Chapter 5
The Application of Visual Analytics to Financial Decision-Making and Risk Management: Notes from Behavioural Economics

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Abstract Understanding how individuals and organizations make financial decisions under uncertainty and with different information settings is fundamental to informing the theory and practice of information management. Due to limitations on cognitive ability and problems of information overload, complex information sets may not be fully understood, resulting in suboptimal economic decision-making. We have applied visual analytics (VA), which enables users to interactively discover information from large information sets, to improve the financial decision-making process. Using an experimental methodology, we find evidence that VA reduces the cost of obtaining information, improves decisions, and increases confidence of users in a range of different financial decision tasks involving risk. This is a nascent area of research, and additional work is needed to develop and evaluate VA tools for financial decision-making and risk management. Best practices guidelines for presenting complex information sets may only develop through rigorous evaluation of the effect of information presentation on actual choice. In addition, the impact of VA in collaborative decision-making environments is not fully understood. The future of applied VA for financial decision-making and risk management must involve an interdisciplinary team of behavioural economists, VA researchers, computer scientists, and cognitive scientists.

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5.1 Financial Decision Process: Theory and Practice

Understanding how financial decisions are made under uncertainty and within different information settings is fundamental to informing the theory and practice of information management. The decision-making problems encountered by individuals and organizations on a daily basis require the analysis of complicated choice sets, and multiple attributes of each choice must be considered. Choice sets may also involve uncertainty and risk or may have incomplete information. This is especially true in financial decision-making, since risk and uncertainty is central to financial choices. Due to overload of information and cognitive limitations, individuals and organizations are often unable to make the utility-maximizing, or optimal, decision.

In practice, an individual's financial decisions may include choosing how to build a financial portfolio that is compatible with his or her risk preferences, choosing between investing in different retirement plans, choosing the level of insurance to purchase for home, auto, life, and health, and selecting a home mortgage or credit card. Difficult decisions faced by organizations or policymakers may include evaluating the potential outcomes of different projects or actions and choosing whether to make new investments or enter new markets.

We propose a simple behavioural economics framework that summarizes the decision-making process. The decision-making process is characterized by (1) retrieving and processing information; (2) developing subjective assumptions for the different probable outcomes of each decision; and (3) making a decision, taking preferences, costs, and benefits into account. This process is not simply sequential but includes recursive processes; for example, after developing subjective assumptions, the user may go back to gather and process additional information. All three components of the decision process may involve overload of information, and should be supported through appropriate decision support systems, which will increase the optimality of choice. We suggest that interactive visual analytics (VA) tools can fill this role. VA is the science of analytical reasoning facilitated by interactive visual interfaces (Keim et al. 2008). Figure 5.1 displays a conceptual framework of the decision process with key concepts and the suggested relevant VA supports. The best practices guidelines for presenting complex information to support all stages of decision-making may develop through rigorous empirical evaluation.

The decision support tools should be optimized for the task requirements. A basic variant of the Task-Technology Fit (TTF) theory can be used to evaluate the benefits of supports during the decision process (Zigurs and Buckland 1998, Savikhin et al. 2011). In the TTF conceptual framework, inputs to the model include the task requirements and the tool functionality, while the output is individual performance (with and without actual tool use). The conceptual framework is symbolized in Fig. 5.2. The improvement in individual performance between users who choose decision path (2) relative to path (1) represents the value-added of the decision support tool.

This chapter includes a discussion of the current state of work in applied VA for economic and financial decision-making and provides a view of future research in

