoc analysis of the surveys, which were given in paper-and-pencil format, revealed that no subjects had attempted to reduce the complex equation.

The dependent variable in the analyses was the total amount risked in the hypothetical investments. The responses were tested using an ordinary least squares regression that accounted for the condition (simple or complex), whether a student was a finance or management student, and the interaction of being a finance student and getting a complex survey. Gender was included as a control because finance students were significantly more likely to be male than management students, creating a potential confound.

Results and Discussion

Results indicate that there was no statistically significant overall difference between the complex and simple conditions and that finance students, in general, invested less than management students. This suggests that complexity does not have an umbrella effect on decision making and, therefore, is not universally used by all decision makers. However, when finance students were given the complex survey, they actually became more risk taking then management students. The positive and statistically significant result of this interaction effect ($p<.001$) suggests that complexity increases the risk tolerance of individuals with backgrounds in finance over above the willingness of individuals to take risk if they do not have such backgrounds. The occurrence of this effect only on finance students suggests that the risk enumeration bias was only used by those with that particular background, showing that a bias may be embedded within a particular style of thought. [Appendix: Figure 1.1]

These results are consistent with the hypothesis that individuals with backgrounds in finance become more risk seeking when risks are described using highly quantitative models. However, these results leave important questions about the mechanism that drives this bias. The first question is whether it is in fact the education that drives the mechanism or some other difference between finance and non-finance students is responsible for the tendency to take greater risks when shown complex models.

Study Two: Within-person effects of economics education on risk taking under complexity

The second study investigates whether education and changes in the perception of credibility drive the tendency to invest more in investments described with complex models. Although the first study found that finance students were more affected by the complexity of the models, it was unclear whether this had to do with some component of their education or another difference between them and the non-finance students. A within-subject design allows this second study to more closely control for potential confounds.

One component of the finance education which may shape their reaction to complex models when deciding whether or not to take risks is courses in economics. Previous theorists have found that the underlying principle of agent self-interest results in students becoming more self-serving after taking economics classes (Frank 1996, 1998). Similarly, an underlying principle to economics, which posits that measuring uncertainty enables decision makers to take some risks profitably, as described in the introduction, may make some students of economics more likely to take risks when they are described using complex equations.

One powerful alternative -explanation is that students who take economics classes tend to have greater respect for the opinions of experts in their fields. The greater quantification of the complex equations may be a powerful signal of the authority of the risk department who in the scenarios, provides the equations for the hypothetical investments. In this explanation, the level of complexity of the equation does not change the nature of the risk, but rather, changes the perception of expertise. To test whether this explanation holds, we controlled for the perceived level of accuracy of the risk department's prediction, the perceived expertise of the risk department, and the level of trust the subjects had in the risk department using individual items with 7-point likert scales that measured how strongly subjects agreed or disagreed with statements such as "The risk department's predictions are highly accurate."

A second counter-explanation is that individuals who have taken economics classes are more comfortable with numbers and, therefore, have less anxiety when presented with complex equations. This counter-explanation is consistent with previous research has established that affective states such as fear and anger can contribute to decision makers risk tolerance (Lerner & Keltner, 2000; Loewenstein et al., 2001; Mellers, Schwartz, Ho, & Ritov, 1997). If students with economics education are more numerate than others, their level of familiarity and comfort with complex equations may change their affective response to seeing sophisticated mathematics. That is, econ majors may simply like math more and be happier to see math and therefore less attentive to the negative aspects of the investment decisions. As a result, they would be more willing to take risks after seeing complex equations because they will be a more positive affective state. To control for this explanation, a variable for the number of math classes is included in the model. If greater risk is taken by economics students but not by students who have taken several math courses, this would indicate that there is something particular to the economics curriculum that prompts great risk taking when risks are described with complex mathematics.

Method

Participants. The subjects in this study were 178 undergraduates who were paid a flat rate for participation.

Task. Subjects were given the same scenarios as in the first study. The most significant difference between this study and the first is the use of a within-subjects design, in which all subjects were shown both the version of the scenarios with the simple equations and the identical scenario with the complex equations; the order in which subjects got the simple or complex equations was randomized. This within-subject design enables us to control for each individual's risk appetite when shown the simple equation; the dependent variable in this analysis is the amount they chose to risk investing in scenarios with complex equations (controlling for the baseline amount they risked in the simple scenarios).

In addition to the investment scenarios with simple and complex conditions, subjects were also given a brief questionnaire at the end of each section asking them about their perception of the chief risk officer who, according to the scenario, has provided the equations. This provides variables measuring accuracy of the risk department's prediction, trust of the risk department, and expertise of the risk department are within-subject measures of the difference of these items between conditions, calculated by subtracting the amount for each item in the simple condition from the amount for each item in the complex condition. The interpretation for the co-efficients for these variables is that a positive (negative) co-efficient represents the increased (decreased) amount of change in risk taking in the complex condition given how much more (less) accuracy or trust worthiness was perceived in the complex condition than in the simple one. Data on subjects' gender was collected but excluded from the model because, as with the first study, the variable was insignificant.

Results and Discussion. The results indicate that, controlling for the amount of risk subjects took in the simple condition, the greater the number of economics courses taken, the greater risk-taking in the complex condition. This holds true even when controlling for subjects' risk appetite (the amount risked in the simple condition); and perception of expertise, trust, and accuracy, which suggests that the bias toward taking risks with mathematical complexity is independent of the perceived authority and accuracy of the individual assessing the risks. [Appendix: Figure 1.2, 1.3]

In addition to the lack of a direct effect of perceptions of trust, accuracy, and expertise on risk taking, mediation tests also show no direct or indirect effects of economics education on increases in how trustworthy, accurate, or expert decision makers see the prediction makers when they use complex model. That is, economics education does not significantly change the perception of prediction makers, which may have lead indirectly to greater risk taking under complexity. Furthermore, tests for moderation show the increase in risking that positive correlation between econ courses and risk taking under complexity is not stronger when individuals perceive the prediction maker to be more accurate, expert, or trustworthy. Both the mediation and moderation tests that there is no relationship between perceiving the prediction maker to be more trustworthy, expert, and accurate and the relationship between taking econ courses and taking more risk under complexity. Although it is precarious to interpret non-findings, these may rule out explanations for the risk enumeration that focus on changes in the perception of the prediction maker as a casual mechanism.

Furthermore, the lack of a strong positive correlation between taking risks with mathematical complexity and completion of math courses suggests that there is something unique to economics courses that shapes the response to complex equations that is separate from literacy in mathematics. Moderation and mediation tests did not find any relationship between mathematics and the relationship between risk taking under complexity and economics courses. There was no significant relationship between taking math courses and economics courses, so no indirect mediated effects were found. Taking more math did not necessarily mean you took more econ courses, and vice versa, so no indirect mediated relationships were found. Nor did taking more math courses make the relationship between econ courses and risk taking under complexity more or less pronounced. Again, interpreting non-findings is unwise, but these seem to suggest that math courses do not have the same relationship to risk taking under complexity that economics courses do.

These findings point to the possibility that people with educations in finance and economics prefer investments that are accompanied by complex equations because they believe that these investments are different from identical investments with simple equations. Like Knight, they may believe that quantified uncertainties afford opportunities for profit that do not exist for measured ones. Indeed, for people with backgrounds in economics, who have been taught in a Knightian fashion to quantify risks, quantification provide a signal that a risk can be profitable. This paper does not throw a hat into the philosophical debate over the validity of this signal, but rather has shown that complex quantification alone may result in greater risk taking when individuals are well-versed in the Knightian style of thinking, even when this quantification is not the product of advanced quantitative analyses. Therefore, the first two studies indicate that a Knightian stance may result in an unintended bias toward taking risks described with heavy quantification.

Study Three: The Belief in the Value of Risk Quantification and Risk Taking Under Complexity

Several previous studies have demonstrated cultural differences in the use of decision making biases (Morris and Peng, 1994; Menon et al. 1999; Miyamoto et al. 2006; Nisbett and Miyamoto, 2005; Choi et al. 1999; Lee et al., 1996). This research on the decision making differences between of "West" vs. "East" research has shown that decision making biases are not necessarily universal, but have not gone far enough to explain why cultural differences emerge. Any of the multitude of cultural institutions and belief systems—could explain the differences in decision making processes. In the final study, the risk quantification is investigated as the product of a particular set of beliefs about the value of quantification. It aims to more directly investigate whether a tendency to take risks when they are accompanied by complex equations is due to a Knightian belief in the value of risk quantification and whether such a belief is the result of education in economics and finance.

Method

Participants. The subjects were 159 undergraduates who completed an online survey as part of their coursework.

Task. The third study was a within-subject scenario-type survey, which included six of the same investment scenario questions as in Studies One and Two (three for the simple and three of for the complex conditions). Again, the simple condition described hypothetical risk scenarios and were accompanied by simple equations, while the complex condition had the exact same scenarios but were companied by much more complex equations, which were reducible to the simple equations.

A questionnaire was completed at either the beginning or end of the survey (due to random ordering) to capture the level of the subjects' belief in the value of risk quantification. This scale included five items such as, "If you can quantify a risk you can safely take it," and "The more kinds of risk you can quantify the more likely you are to succeed." The responses were measured on a seven-point likert scale from 1 (strongly disagree) to 7 (strongly agree). Principal component factor analysis with varimax rotation reveled that these items loaded onto a single (orthogonal) factor, which accounted for 61 percent of the total variance in the items. A factor analysis with oblique rotation (allowing for high correlation among the items) had similar results. The alpha for the entire scale is .8052.