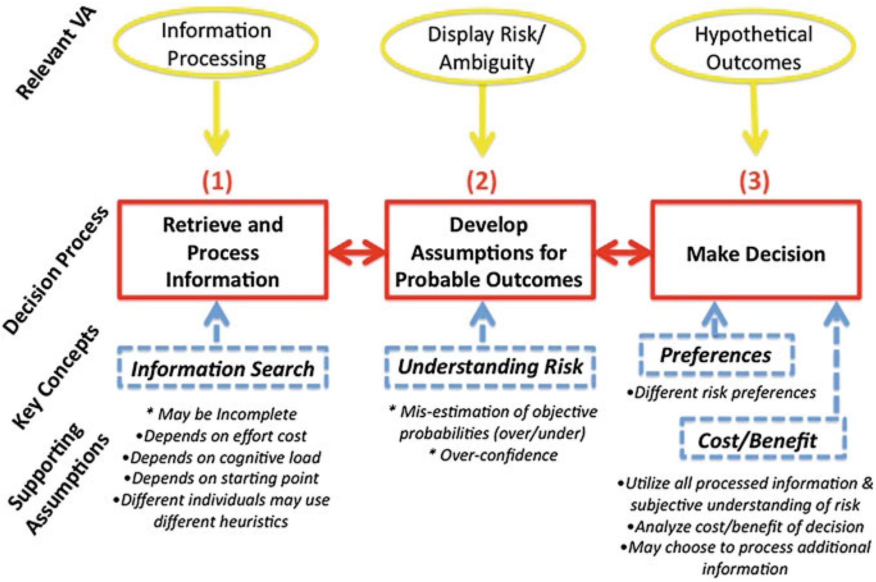
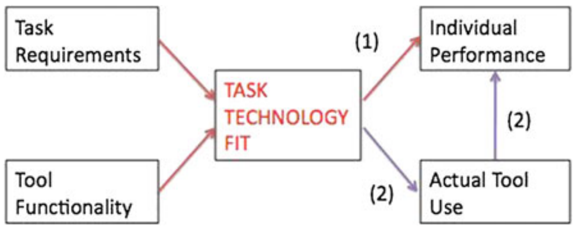


Fig. 5.1 Conceptual framework of the decision process and VA supports

Fig. 5.2 Basic TTF model



this area. In Sect. 5.2, the empirical approach that should be used to evaluate the decision process and the impact of VA tools is described. Section 5.3 describes the role of VA in financial decision-making. Section 5.4 discusses recent developments in the field as they relate to each of the three components of the decision process. In Sect. 5.5, open questions in this field are presented, focusing on challenges for transforming knowledge into practice.

5.2 The Experimental Methodology

5.2.1 Laboratory Experiments

Several complementary and rigorous empirical approaches can be utilized to investigate the financial decision-making process and evaluate the impact of VA on decision-making. The first of these is the economics laboratory experiment (Davis and Holt 1993; Smith 1994). Controlled laboratory experiments allow the researcher to rule out potential distractions that individuals face in the real world, and are a good first step to understanding the decision-making process.

In a laboratory experiment with VA application, a group of participants (often university students) participate in a decision-making task on the computer. In order to allow for learning, participants may complete the task several times, or over several ‘decision periods.’ The task is incentivized to ensure that the participant is making a choice that is closer to the choice he or she would really make.[1] Each participant typically earns between 10 and 40 US dollars in an experiment lasting 1–2 h, with earnings depending on the choices the participant actually makes. The dataset used in the experiment is generally artificial data, although actual data can also be used. Finally, every laboratory experiment has a clear and defined ‘institution’ known to all participants, which is characterized by the language used (with context or context free), the rules explaining what information is available and what outcomes are possible, and procedures to be followed (Smith 1994).

Laboratory experiments are ideal for testing existing theories of decision-making processes or documenting behavioural results as a basis for new theories. Experiments are also an excellent way to compare behaviour under different environmental conditions or within institutions. In our case, participants can be randomized into several treatments, including treatments with information presented in textual form and information presented in different interactive VA environments. More recently, Caplin et al. (2009) introduced the ‘decision process methodology’ for laboratory experiments. With this approach, participants are incentivized to reveal all intermediate choices that were made during decision-making. The ‘decision process methodology’ is particularly relevant for experiments evaluating VA, because we can better understand productivity of effort and document the process of gaining insight with and without VA (for an overview of the importance of gaining insight to VA, see Chang et al. 2009). One can also record mouse clicks and track eye movements for a fuller understanding of the decision process.