Results

The results only partially support the theory coursework in economics increases how much individuals value risk quantification, which in turn increases how much risk they are willing to assume when decisions are framed with complex equations. Economics courses and belief in the value of risk quantification had significant positive effects on risk taking in the complex condition (controlling for baseline risk taking in the simple condition). These results suggest that both economics education and valuing risk quantification results in greater risk taking when investment decision are accompanied by complex mathematics.[Appendix: Figure 1.4] The finding the economics courses increased risk taking under complexity replicates the finding in Study Two. [Appendix: Figure 1.5]

Sobel-Goodman mediation tests with bootstrapping (similar results were found without bootstrapping), however, do not support the theory that economics classes instill a risk quantification values in students, which results in greater risk taking when decisions are framed with complex equations: belief in the value of risk quantification was not found to mediate the effect of economics classes and risk taking in the complex condition. [Appendix: Figure 1.6] Instead, both economics education and risk quantification appear to work separately to increase risk taking under mathematical complexity. These findings suggest that any individual, regardless of their economics education, will be more likely to take risks when they have a firm belief in the value of risk quantification.

General Discussion

The risk quantification bias, like previous studies of framing, demonstrates that two objectively identical frames with the same meaning, may have different consequences for risk taking behavior. These three studies have demonstrated that when investment decisions are framed with complex mathematics, some individuals will have a tendency to take greater risks. There are two conditions that increase the likelihood of this risk quantification bias: having coursework in economics and/or finance and a strong belief in the value of risk quantification. These findings make three contributions. First, they lend some empirical evidence to the debate on role of risk management practice in the financial crisis and lend some credence to the claims of pundits that risk management rhetoric and tools may actually result in greater risk taking. These findings suggest the increase risk taking due to mathematical sophistication may account for why financial decision makers assumed so much risk prior to the financial crisis, a time when risk management was pervasive in the financial industry. Second, these studies add to the literature on judgment and decision making and its growing list of cognitive biases that shape risk taking. Third, in addition to describing another way in which frames influence congition, the risk quantification bias also deepens this literature by demonstrating how social norms, such as those within economics and finance, may produce biases that are embedded within particular styles of thought.

Limitations and future research

So far, the risk quantification bias has been demonstrated in the decisions of students taking surveys and is by no means concrete, conclusive evidence that this bias is at fault for excessive risk taking within the financial industry. Instead, this paper does show possibility that complex mathematics can frame decisions and result in greater risk taking by decision makers. Whether or not this finding can be generalized to organizational settings, such as banks and regulatory offices, has yet to be confirmed. Future research may use the paradigm developed here (simple vs. complex equations) and bring it into actual organizational settings where such risky decisions are much more consequential. One can also examine the risk quantification bias using archival data on the financial industry, a research direction to which we turn in the second chapter of this dissertation.

Conclusion

The risk quantification bias is embedded within a particular style of thinking (Hacking, 2007) that is unique to decision makers with backgrounds in economics and finance and/or believe in the importance of quantification. These conditions suggest that the risk quantification bias is the product of a particular kind of education and a result of particular kinds of beliefs—it is not “hard-wired” into all decision making processes.

Because it is contingent on education and beliefs, this bias diverges significantly from those traditionally described within the judgment and decision making literature. Social psychologists have chosen to focus on the most prevalent decision making biases and heuristics, which exist for all decision makers in nearly every context (or so it is assumed). The risk enumeration bias has sharp boundary conditions that limit its influence on how decisions are made. It is embedded in a social context: It is socialized within classrooms where modern risk management techniques are taught and related to a set of beliefs that emphasize the importance of measuring future likelihoods. Some may argue that studying biases with such well-defined boundary conditions limits research to the inconsequential quirks of decision making in particular situations. Real world decisions, however, are always embedded in social contexts, places where people have differing educations, beliefs, and different ways of making decisions. Understanding how beliefs result in embedded biases and heuristics may enable us to better understand how something as nebulous and difficult to define as culture shapes individual decision making and therefore results in consistent patterns of behavior.

Model Behavior:

Firm Risk Taking and Embedded Heuristics in American Finance 1994-2007

Given the current state of the economy, it is easy to forget that prior to the mortgage meltdown, the financial industry had not, in fact, been ignoring risks. Financial experts were not acting as mathematical Houdinis who constructed bizarre, risky instruments while ignoring the potential downsides of their actions. Instead, the three decades prior to the current economic crisis brought the meteoric rise of the chief risk officer (a title invented in 1993 by GE Capital); new techniques and technologies for measuring risks such as value at risk (VAR) and risk-adjusted return on capital (RAROC). There was also a cornucopia of books published on risk management (about 9,800 according to a quick search on "risk management" on Amazon); and a barrage of risk-related associations and conferences. At the top of the financial food chain, Federal Reserve Chairman Alan Greenspan adopted what he called "the risk management approach to monetary policymaking"(2004). Identifying, measuring, and managing risk had been a powerful obsession within the financial sector prior to the mortgage meltdown, which begs the question: What is the relationship between risk management and financial risk taking?

To answer this question, this paper takes a cue from Nassim Taleb, who has popularized the notion of the black swan, negative events beyond the range of human expectations (Taleb, 2007). He argued before a congressional oversight committee that innovative and popular risk management metrics, such as VAR, have disastrous side effects because they create the illusion that all risks can be measured and understood:

> VAR has severe side effects. Many people favor the adjunct application of VAR on grounds that it is "not harmful," using arguments like "we are aware of its defects." VAR has side effects of increasing risk taking, even by those who know that it is not reliable…Leverage is a direct result of underestimation of the risks of extreme events -- and the *illusion that these risks are measurable*. (2009, emphasis added)

Taleb's assertions have been echoed throughout the media. Nobel-Prize-winning economist Paul Krugman similarly argued that economists suffered from "blindness to the very possibility of catastrophic failures" in part because they "mistook beauty, clad in impressive-looking mathmatics, for truth" (2009). The present debate on financial models provides an illustrative example of the potential, unintended effects of formal models on decision making within organizational settings and highlights an unexplored topic in organizational behavior: how does the use of formal risk assessment models shape the behavior of organizational actors? Using the financial industry during the run-up to the mortgage crisis as its empirical setting, this paper seeks to understand the social processes through which these models become embedded within organizational decision making and the ways purposive adoption of formal risk assessment models may have resulted in unintended consequences.

Just as banks adopted formal models to price contracts, assess risks, and evaluate markets, organizational leaders and experts in nearly every industry intentionally adopt formal risk assessment models which teach organizational actors how to interpret and respond to uncertainty. Insurance companies provide their employees with concrete models with which to understand an individual's health risk; schools offer evaluations that enable teachers to tell which students are "high risk" and likely to drop out; oil companies adopt models that enable their employees to determine the risk of potential declines in oil prices. In all of these examples, organizations provide their members with concrete, overt models for reducing uncertainty. Some organizational theorists, drawing from linguistic relativism (Sapir, 1921; Whorf, 1956), have speculated that all forms of discourse "make certain ways of thinking and acting possible, and others impossible or costly," (Phillips, Lawrence and Hardy, 2004, pg. 635 ; also Fairclough, 1995) formal models are one of the most direct means of understanding how discourse comes to shape decisions and action because they are purposively created to do just that.

Firms influence how their members make decisions by providing them with formal risk assessment models. Over time these models become institutionalized and begin to seem less and less like artificial representations and more and more like reality. As this happens, organizational actors begin to use the models less deliberatively and with less awareness of the model's limitations; instead, the models themselves become a habitualized decision-making norm, which I refer to as an "embedded heuristic." Like other cognitive heuristics, this socially embedded heuristic is used automatically with little awareness of its impact on decision making and, therefore, it can have unintended consequences on organizational decision making.

The concept of embedded heuristics adds to three areas of organizational theory. First, it answers many institutional theorists' calls for more concrete specification of the ways institutional processes play out through individual actions (DiMaggio, 1997; DiMaggio and Powell, 1991; Phillips and Malhotra, 2008; Powell and Colyvas, 2008; Schneiberg and Clemens, 2006; Zucker, 1977). It does so by showing how the use of risk assessment models becomes institutionalized and converted into rules of action that systematically shape how decisions are made within organizations and, therefore, how organizational actions unfold. Second, it extends heuristics and biases research outside of the laboratory (Staw, 2010), demonstrating how organizations can influence how heuristics become institutionalized--first, by providing formal models for decision making and ultimately by influencing which criteria become implicit in decision making. Finally, this paper adds to a growing literature within organizational theory (Ferraro, Pfeffer, and Sutton, 2005; MacKenzie, 2003; MacKenzie, Muniesa, and Siu, 2007; MacKenzie and Millo, 2003) that draws from semiotics and social studies of science (e.g. Callon, 1998; Giddens, 1984; Hacking, 1983; Wittenstein, 1953) to explain the effects of economic models on business practices.

This paper unfolds as follows. First, it begins by offering definitions for uncertainty and risk, adopting definitions that stress the social, subjective origins of each. Then, the paper argues that by providing their members with formal risk assessment models--such as risk measures within banks--organizations minimize the uncertainty of their members. It describes how over time these models gain legitimacy, become taken-for-granted, and are gradually reified within organizational contexts. Thus, their use by organizational members becomes more and more automatic, unreflexive, and similar to cognitive heuristics. This paper tests its theory using archival data on commercial and investment banks and demonstrates how the use of formal models led to greater risk taking within banks that adopted them.

The social meaning of uncertainty and risk within organizations

Before proceeding to the discussion of embedded heuristics, it is necessary to define uncertainty and risks, which are concepts needed to understand how formal models function within organizational decision making. Throughout much of classic organizational theory, uncertainty has been thought to be synonymous with environmental change and organizational actors have been depicted as being uniformly aware of these environmental instabilities (e.g. Emerson, 1962; Thompson, 1967; Lawrence and Lorsch, 1969; Pfeffer and Salancik, 1978; Hannan and Freeman, 1977; DiMaggio and Powell, 1983). Drawing on this tradition, operationalizations of uncertainty have equated it to external factors, such as volatility (Haunschild, 1994, 1997; Mezias, 1990) or high likelihood of failure (Haveman, 1993). Yet, as several previous theorists have pointed out (Duncan, 1972, March & Shapira, 1987; Milliken, 1987; Lawrence and Lorsch, 1973; Miles, Snow and Pfeffer, 1974; Pfeffer and Salanick, 1978), little is actually known about whether these kinds of external factors are actually recognized by organizational decision makers. As March and Shapira (1978) note, individuals within organizations exhibit risk preferences that are removed from the classical economic processes of determining expected values. They suggest that decoupling environmental factors from evaluations of uncertainty enables a greater understanding of how actors interpret environmental signals. Building on this recommendation, uncertainty is defined here as *an awareness of one's limited ability to predict the future, regardless of the external signals that may (or may not) prompt such a sense of uncertainty*. Using this definition of uncertainty, which emphasizes its subjectivity, facilitates investigations into how organizational actors evaluate their own abilities to forecast the future and how social context and organizational practices, like the use of formal risk models, change those evaluations.

Similarly, the definition of risk used in this paper—*the predicted potential downsides of actions*—emphasizes risk as the product of sense making, rather than a fixed feature of an environment. Perhaps more than any other form of organizational assessment, prediction is a social construction created through "rational myths" (Meyer and Rowan, 1977). The future has yet to happen. It is always entirely imaginary, made-up, and unobservable. Therefore, how organizations define risks is an exercise in meaning making for which institutional theory, with its focus on organizational myth making, can provide insights (Davis, Diekmann, and Tinsley, 1994; DiMaggio and Powell, 1983; Meyer and Rowan, 1977; Phillips, Lawrence, and Hardy, 2004; Zilber, 2002, 2008; Zucker, 1977).

Every day, organizations undertake analyses of risks in order to reduce uncertainty and to make the future seem more knowable. A weather forecaster can say that there is a 90 percent chance of rain and an industry analyst can say it is likely revenues for a firm will decrease; audiences will think of these assessments of the future as legitimate if they are aligned with broader value systems (Ewald, 1993). If observers want to contest the weather forecast or the predicted future profitability of a corporation, they cannot point to an external reality. One cannot argue on Monday that the weather forecast of a beautiful sunny day on Tuesday is wrong because on Tuesday it rains--no one knows yet. Instead, if one wants to argue with the prediction on Monday, one can only point to social validity of the processes of prediction: Did the meteorologist have the right training, the proper credentials, and use the right techniques? "The idea of an objective measure of risk has no meaning: everything depends on the shared values of the [group]" (Ewald, 1993: 225). The social and subjective natures of risk and uncertainty are critical to understanding how formal models shape organizational actions: When the downsides of actions (risks) are assessed using socially acceptable models (embedded heuristics), the perceived inability to understand the future (uncertainty) is reduced. Despite the impossibility of risk calculations actually describing an objective, inevitable future, when fully institutionalized and firmly embedded in social value systems, organizational actors behave as though perceptions are objective facts: when a risk of rain is forecast, umbrellas are carried; when declines in revenues are predicted, stocks are dumped. As Douglas and Wildavsky (1983, pg. 1) poetically explain, “Can we know the risks we face, now or in the future? No, we cannot; but yes, we must act as if we do.”

Risk assessments as embedded heuristics

Psychologists, most famously Kahneman and Tversky (e.g. Kahneman and Tversky, 1973; Tversky and Kahneman, 1981), have demonstrated that individuals make decisions under uncertainty through "a limited number of simplifying heuristics" (Gilovich, Griffin, and Kahneman, 2002: xv). DiMaggio (1997) has pointed to psychological research on the development and use of these cognitive heuristics as one potential way of exposing the “interaction of shared cognitive structures and supra-individual cultural phenomena…that activate those structures to varying degrees” (pg 264). Indeed, these heuristics offer strong examples of the “shared cognitive structures” institutional theorists have sought to explain. Psychologists, however, have focused on heuristics, such as availability, representativeness, and anchoring and adjustment, which have been implicitly assumed to be universal and impervious to broad social and historical contexts (Staw, 2010); therefore, this research has shed little light on role of “supra-individual cultural phenomena” in activating their use. On the other hand, formal decision making heuristics, once socially embedded in an organization or other cultural context, provide one example of a phenomenon that activates the use of particular cognitive structures.

The analogy between formal risk assessment models adopted by organizations and cognitive heuristics may seem a bit awkward. Indeed, there are two crucial differences between the kinds of cognitive heuristics studied in lab experiments and the embedded heuristics used within organizations. First, cognitive heuristics are usually depicted as part of unconscious, automatic reasoning, whereas the formal risk assessment models used within organizations are explicit, intentional, and sometimes even physically tangible as texts. An expert on risk management can easily describe the way a risk measure is calculated and what that calculation implies for decision making, whereas individuals who are directly told that their decision making is being influenced by heuristics may still be unable to account for them in their decision making (Fischhoff, 2002). Formal models are also noticeable and obvious to external audiences in ways that cognitive heuristics rarely are.

One key to bridging this difference between risk models and cognitive heuristics is is to understand that risk models may become more and more like cognitive heuristics the more highly institutionalized they become. When individuals first implements a new model, they are usually highly aware of its artificialities, assumptions, and omissions, and thus there is little similarity to a cognitive heuristic. Years later, however, the model may become a fully embedded institution—those who use the model may not even remember who first implemented it or why, nor will they be fully aware of its assumptions and limitations. Instead, as the risk model becomes institutionalized, its use may become more unreflective, automatic, and taken-for-granted; that is, it becomes like a cognitive heuristic. The processes through which heuristics become embedded will be more thoroughly discussed in the empirical setting below.

Another key to understanding the difference between formal models and cognitive heuristics is that, unlike the kinds of biases and heuristics commonly studied by psychologists, the kinds of risk models provided by organizations to their members have little meaning outside of specific organizational contexts. With the exception of some work on cross-cultural variation in heuristics (for reviews, see Yates et al., 2002; Fischhoff, 2002), which is usually conducted at the national or continental level, social psychologists are primarily interested in describing cognitive heuristics that are generalized across contexts, persons, and decision types (Staw, 2010). Embedded heuristics are highly specific: Models used by insurers for determining health risks are not very relevant to a school teacher; employees of an oil company will not use the same risk models at work as they will in their personal investments. Furthermore, formal heuristics are subject to historical context; they change along with fads, trends, scientific advances, and technological innovation. The risk models used by banks today had no equivalent during the Great Depression. Both context-specific heuristics (as investigated in this paper) and highly generalizable types of heuristics (as typically researched by social psychologists) govern individuals' thoughts and actions. In order to comprehend behavior in context, it is therefore necessary to recognize and understand both type of heuristics. This paper aims to complement what we already know about generalizable heuristics with a deeper understanding of those heuristics which are embedded in particular situations. The precise relationship between an embedded heuristics and its effects, like the relationship between all forms of discourse and action (Wittengstein, 1953), will depend on the social context of the heuristics, what kinds of decisions it applies to, and the context within which it is used. Nonetheless, the process by which a heuristic becomes embedded may be applicable across embedded heuristics.

EMPIRICAL SETTING AND HYPOTHESES

The logic and consequences of embedded heuristics depend on the organizational contexts in which they operate and the kinds of realities the formal models represent. To illustrate how organizationally-embedded heuristics shape organizational behavior, this paper investigates a setting that has experienced remarkable proliferation in the use of formal risk assessment models: risk management within finance. In the wake of the financial crisis, the use of risk models within banks has been of central interest to policy makers. For organizational theorists, this setting thus provides a rich opportunity to understand how risk assessment models become reified into embedded heuristics.

The use of innovative risk models varied greatly from the mid-1990s to 2007, moving from a peripheral practice to one of the central practices within finance. As one textbook on risk management explains,

> Risk management has truly experienced a revolution in the last few years. This was started by value at risk (VAR), a new method to measure financial market risk...Initially confined to measuring market risk, VAR is now being used to control and manage risk actively, both credit and operational risk. The VAR methodology is the holy grail of firm-wide risk management (Jorion, 2001).

As this passage suggests, the brief history of risk management is one in which models, which were originally designed to measure risk and enable decision making, have become increasingly legitimated and reified. Risk measures shifted from being thought of as a way of *measuring* one kind of risk to a more general means to *control and manage* many kinds of risk, capable not just of depicting future likelihoods but also of controlling them. Risk measures, such as value at risk, expanded from being used solely for market risk (the potential to lose value on investments due to changing prices, interest rates, or exchange rates) to being used for a greater variety and more broadly defined risks, including credit risk (loss due to counterparty default) and operational risk (potential harm done by the way a firm's business is run, such as fraud, environmental damage, law suits, or technology failures).

Today, risk management is usually conducted by specialized departments within commercial and investment banks, often led by chief risk officers, who occupy one of the highest positions in the bank (Power, 2004; 2007; 2009). These departments use massive amounts of data, sophisticated statistical software, and risk measurement techniques to calculate the amount of risk a bank has taken. Then, working closely with executives, they decide whether this amount of risk is acceptable or whether certain risky investments should be sold or hedged, and whether the bank should sell its risky assets or create a buffer against the potential losses by adding to its capital reserves or hedging risks.