Financial choices should be in line with the individuals’ risk preferences, but we know from behavioural economics that individuals have heterogeneous risk preferences: most individuals are what we call risk averse, while other individuals are what we call risk neutral or risk seeking (Arrow 1965). An objective ‘risk preference elicitation’ task can be conducted immediately before or after the experiment to determine the risk preference of each individual (Holt and Laury 2002). Subjective reporting or questionnaire, risk preference elicitation tasks can

[1] Incentives are also present in practice, as individuals often make choices that are motivated by monetary and non-monetary incentives. For example, individuals preparing a financial portfolio will realize monetary outcomes and therefore have an incentive to select a portfolio that is closest to their risk preference. As another example, in the workplace, individuals receive bonuses as an incentive to improve performance. For a discussion of the use of financial incentives in experiments, see Camerer and Hogarth 1999.

also be used (Barsky et al. 1997).[2] The elicited risk preference parameter can then be compared to the choice actually made. If relevant to the experiment, 'time preference elicitation' tasks can also be conducted (Andersen et al. 2008; Andreoni and Sprenger 2010).

5.2.2 *Surveys/Financial Literacy*

The second approach to evaluating the effectiveness of VA focuses on knowledge acquisition. Using a series of surveys, as well as exposure to information in textual or VA form, we can evaluate the effectiveness of VA on financial literacy and financial knowledge (Lusardi and Mitchell 2005). Actual or artificial data is entered into the VA program prior to beginning the study. For example, in a credit card choice task, the user could view sample data, or could input his or her information about debt and credit card interest and fees. Participants are asked a series of financial knowledge questions before and after being exposed to the relevant information. Post-surveys can be immediate or delayed, with delayed surveys enabling the measurement of retention of financial knowledge. Groups who receive the VA are compared to groups who receive information in the standard, textual format.

Because VA requires a computer, computerized surveys are ideal. A cost-effective way to administer such surveys is via the Web. Bringing participants into a lab and conducting the survey is also possible and allows the researcher to control for external factors.

5.3 Visual Analytics for Financial Decision-Making

VA represents large amounts of information visually on the computer screen and allows the decision-maker to interact with the information, enabling him or her to gain insight, draw conclusions, and make improved decisions (Keim et al. 2008; Thomas and Cook 2005). Several key visualization research areas are related to the study of applied VA for economic and financial decision-making, including VA (Keim et al. 2008), financial visualization (Brodbeck et al. 1997; Plaisant et al. 1996; Varshney and Kaufman 1996; Ziegler et al. 2008), casual information visualization (Pousman et al. 2007) and visualization of risk (Csallner et al. 2003; Schreck et al. 2007).

VA is an ideal method of providing decision support for several reasons. Humans have highly developed skills of perceptual sense-making, which can be

[2] Note that design research uses a qualitative approach as well (see Chap. 4, Users: Qualitative Research, Cooper et al. 2007).

harnessed with new interactive visual technologies (Keim et al. 2008). Graphical representations shift information processing to the perceptual system, enlarging problem-solving capabilities (Lurie and Mason 2007). In particular, graphical representations allow decision-makers to quickly identify outliers, trends, and patterns, and more easily assess information (Lurie and Mason 2007; Jarvenpaa 1989). However, VA is more likely to result in biased decisions than textual information, which must be considered in the design of appropriate systems. Lurie and Mason (2007) suggest that VA may bias consumers by focusing attention on a limited number of alternatives, increasing the saliency of irrelevant information, and (if designed inappropriately) encouraging inaccurate comparisons.

When VA is not available, the user goes through decision-making steps 1–3. That is, the user considers the limited information that was processed and the subjective risk measures, does a calculation about the probable outcomes, and then makes a decision. Appropriate VA facilitates the user decision process by giving intermediate feedback and allowing the user to actually interact with the data throughout the decision-making process. VA allows the user to quickly view all information and, if relevant, find outcomes for hypothetical risky choices. Because steps 1 and 2 are augmented by VA, the user is free to expend cognitive resources on step 3. In our work (discussed in Sect. 5.4 below), we find that appropriate VA systems improve performance, reduce time spent on decision-making, and increase confidence across several different financial decision-making tasks (Savikhin et al. 2008; Rudolph et al. 2009; Savikhin and Ebert 2012).