Risk management departments like these barely existed twenty years ago. Their development is the result of theoretical, technological, and policy changes that prompted the greater use of risk measures within banks and increased the legitimacy of their use within finance (Powers, 2004; Powers, 2009; Bernstein, 1995; Bernstein, 1996; Rothstein et al., 2006). Some economists have noted that “Risk is no longer the exclusive preserve of scientists and technocrats, but is fast becoming the lingua franca of business management” (Rothstein et al. 2006, pg. 92). Theoretical advancements in finance enabled new ways to price the risk of price chances in assets and enabled those risks to be bought and sold without trading the underlying asset (MacKenzie, 2003). The seeds of modern risk management were sown with the 1973 publication of the Black-Sholes formula (Black and Sholes, 1973) and Robert C. Merton's revision to it in the same year (Merton, 1973), which were was followed immediately by its embrace by the Chicago Board Options Exchange (MacKenzie and Millo, 2003). The formula allows a price to be created for the volatility (or risk) of an underlying asset independent of the actual value the asset. Essentially, it puts a price tag on an asset’s volatility and enables it to be bought and sold without trading the actual asset that is changing value. The result of this advance in financial theory was a proliferation of new kinds of financial instruments, including options, and credit default swaps. These innovative instruments enable firms to "manage" risks without having to mitigate them. No longer just a "nexus of contracts" (Williamson, 1990), a bank becomes a "nexus of risks," which must be assessed and controlled.

Just as theoretical developments were enabling the new kinds of financial instruments to be created and priced, advancements in computer technology enabled greater and greater amounts of data to be stored and analyzed (Bernstein, 1996; Rosen, 2006). In 1973 Texas Instruments used the Black-Sholes model to show off in the *Wall Street Journal* the business applications of its handheld calculator (Bernstein, 1996). The invention of the VisiCalc, the first spreadsheet software, in 1979 enabled traders to measure risk by manipulating variables in "what-if" scenarios and in 1986 Apple introduced the first currency swaps pricing program Swapware. Thus, the ability to collect, store, and analyze more and more data meant that firms had an increasing opportunity or capability to use statistical risk analysis.

Along with heightened ability to calculate and computationally analyze risk came greater accountability for measuring future outcomes. In 1988 the first Basel Accord produced by the Bank of International Settlements, the UN of banking, required banks to set aside capital to cover credit risk, the risk of default on a loan given by the bank. In 1996 this Accord was amended to include a capital charge for market risk, which includes the risk that banks will lose money due to changes in interest-rates, exchange rates, or commodity prices. Three years later it became apparent that the combination of market risk and credit risk did not cover all of the risks faced by banks and a new accord was drawn up. Unlike the relatively simple first accord, which had 37 pages and took less than a year to develop, the second accord reached over 300 pages, took nearly a decade to be finalized, and requires firms to disclose any "risk of loss resulting from inadequate or failed internal processes, people and systems or from external events" (Bank of International Standard, 2006: 37). These new risks include fraud, tax evasion, bribery, hacking, forgery, worker injury, discrimination, pandemics, software and hardware failures, power outages, data entry mistakes, and others. Power (2004) describes this expansion as the “risk management of *everything*.” The Second Basel Accord epitomizes the heightened attention finance was paying to quantifying a wide array of risks, a result of theoretical advances and technological breakthroughs the industry had experienced.

The organizational embedding of heuristics.

In order to understand the social and psychological effects that the proliferation of risk quantification had within finance, it is necessary to describe how formal models become embedded heuristics and, more specifically, how the institutionalization of formal risk modeling became a source of decreased uncertainty with decision-making in finance. Zucker (1977) has demonstrated that merely instructing experimental subjects to pretend they are in an office setting increases certainty in judgments. In actual office settings, there are numerous institutionalized practices that further increase certainty. For example, the use of formal models within organizations was a concrete practice that was specifically designed to reduce uncertainty. Therefore, the institutionalization of formal risk modeling should have similarly decreased uncertainty as risk management became embedded within finance. By providing decision makers with these models (adoption), giving them experience in using them (habitualization), and using discourse that touted the importance of “risk management” (legitimating discourse), organizations both gave decision makers' access to such models and legitimated their use. Below, this paper describes how these three processes influenced how risk models became embedded within banks.

Adoption. Adopting a formal risk management tool is the first step a firm takes toward embedding it within its decision-making process. Although this may seem obvious, it is important to remember that models may exist outside of firms and never be adopted; firms act as curators of decision making models--determining which models are appropriate for use by their members and which are not. The adoption of a model by a firm usually entails decisions by executives or experts within a firm that the model is valuable and suitable for the firm's business. These models teach organizations' members how to interpret and respond to their external and technical environments. Once a model is deemed useful, it can be either formally or informally adopted by decision makers within the firm. Formally, an organization can make a strict policy that a model must be used to justify decisions and sanction members who do not adopt the model, thus encouraging the use of the model through normative measures. Informally, the use of a model can be adopted through mimicry (March, 1991) and social pressure or social sanctioning (O’Reilly & Chatman, 1986).

Formal models are further embedded through social conformity within the organization. A model’s ability to create a standardized style of thought is much more influential in shaping perceptions of reality when others within the firm are using the same model, making the same assumptions, and forming the same conclusions. The use of models within an organization has the potential to create a confirmation cycle in which one uses a model to form a conclusion and then compares it to others' conclusions, which were made with similar models, therefore confirming the original model's conclusion and further promoting the use of the model. Thus, formal models may limit individuals' ability to consider alternative courses of action by directing attention toward the singular outcome of the model (March and Simon, 1958: 138-149; 150-151). As a result, organizational members will be guided toward conforming with the behaviors prescribed through the model.

In the case of risk management within finance, when banks adopted risk measures, their employees arrived at estimations of risk that reflected those models' assumptions.. The adoption of these risk models gave decision makers tools with which to measure future probabilities, enabling them to discard the infinite number of possible future outcomes in exchange for a singular prediction. The future became simpler, less contingent, more knowable, and this resulted in reduced uncertainty. As a result, bankers began to feel more comfortable taking greater risks. Hence,

H1a) The more formal risk modeling a bank adopts at time t, the more risk seeking a bank will be at t+1.

Although quantitative risk measures cab result in greater risk taking, qualitative descriptions of risk nat have the reverse effect. To use a quantitative model, a risk must be measured, which means that there must be data available and some past records from which to infer the level of risk. This limits risk models to describing only risks that can be somehow quantified and which have occurred in the past. Qualitative ways of describing future possibilities, on the other hand, do not have these restrictions. We can easily discuss the possibility of an earthquake or a rainstorm even though our ability to predict whether it will rain tomorrow is much stronger than our ability to predict whether there will be a tectonic event. Because we can qualitatively describe more risks than we can assign probabilities to, using qualitative descriptions of risks greatly increases the number of risks we can attend to. Furthermore, the kinds of risks that can be qualitatively described may be less familiar than those that can be given probabilities. For example, we can qualitatively discuss the risks of events that have no precedent, (e.g., bioterrorist attack on the California, a large asteroid hitting a major city), even though we have no way assigning these risks meaningful probabilities based on past occurrences. For similar reasons, qualitatively we can describe risks that are far outside the normal range of past occurrences, which means that qualitatively described risks can be more extensive and extreme than those we can assign probabilities to. The kinds of risks we can describe qualitatively are more numerous, less familiar, and more extreme than those we can assign meaningful probabilities (for further discussion, Taleb, 2007; Power, 2009). Furthermore, qualitative descriptions of risk do not carry with them the inherent assumption that such risks can be insured, diversified, or hedged the way quantified risks can, because such risks cannot be specified in dollar terms. As a result, although quantitative risk description limits the kinds of risks we give attention to and provides a way to manage such risks, qualitative risk descriptions open up our ability to attend to more risks, even though there may not be any means to protect against them. Consequently, qualitative risk descriptions may increase uncertainty and lead to decreased risk taking. Thus:

H1b) The more qualitiative risk measures use at time t, the risk taking they will be in t+1.

Habitualization. The embedding of heuristics is a process that takes place over time as organizational members become familiar with the models and habituated to their use. As Berger and Luckmann explain,

> The habitualisations and typifications undertaken in the common life of [person] A and [person] B, formations that until this point still had the quality of ad hoc conceptions of two individuals, now become historical institutions. With the acquisition of historicity, these formations also acquire another crucial quality . . . objectivity. (Berger and Luckmann, 1966, pg. 76)

By becoming historic, models, like other institutions, also become increasingly objective, moving from "the way we do things" to "the way things have been done" and finally to "the way things should be done." As Barley and Tolbert (1997, pg. 5; also Tolbert and Zucker, 1996) argue, "Institutions that have a relatively short history or that have not yet gained widespread acceptance are more vulnerable to challenge and less apt to influence action."

Zucker (1977, pg. 729-730) has argued that transmission of ideas between people or generations is evidence of institutionalization. This relationship, however, is also recursive: the more often an idea is transmitted, the more highly institutionalized it will become. As they are reused, models lose their association with the single actors and situations that initiated their use; their applications become more generalized and their use becomes more taken-for-granted. The transmission of a model's use from one individual to another creates distance between an idea and its social origins. Continuity of model use will create objectivity and generate exteriority, just as it does with other institutions (Zucker, 1977, pg. 729), because the very continuity of their use provides evidence that such models are valuable and worth reusing. For formal risk assessment models, this means that the more often they are used, the less like artificial, socially constructed tools they will seem and the more fact-like they will become. As Power describes, within firms, managers had to "constantly create appearances of process, via risk modeling and other techniques, in order to defend the rationality of their decisions" (2004, pg. 25), which suggests that over time the use of risk models became the standard of rationality, the very criteria by which facts became facts. Even if such modeling did or did not have economic consequences, its repeated use may have become evidence for following a defensible and rational procedure.

Furthermore, as a model becomes ingrained in daily, routine decision making, it becomes easier to use. When a model has been used several times, others in the organization have already grown accustomed to its use so do not need it to be explained; this saves the time and effort of educating others. Calculations often become automated, as risk metrics were through software; this reduces the amount of time and effort it takes to make calculations. The *Economist* has reported on one example of how habitual use of an over simplified model by The Bank of England contributed to its use within the bank:

> [The model] does not even try to incorporate financial middlemen, such as banks. "The model is not, therefore, directly useful for issues where financial intermediation is of first-order importance," its designers admit...Convenience, not conviction, often dictates the choices economists make. Convenience, however, is addictive. Economists can become seduced by their models, fooling themselves that what the model leaves out does not matter (2009).

These reductions in the cost of using the model make the search for alternatives relatively more costly, because creating alternative models would require the additional burden of thinking of new ways of making estimations, predictions, and decisions; describing and justifying these methods to others; and running the calculations necessary to use them. As a result, decision makers become even more focused on the convenient outcomes of the model to which they are habituated.

For financial risk models, this accretive objectivity resulted in even greater certainty about a models' predictions as the social origins and assumptions behind the models were forgotten. After the subprime mortgage crisis, Alan Greenspan noted that risk models had been based on faulty assumptions: "In recent decades a vast risk management and pricing system has evolved based on the best insights of mathematicians and finance experts, supported by major advancements in computer and communications technology...The whole intellectual edifice, however, collapsed...because the data inputted into the risk management models generally covered only the past two decades, a period of euphoria" (2009). The use of risk models contributed to the use of limited data because as decision makers became habituated to their use, the limitations of the data seemed less relevant. The more often risk models were used, the less significant their violations seemed: the model had been used hundreds, then thousands, and then hundreds of thousands of times in the past and had not caused problems. This continuity alone could be taken for evidence of the model's value and as reason for ignoring its limitations.

Hence,

> H2) Past use of risk models (at time t) will positively moderate the positive effect of using risk models (at time t) on increases in risk taking at t+1.

Interdiscursivity. Formal models, which are themselves a (usually textual) form of discourse, gain additional significance when they are legitimated by other organizational discourse. For example, statements by organizational leaders about a model's effectiveness, conversations about the use of a model, texts that teach organizational members about model use, and reports that include models' estimations can all embed formal models in organizational decision making. Such discourses can stress a model's importance, accuracy, and legitimacy and increase the likelihood of models becoming embedded within organizational contexts. Fairclough (1995, pg. 85) calls this phenomenon, in which references to other texts influence the interpretation of a focal text, interdiscursivity. Phillips, Lawrence and Hardy (2004, pg. 645) argue that interdiscursivity results in the social embedding of a text: "Texts that draw on other texts within the discourse and on other well-established discourses are more likely to become embedded...than texts that do not."

Within banks, discussions of the importance of risk management stressed that risk could be controlled through proper measurement and the exchange of financial instruments. One popular risk management textbook explains:

> The future cannot be predicted....Yet, the financial risk that arises from uncertainty can be managed. Indeed, much of what distinguishes modern economics from those of the past is the new ability to identify risk, to measure it, to appreciate its consequences, and then to take action accordingly...This simple sequence of activities...is often used to define risk management. (Crouhy et al., 2006: 2)

The notion that the future is unpredictable but the financial risks it will bring can be measured and managed is one of the central tenets, and paradoxes, of risk management. This risk management discourse strengthens the perception that risks can be measured and, once measured, can be managed; such rhetoric results in decreased uncertainty and greater confidence when models are used to calculate risks.

> H3) The more risk management is discussed within an organization at time t, the greater the greater the increase in risk taking in t+1.

RESEARCH DESIGN

Sample

To understand the relationship between risk taking, and both risk models and risk management language, this paper uses computerized textual analysis of annual reports from commercial and investment banks and financial fundamentals from 1994 to 2007.

The annual statements, which are yearly reports intended to give a detailed description of the companies' activities and financial performance for the fiscal year to shareholders and regulators, have been gathered from EDGAR, the Security Exchange Commission's web archive of securities-related documents. This observation period starts at the beginning of the era of modern risk management. In 1993, the first chief risk officer was named at GE Capital and in 1994 RiskMetrics Software, which was largely credited with the diffusion of VAR-type risk management, became available. This is also the first year that annual reports on EDGAR were available. The time period ends just prior to the subprime mortgage crisis, in 2007.

The sample consists of all publicly-held commercial and investment banks from 1994 to 2007 that were included in the COMPUSTAT database of financial fundamentals. This sample contains banks from the following SIC codes: 6021 and 6022 and 6029 (national, state, and miscellaneous commercial banks), 6035 and 6036 (state and federal savings institutions), 6211 (security brokers and dealers), and 6221 (commodity brokers and dealers). For firms that were not publicly held during the entire time frame, data collection begins the first year they file an annual report and/or ended the last year they file an annual report. Firms that had less than two consecutive years of data were excluded from analysis.

The primary assumption behind this methodology is that firms' descriptions of risk measures and risk management language in annual reports is reflective of their actual use of risk management techniques (Staw and Epstein, 2000). A counter-explanation for the relationship between risk language in annual reports and risk taking is that such language is used as "window dressing" to justify increased risk taking. Indeed, previous studies have found that the wording of annual reports can be used to address the fears of shareholders and rationalize firm actions (Staw et al. 1983; Bettman and Weitz, 1983) in ways that are decoupled from actual actions. These studies, however, looked at linguistic strategies, such as rationalizing poor performance that required no special expertise, resources, or technology. In order to include risk management language in annual reports the accounting and finance departments that created them had to have necessary expertise within their ranks and the technological capabilities needed to create such metrics. Furthermore, unlike rationalizations for poor performance which cannot be easily regulated, there are regulatory pressures on institutions to provide meaningful metrics within their financial reports. There could be serious consequences if a bank were found to be simply making up numbers or feigning procedures only to appease shareholders. To control of issues of direction of causality within this study, it uses lagged variables that show the relationship between a prior year's risk language and the focal year's risk raking (controlling for the focal year's risk language) in order to show that an increase in risk language leads to greater risk taking in the subsequent year.

Dependent Variable

The dependent variable, change in risk taking, was operationalized as the change from one year (t) to the next (t+1) in a firm's debt-to-equity ratio, usually referred to as financial leverage, and was collected from COMPUSTAT. It is the most commonly used measure for risk taking within finance and it is widely assumed that banks that increase their leverage increase the magnitude of potential losses. Fund manager and investment guru Warren Buffet described leverage this way in his 2008 letter to shareholders:

> Unquestionably, some people have become very rich through the use of borrowed money. However, that's also been a way to get very poor. When leverage works, it

> magnifies your gains....[A]s we all learned in third grade – and some relearned in 2008 – any series of positive numbers, however impressive the numbers may be, evaporates when multiplied by a single zero. History tells us that leverage all too often produces zeroes, even when it is employed by very smart people (pg. 21).

That is, leverage may increase the magnitude of potential gains from an investment, but it also increases the size of the potential loss. Because the idea that leverage increases the size of loss is a common belief within finance, increasing leverage fits within the definition of risk taking used within this paper--*to increase the perceived chance or magnitude of loss.*

Independent Variables

. *Risk-based measures (adoption)*. To calculate the use of risk-based measures, I constructed a count of every time a risk-based measure was mentioned in an annual report. The list of words used to search for risk-based metrics was compiled from measures listed in indexes of risk management textbooks. This measure includes use of the following terms and similar terms with slight variation (e.g. with hyphens, abbreviations) and were insensitive to the difference between upper and lower case letters: value at risk, VAR, iVAR, risk adjusted returns, risk adjusted returns on assets, RORAA, risk adjusted returns on capital, RAROC, earnings at risk, risk adjusted performance, and any term that included the phrase "risk-adjusted."

Qualitative risk description. Qualitative risk descriptions were operationalized as a count of every time the term "risk" or "uncertainty" (or their plural forms) were used in the annual report without being part of a description of a measure or used in a way the connoted risk management rhetoric. For example, the term 'value at risk' would not count as a qualitative description of risk. The sentence 'Our business faces many risks," however, would count as one qualitative description of risk.

Past use of risk measures on the present use of such measures (habitualization). The past use of risk models is measured using a sum of all the risk measures used in annual reports prior to the focal year. This variable is only included in the models to account for the main effect, but its effects are not hypothesized. Instead, because it is hypothesized that past use will increase the effects of present use, the number of risk measures used in prior years is multiplied by the number of risk measures used in the focal year in order to create an interaction term that is used to test the habitualization hypothesis (H2).

Risk management discourse (interdiscursivity). The use of risk management rhetoric is measured through counts of the number of times a risk management phrase is used in an annual report. This includes the use of the phrases "risk management," "managing risk," "managed risk," and similar phrases using different conjugations of the verb "to manage." It also includes phrases in which the words "risk" and "manage" (or similar terms) are three or less words apart. This method of counting phrases was created after reviewing several annual reports and noticing that they often contained references to managing certain kinds of risk, such as “managing operational and political risk.” According to this methodology, this phrase would count as one instance of a mention of “managing risk.”

Additional Controls. Revenues (earnings before taxes and interest), size (assets) and total amount of leverage at time t were all controlled using data from COMPUSTAT. Previous research (Baxter, 1967; Hurdle, 1974) has found some link between these variables and risk taking, and it is also likely that these variables could have some relationship to the use of risk management. For example, large firms may have additional resources to commit to both risk management and risk taking. Dummies for each year after 1994 were used to control for any spurious correlations caused by underlying time trends in changes in leverage, including changes in the policy environment. A variable for the number of words used in the annual reports was used to control for the length of annual reports. The dependent variable, which is the ratio of debt to assets, includes assets in the denominator, essentially already controlling for the effect of size on borrowing. However, this ratio may also be size dependent; firms with larger assets may be more comfortable taking on greater debt relative to their assets. To control for this, size is included as an independent variable.