5.4 Decision Process and the Role of Visual Analytics

While each decision problem requires all three steps of processing information, assessing probable outcomes, and making a decision, we have begun to develop a better understanding of how VA can support decision-making by analyzing each type of task separately. Thus, in Sect. 5.4.1, we discuss a new tool we developed specifically for information search and processing. In Sect. 5.4.2, we discuss another tool developed specifically for evaluating probable outcomes. The decision problem discussed in Sect. 5.4.1 also has a component of evaluating outcomes, but the tool does not directly measure the process selected by the user for this task. Likewise, the decision task in Sect. 5.4.2 also has an information-processing component, but the tool is not designed to capture the information process in the same way as in Sect. 5.4.1.

5.4.1 Information Processing and Search

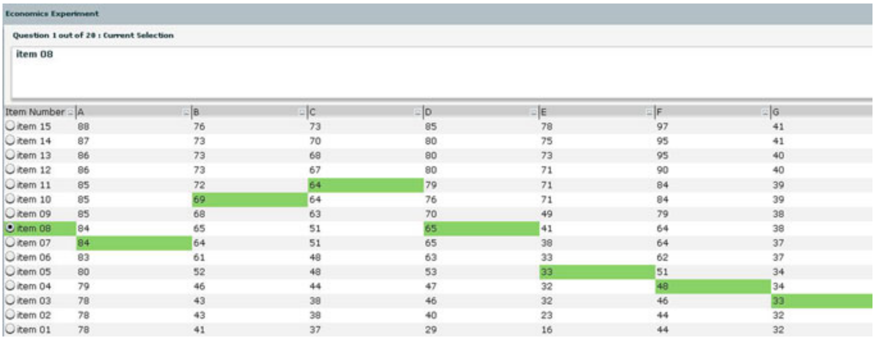
The first step in making the decision is to process the available information. The information search process literature has been an active topic of investigation in behavioural economics and cognitive science since Stigler's (1961) seminal paper on search with imperfect information. We observe that when faced with large choice sets, individuals fail to choose the best possible option, often due to incomplete search or bounded rationality (Caplin et al. 2009; Iyengar and Lepper 2000; Simon 1987). The bounded rationality concept suggests that individuals make rational choices but that these choices are bounded in some way. For example, a limited search due to limited processing capacity creates a bound on rationality in one class of search models (Simon 1972). The individual may stop search when a satisfactory, but not optimal, solution is reached—this type of incomplete search is called satisficing (Simon 1987). Similarly, when faced with a large information set, individuals may stop after processing some, but not all, of the data. Thus, a limited amount of information is actually processed in this step.

Depending on the aspects of the decision task, individuals may utilize any number of different information search heuristics to discover a satisfactory solution (Einhorn 1970, 1971; Payne et al. 1990; Tversky and Kahneman 1974; Gigerenzer and Goldstein 1996). Individuals may react to information overload by selectively processing only subsets of available information or simplifying the processing of particular elements of the problem (Payne et al. 1990). Another common search method is sequential search, in which individuals compare one solution or choice at a time (Caplin et al. 2009).

VA tools can be designed to support information search in several ways. First, information is synthesized in the tool, so that a greater amount of information can be processed at once. This increases the 'productivity of search,' allowing the decision-maker to search through a greater number of options with the same amount of time or effort. Second, VA tools could be designed to 'guide' search, or to encourage certain more advantageous heuristics over others in any particular task. The VA designer can achieve the latter by displaying the appropriate information more prominently.

We experimentally evaluated a novel VA tool, which is aimed at optimizing the information search process in one particular task (Savikhin 2010). In our task, participants selected one of 15 separate options, each of which had seven different numerical attributes (each 'attribute' was a two-digit number). The value of each option, payable in cash at the end of the experiment, was linked to the sum of its attributes. In order to choose the utility-maximizing option, the participant needed to process all available information. The task was intentionally designed to create information overload: in most cases, the utility-maximizing option was not discovered in the time allotted. This task is similar in practice to the decision of choosing a retirement plan or an insurance plan.