MODEL SPECIFICATION

An OLS regression model with firm-level fixed effects and year dummies was used to estimate changes in bank leverage. The firm-level fixed effects control for all between-firm variance, which means that the invariant differences between firms, such as industry (commercial or investment banking) and date of founding, were controlled, and the model estimates the effects of variables as they change with-in firms rather than between firms. Thus, when interpreting the co-efficient of assets, for example, the result signifies the effect of changes in assets within a firm as it grows or contracts, rather the difference between firms with large or small assets.

RESULTS

These descriptive statistics indicate that there are no major correlation problems with most of the variables used to test hypotheses, but there is a high correlation between the controls for assets and earnings (.83), which is expected because larger banks typically have greater earnings, which is why these variables are entered into the model separately before being entered together. [Appendix: Figure 2.1]

The models [Appendix: Figure 2.2, Figure 2.3] provide support for all three hypotheses. All models show a significant to marginally significant positive correlation between use of risk measures and the subsequent change in risk taking within both investment and commercial banks supporting Hypothesis 1a. Furthermore, the unhypothesize significant positive relationship between risk metrics used in the annual report (t) and the amount of risk reported in that report (leverage at time t) lends further support for the relationship between risk metrics and risk taking. The hypothesized negative relationship between the use of qualitative risk descriptions (Hypothesis 1b) and risk taking in the following year is also found. This suggests that, while use of quantitative risk description results in greater subsequent risk taking, the use of qualitative risk description reduces risk taking, as hypothesized.

The main effect for risk management discourse, as seen in all the models, is significant. Risk management discourse, on its own, appears to increase risk taking, although this effect was not hypothesized. The hypothesized interaction, between risk management discourse and risk taking is evident in the positive interaction term. This suggests that the risk-increasing effect of risk metrics is stronger when they are used in contexts that emphasize risk management (H2).

The positive correlation between cumulative past use of risk measures ((t-2)+(t-3)+(t-4)….)) and subsequent change in risk taking (t) is not surprising given the positive effects these measures have when used in the focal year(t) and previous year (t-1). The results suggest that the positive relationship between risk measures and risk taking lingers, effecting firms in following years. More interestingly, the past use of risk measures strengthens the relationship between risk measures and risk taking in an (marginally significant, $p< .052$) interaction, indicating that the more habituated banks become to the use of risk measures by using them in the past, the more risk taking they become when they use them in the present.

Overall, these results suggest that the adoption of risk metrics resulted in greater risk taking at the firm level. Firms embedded these models through habitualization and discourse, further strengthening the relationship between formal risk measures and risk taking. In this way, firms institutionalized models, creating embedded heuristics and shaping decision making and firm behavior.

DISCUSSION

The specific embedded heuristic investigated in this study, which lead to greater risk taking after firms adopted risk metrics and management, may be limited to a specific time and industry. As the laboratory studies in this dissertation demonstrate, not everyone equates quantification with opportunities to profit from risk; in fact, it appears to be a style of thought limited to individuals with background in finance. Furthermore, there is also some chance that individuals within finance have changed their thought processes after the subprime mortgage crisis. Although the boundary conditions of time and industry limit the applicability of this particular decision making bias to a broad range of time periods, industries, and other situations, the concept of embedded heuristics is relevant to more general theoretical debates about the role of cognition in shaping socialized behavior.

Schneiberg and Clemens (2006, pg. 173) have argued that a "case for institutional theory requires more direct investigation of...the processes by which the range of 'thinkable' alternatives expands and contracts over time and across settings." The reification of organizational risk assessment models into embedded heuristics provides one concrete example of how an organizational practice shapes what is conceivable by decision makers.

More specifically, when banks adopted risk models, they shaped how individuals within them conceived of possible future outcomes and how certain they perceived these predictions to be.

In this way, embedded heuristics offer one mechanism to explain a central quandry within organizational theory: how do institutions shape individual and collective action (Barley and Tolbert, 1997; DiMaggio 1988, 1991; Lawrence and Suddaby, 2006; Oliver 1991)? When formal models become fully legitimated, individuals use these embedded heuristics to guide their decisions and their actions. Barley and Tolbert describe institutions as "abstract algebras" which provide the frameworks of rules and typifications that provide scripts for social actions (1997, pg. 5). These abstract algebras are sometimes articulated in very concrete mathematical formulas that dictate how actors are to make decisions within social settings, as risk measurements structured decisions within banks.

Like the kinds of heuristics and biases typically studied within judgment and decision making research, organizationally-embedded heuristics inform how decisions are made and can lead to systematic biases. For banks, the use of risk-based metrics lead to a systematic bias toward taking risks because they were seen as more predictable and, therefore, more controllable. The greater legitimacy accorded to risk measures through risk management rhetoric used by the firm, the greater risk taking became, suggesting that organizational context shapes both the use and the consequences of embedded heuristics. This finding provides preliminary evidence for the value of considering the ways heuristics emerge from and are strengthened by organizational contexts, an avenue of research several theorists have previously speculated could be valuable both within social psychology and sociology (Dalal et al., 2010; Hayes and Wooldridge, 2010; Whyte, 2010; Naylor, 1984; Boudrea, 1984; Highhouse, 2001l; Moore and Flynn, 2008; Powell and Colyvas, 2007; DiMaggio, 1997).

This paper also adds to a growing literature within organizational theory (Ferraro, Pfeffer, and Sutton, 2005; Merton, 1948; MacKenzie, 2003; MacKenzie et al. 2006; MacKenzie and Millo, 2003) that draws from semiotics and social studies of science (e.g. Austin, 1975; Callon, 1998; Giddens, 1984; Hacking, 1983; Law and Urry, 2004; Wittenstein, 1953) to explain the effects of economic models on the practice of economic activity. Recent theorizations argue that social science theories, such as those used to generate statistical predictions, can bring about the very outcomes they seek to describe, a phenomenon referred to as performativity (Callon, 1998; Latour and Woolgar, 1979; Giddens, 1989; Ferraro et al. 2009; MacKinsey and Millo, 2003). As Giddens explains, “the theories and findings of the social sciences cannot be kept wholly separate from the universe of meaning and action which they are about” (1984, xxxiii). Instead, finance, as a branch of economics, “does not describe an existing external ‘economy,’ but brings that economy into being: economics performs the economy, creating the phenomenon it describes” (MacKenzie and Millo, 2003).

So far, theorizations of performativity have focused on self-fulfilling theories. For example, in MacKenzie and Millo’s study of derivatives markets, they describe how the pricing models used to price futures influenced how much investors thought futures were worth, resulting in prices that matched those of the model. Similarly, Ferraro et al. zoom in on economic theories that "create the behavior they predict" (pg. 8). This strong form of the performativity argument dramatically illustrates the extent to which causality between theories and behavior can run in both directions. The focus on self-fulfilling theories, however, often neglects the diverse ways social science theories shape behavior. In this paper, I have described how risk models and risk management rhetoric brought about higher levels of risk taking, a consequence that lay outside the predictions of the models themselves. Further consideration of the unintended effects of using financial, economic, and other social science-based models will further illuminate the many ways theory shapes action.

Future investigations of embedded-heuristics could take on two divergent methodological approaches. First, more direct investigation of how embedded-heuristics affect individual decisions could illuminate how contexts, rhetoric, and formal models influence how decision making heuristics become increasingly institutionalized, reified, and automatic in decision making. Second, exploration of the ways shifts in institutional fields and in organizational structure (such as network position) shape whether firms adopt or create embedded-heuristics for their members would illuminate the origins of embedded-heuristics. Such investigations of how organizational change is both affected by and affects the use of embedded-heuristics would further shed light into the "black box" of institutional theory (Zucker, 1991).

Finally, on a practical note, the analysis in this paper suggests that models that aim to describe the future do not merely create neutral predictions. Instead, they enable greater risk taking by reducing uncertainty of the decision makers who use them. Myron Scholes, the economist whose model for pricing volatility is a bedrock of modern risk management, has said, "There are models, and there are those who use the models," (quoted in Economist, 2009), suggesting that human errors, rather than faulty models, are to blame for mistakes made within finance. The distinction, however, is false. Models are made for human use and would not be meaningful tools otherwise. Therefore, to comprehend the impact of a model, we must understand them in the contexts in which they are used. Borrowing from human factors engineering, it is possible to argue that a model, like any technology, "is effective (which is to say that it is useful) to the extent that the human responds to the technology as the designer of the technology has intended the user to respond" (Meister, 1999: 8). This points to the need for caution when implementing highly quantitative risk management systems. After the financial crisis, the fate of the risk management profession seemed, momentarily, unclear. Many experts wondered out loud why risk management had failed. Ironically, the response has been a call for greater risk measurement and greater risk management, rather than less. Several bills in the US Congress have sought to mandate risk-based salaries for banks and greater risk-based regulation. Although the research presented in this study is by no means comprehensive, it does provide compelling evidence that risk-based measures may have organizational and psychological effects that need to be considered in the mandated use of risk-based models.

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APPENDIX

Figure 1.1

DV= Total amount risked	Coef. (SE)
Complex (=1)	5.59
	(3.40)
Finance Student (=1)	-14.50***
	(3.59)
Complex*Finance Student	16.10**
	(5.47)
Male (=1)	3.55
	(3.04)
Constant	7.413285***
	(.201)

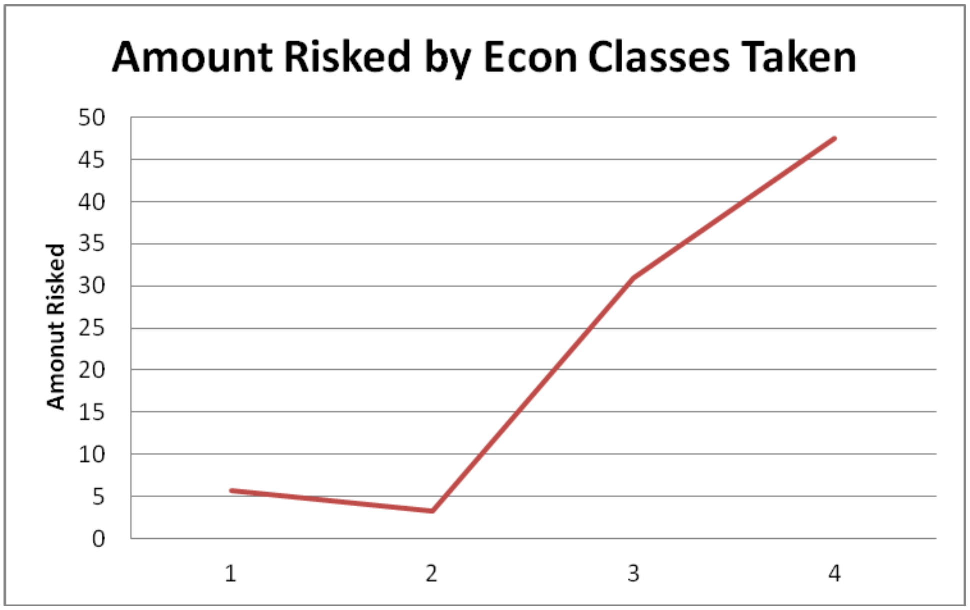
***p<.001 **p<.01

Figure 1.2

DV= Investment in complex	Co-Ef. (SE)
Total amount invested in simple condition	.8991**** (.06006)
Number of econ classes taken	34.6903* (14.615)
Number of math classes	7.329 (5.2668)
Difference in perception of accuracy (complex-simple)	-2.04866 (7.45)
Difference in trust in CRO (complex-simple)	-.83868 (2.03)
Difference in perceived expertise (complex-simple)	-10.290 (9.0354)
Constant	-7.565 (21.7688)

****p<.0001 *p<.05,
F<.0001

Figure 1.3



Amount Risked by Econ Classes Taken
Amonut Risked
50
45
40
35
30
25
20
15
10
5
0
1
2
3
4

Figure 1.4

DV= Amount risked in complex condition	
Total amount invested in simple condition	1.81e-10
	(3.02e-09)
Number of economics classes	0.2991**
	(.10)
Belief in Value of Risk Quantification	0.08*
	(.0377)
Number of Math classes taken	.0111
	(.2279)
Constant	4.2121*
	(1.890)

**p<.01 *p<.05

Figure 1.5

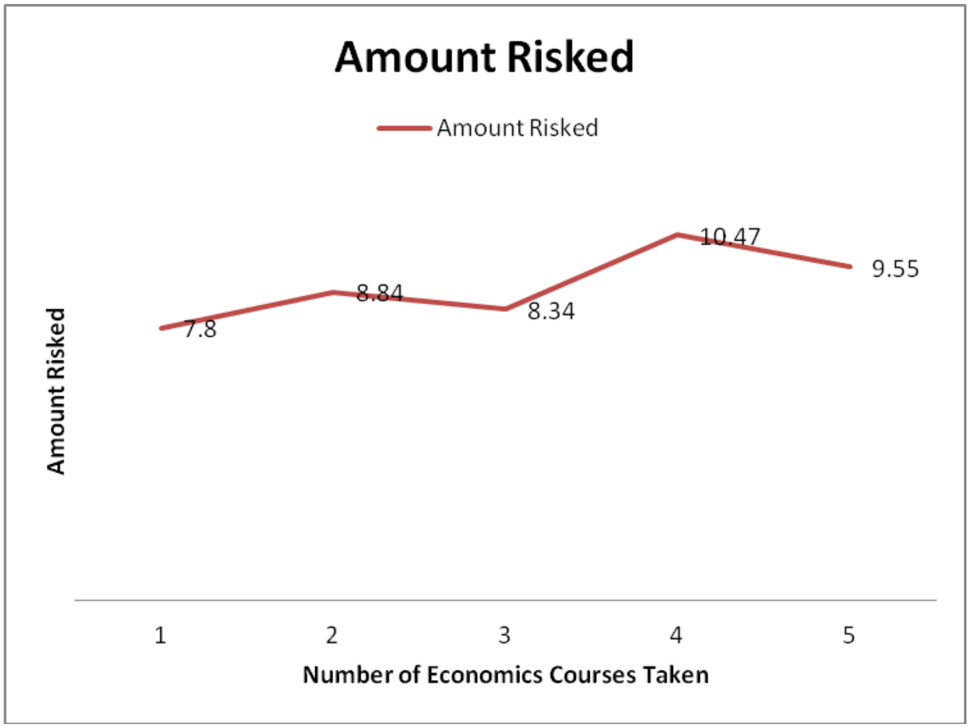
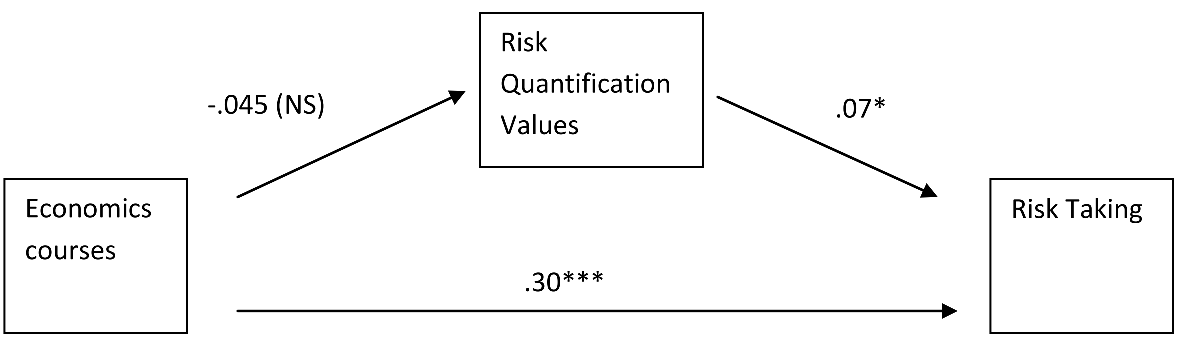


Figure 1.6



Sobel Mediation with Bootstrapping

*p<.05 ***P<.01 NS (Not significant)

Figure 2.1

	Risk Metrics	Risk Management Terms	Qualitative Descriptions of Risk	Total Past Uses of Risk Metrics	Leverage	1995	1996	1997	1998	1999
Risk Metrics	1									
Risk Management Terms	0.272	1								
Qualitative Descriptions of Risk	0.5058	0.6016	1							
Total Past Uses of Risk Metrics	0.2954	0.2759	0.4767	1						
Leverage	0.0707	0.1519	0.1766	0.2324	1					
1995	-0.0141	-0.0575	-0.1194	-0.1773	0.0056	1				
1996	-0.0313	-0.0791	-0.1294	-0.1982	-0.0032	-0.0697	1			
1997	-0.0182	-0.0357	-0.0787	-0.1471	-0.008	-0.0676	-0.0674	1		
1998	-0.0105	-0.0294	-0.0449	-0.1118	-0.0167	-0.0692	-0.0691	-0.067	1	
1999	-0.0124	-0.033	-0.0713	-0.0798	-0.0079	-0.0724	-0.0722	-0.07	-0.0717	1
2000	-	-0.0325	-0.067	-	-	-	-	-	-	-

	0.0115			0.0343	0.0015	0.0715	0.0714	0.0692	0.0709	0.0741
2001	-0.0077	-0.0177	-0.0439	0.008	0.0106	-0.0717	-0.0715	-0.0693	-0.071	-0.0743
2002	0.0138	0.0036	0.0015	0.0539	0.0147	-0.0708	-0.0706	-0.0685	-0.0701	-0.0733
2003	0.0073	0.0305	0.04	0.0952	0.0121	-0.0709	-0.0707	-0.0686	-0.0702	-0.0734
2004	0.0195	0.0376	0.0644	0.1287	-0.0072	-0.0693	-0.0691	-0.067	-0.0686	-0.0718
2005	0.016	0.0827	0.1448	0.1616	-0.0033	-0.0683	-0.0681	-0.066	-0.0676	-0.0707
2006	0.0214	0.075	0.1788	0.1934	-0.0148	-0.0668	-0.0667	-0.0646	-0.0662	-0.0692
2007	0.0286	0.0817	0.2073	0.2244	-0.0172	-0.0635	-0.0633	-0.0614	-0.0629	-0.0657
Assests	0.5679	0.3913	0.6183	0.2479	0.0965	-0.029	-0.0264	-0.0205	-0.0168	-0.0169
Profits	0.4999	0.3689	0.5662	0.1589	0.0913	-0.0291	-0.0251	-0.0161	-0.012	-0.0118
Words	0.2351	0.2284	0.3833	0.337	0.0458	-0.0988	-0.12	-0.1168	-0.1202	-0.1193

Figure 2.1 cont.

	2000	2001	2002	2003	2004	2005	2006	2007	Assets	Profits	Words
2000	1										
2001	-0.0734	1									
2002	-0.0725	-0.0726	1								
2003	-0.0726	-0.0727	-0.0718	1							
2004	-0.0709	-0.0711	-0.0702	-0.0703	1						
2005	-0.0699	-0.07	-0.0692	-0.0693	-0.0677	1					
2006	-0.0684	-0.0686	-0.0677	-0.0678	-0.0662	-0.0653	1				
2007	-0.065	-0.0651	-0.0643	-0.0644	-0.0629	-0.062	-0.0607	1			
Assests	-0.0087	-0.0011	0.006	0.0142	0.029	0.0362	0.0498	0.0675	1		
Profits	-0.0009	0.0008	0.0022	0.01	0.0179	0.0346	0.0539	0.0563	0.8391	1	
Words	-0.103	-0.032	0.0439	0.0838	0.1314	0.1501	0.2004	0.1747	0.2032	0.1695	1

Figure 2.1 Models with main effects only

Dependent variable= leverage (liabilities/assets), t		MODEL 1	MODEL 2	MODEL 3
		main with assets	main with earnings	main with both
MAIN EFFECTS				
Risk-based metrics	(t-1)	0.04253	0.03773	0.03768
		.00831 (.000)	.0134 (.005)	.001152 (.001)
Risk management discourse	(t-1)	0.11935	0.13325	0.12598
		.04072 (.003)	.04629 (.004)	.04565 (.006)
Qualitative risk descriptions	(t-1)	-0.01152	-0.01278	-0.01347
		.00354 (.001)	.00397 (.001)	.00398 (.001)
Cumulative past use of risk metrics	(t-1)	0.003681	0.002522	0.003683
		0.000989 (.000)	.000776 (.001)	.00099 (.000)
INTERACTIONS				
Risk management discourse * risk-based metrics	(t-1)			
Cumulative past use of risk metrics & Risk-based metrics	(t-1)			
RISK LANGUAGE CONTROLS (t)				
Risk-based metrics	t	0.05188	0.0476	0.0598
		.01382 (.000)	.01196 (000)	.01382 (.000)
Risk management discourse	t	0.14661	0.15236	0.16024
		.03927 (.000)	.04397 (.001)	.04471 (.000)
Qualitative risk descriptions	t	-0.01429	-0.01351	-0.01548
		.00422 (.001)	.00377 (.000)	.00427 (.000)
CONTROLS				
Leverage (t-1)	(t-1)	0.4512829	0.4524768	0.4524768
		.0098824	.0098651	.0098651

		(.000)	(.000)	(.000)
Assets (millions)	(t)	2.19E-06 7.03e-7(.002)		1.89E-06 1.43e-06 (.186)
Earnings (millions)	(t)		0.0000884 .0000317 (.005)	0.0000305 .000054 (.572)
Words in annual report	(t)	8.78E-06 0.000007073 (.215)	9.87E-06 7.15e-06 (.167)	9.40E-06 7.14e-06 (.188)
Words in annual report	(t-1)	1.14E-06 7.59e-06 (.881)	1.99E-06 7.62e-06 (.793)	1.35E-06 7.60e-06 (.859)
1994 (baseline)				
1995		1.427602 0.4583422(0.002)	1.305288 0.586101(0.026)	1.321071 0.5865706(0.024)
1996		1.048595 0.4095325(0.01)	1.222915 0.5022357(0.015)	1.236889 0.5026619(0.014)
1997		0.7156705 0.3269939(0.029)	0.6623969 0.4004548(0.098)	0.6774429 0.4010626(0.091)
1998		0.5776631 0.29491(0.05)	0.4515849 0.352555(0.2)	0.4625231 0.3529302(0.19)
1999		0.1822347 0.2909214(0.531)	0.1520618 0.3412035(0.656)	0.1613839 0.3414859(0.637)
2000		1.144393 0.2851869(.000)	1.202277 0.3198366(.000)	1.212991 0.3202323(.000)
2001		0.6863878 0.2747824(0.012)	0.7095641 0.3093254(0.022)	0.7196824 0.3096863(0.02)
2002		0.9709087 0.2675752(.000)	0.9941096 0.2998521(0.001)	1.004812 0.3002675(0.001)
2003		0.5441031 0.259999(0.036)	0.5723104 0.2899933(0.048)	0.5831833 0.29043(0.045)

2004	0.2853691 0.2570046(0.267)	0.2867793 0.2843399(0.313)	0.2963878 0.2846873(0.298)
2005	0.142003 0.2567447(0.58)	0.1774131 0.2811083(0.528)	0.1881129 0.2815444(0.504)
2006	0.1963747 0.2516641(0.435)	0.2239742 0.2752537(0.416)	0.2251785 0.2752591(0.413)
2007	-0.1925159 0.2506691(0.442)	-0.1850569 0.2533554 (.01)	-0.1886224 0.2780915(0.498)
CONSTANT	5.575245 0.483144 (<.001)	5.510546 0.4699974 (<.001)	5.469776 0.5001961(<.001)

Figure 2.1 continued
Model statistics

	Model 1	Model 2	Model 3
R-sq (within)	0.2267	0.2267	0.2267
R-sq (between)	0.8816	0.8816	0.8816
R-sq overall	0.8398	0.8398	0.8398
Rho	0.79312466	0.79315109	0.8695

Figure 2.2 Main Effects and Interactions

Dependent variable= leverage (liabilities/assets), t		MODEL 4	MODEL 5	MODEL 6
MAIN EFFECTS		interactions with assets	interactions with earnings	interactions with both
Risk-based metrics	(t-1)	0.0222638	0.0208206	0.0217964
		.0112787 (.050)	.0112347 (.064)	.011267 (.053)
Risk management discourse	(t-1)	0.123835	0.1317638	0.1394037
		.0409092 (.002)	.0460872 (.004)	.0467172 (.003)
Qualitative risk descriptions	(t-1)	-0.0092441	-0.0078049	-0.0077508
		.0032242 (.061)	.0038043 (.040)	.0038054 (.042)
Cumulative past use of risk metrics	(t-1)	0.004981		0.004811
		.0010493 (.000)		.0010667(.000)
INTERACTIONS				
Risk management discourse * risk-based metrics	(t-1)	0.00417	0.00331	0.00396
		.00172 (.015)	.00149 (.026)	.00197 (.044)
Cumulative past use of risk metrics & Risk-based metrics	(t-1)	0.0001683	0.00017063	0.0001718
		.00008712 (.053)	.00008735 (.051)	.0000885 (.052)
RISK LANGUAGE CONTROLS (t)				
Risk-based metrics	t	0.032769	0.0329878	0.0339558
		.0116122 (.005)	.0114967 (.004)	.0115335 (.003)
Risk management discourse	t	0.1412465	0.1437009	0.1525425
		.0396848 (.000)	.0446713 (.001)	.0453451 (.001)
Qualitative risk descriptions	t	-0.0092441	-0.0107468	-0.0110367
		.0033772 (.004)	.005935 (.003)	.0036258 (.002)
CONTROLS				
Leverage (t-1)	(t-	0.4519903	0.4532435	0.4532014

	1)			
		.0098734 (.000)	.0098543 (.000)	0.0098567 (.000)
Assets (millions)	(t)	2.12E-06		1.84E-06
		7.03e-07 (.003)		1.43e-06 (.199)
Earnings (millions)	(t)		0.0000841	0.0000279
			.0000317 (.008)	.000054(.606)
Words in annual report	(t)	9.58E-06	9.07E-06	9.19E-06
		7.22e-06(.184)	7.18e-06 (.206)	7.21e-06 (.203)
Words in annual report	(t-1)	2.63E-06	2.11E-06	2.12E-06
		7.67e-06 (.732)	7.65e-06 (.783)	7.65e-06 (.782)
1994 (baseline)				
1995		1.400471	1.270731	1.28724
		0.4611995(0.002)	0.5888229(0.031)	0.5893419(0.029)
1996		1.019628	1.189299	1.20417
		0.4130976(0.014)	0.5054138(0.019)	0.5059(0.017)
1997		0.6873883	0.6283836	0.6442638
		0.3313038(0.038)	0.4044095(0.12)	0.40509(0.112)
1998		0.5475885	0.4145537	0.4265674
		0.3006181(0.069)	0.3580798(0.247)	0.3585309(0.234)
1999		0.1517783	0.115198	0.1256949
		0.2969892(0.609)	0.3470581(0.74)	0.3474135(0.717)
2000		1.11589	1.167675	1.179549
		0.2907954(.000)	0.3255197(.000)	0.3260026(.000)
2001		0.656707	0.6732627	0.6845394
		0.2808904(0.019)	0.315592(0.033)	0.3160364(0.03)
2002		0.9400853	0.9569933	0.9687605
		0.2739532(0.001)	0.3063066(0.002)	0.3068045(0.002)
2003		0.5149877	0.5377022	0.5490123
		0.264944(0.05	0.2950899(0.068	0.2955615(0.0

	2)	)	63)
2004	0.2706679 0.2587186(0.295)	0.2699541 0.2859818(0.345)	0.2801612 0.2863773(0.328)
2005	0.1240084 0.2588024(0.632)	0.1561727 0.2831809(0.581)	0.1672505 0.2836523(0.555)
2006	0.1829095 0.2528367(0.469)	0.2081505 0.276412(0.451)	0.2096316 0.276(0.448)
2007	-0.2018809 0.2512847(0.422)	-0.1958515 0.2786071(0.482)	-0.1993736 0.2786519(0.474)
CONSTANT	5.47331 0.458323(<.001)	5.287455 .4336461 (<.001)	5.207105 0.4425317(<.001)

Figure 2.2 continued

Model statistics	Model 4	Model 5	Model 6
R-sq (within)	0.2284	0.2284	0.2284
R-sq (between)	0.871	0.871	0.8709
R-sq overall	0.8297	0.8297	0.8295
Rho	0.80014919	0.800141919	0.80018946