In the experiment, 120 participants were randomized to either receive the information about options in table form, to receive the information in a table that allowed for typical sorting similar to the interaction capability available in typical spreadsheet software, or to receive the information in the VA tool, SimulSort format (Hur and Yi 2009). SimulSort automatically sorts all items by attribute and uses visual cues to assist with comparisons (see Fig. 5.3). By highlighting only two items at any time, SimulSort encourages the use of the sequential search heuristic.



Economics Experiment

Question 1 out of 20 : Current Selection

item 08

Item Number	A	B	C	D	E	F	G
item 15	88	76	73	85	78	97	41
item 14	87	73	70	80	75	95	41
item 13	86	73	68	80	73	95	40
item 12	86	73	67	80	71	90	40
item 11	85	72	64	79	71	84	39
item 10	85	69	64	76	71	84	39
item 09	85	68	63	70	49	79	38
item 08	84	65	51	65	41	64	38
item 07	84	64	51	65	38	64	37
item 06	83	61	48	63	33	62	37
item 05	80	52	48	53	33	51	34
item 04	79	46	44	47	32	48	34
item 03	78	43	38	46	32	46	33
item 02	78	43	38	40	23	44	32
item 01	78	41	37	29	16	44	32

Fig. 5.3 SimulSort display

We found that typical sorting capability does not cause a significant improvement in decision-making in this context. However, the VA technology increases the value of the initial and final item selected by the user, decreases time spent deliberating, and improves users' confidence. On average, users of SimulSort capture significantly greater value in each round and spend just 75 % of the time spent by users in the baseline or sorting treatments. These results suggest that interactive VA tools may be a new way to increase productivity of search (thus increasing the amount of information processed) and improve the outcome of information search for consumers in practice.

5.4.2 *Risk and Decision-Making*

The second step in the decision process is to evaluate the probable outcomes of each option. For example, in a financial planning task, the individual chooses a set of assets for his or her portfolio. The individual has processed some information about the historic annual percentage yield and standard deviation of the assets under consideration. This information can be used to predict the expected return of any asset or combination of assets, or at least to understand which assets are riskier than others. Finally, in step 3 the user makes a final choice. The purpose of the tools discussed in this section is to target just the evaluation component, not to keep track of the amount of information processed directly.

While objective measures of probability are available, what the individual actually calculates in step 2 is a subjective measure of probability. This measure is close to the actual probability, but due to cognitive biases it is not always exactly equal (Harrison and Rutstrom 2008). Several cognitive biases play into the decision, including prospect theory, whereby individuals often overestimate small probabilities and underestimate large probabilities (Kahneman and Tversky 1979). Difficulty in interpreting risk may result in a choice that is not compatible with the

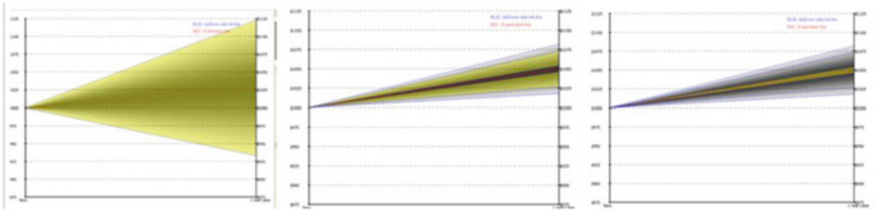


Fig. 5.4 FinVis possible outcomes gradient (three different scenarios)

risk preferences of the individual. Related work suggests that visual representations of probabilities may be effective at combating these issues (Camerer 1989; Cleveland et al. 1982).

There are two key design concepts for helping the user understand risk and the link between decision and outcome on which we base our VA tools: the first is the visualization of all possible outcomes for each intermediate choice; the second is the ability to sample random "probable" outcomes from the possible outcome space. Tools designed with these concepts in mind are particularly effective because individuals use the tool to explore the link between decisions and outcomes during, rather than after, the decision-making process.

Figure 5.4 displays the possible outcomes gradient used in the VA tool FinVis. FinVis was developed to help users create a financial portfolio. In FinVis, the y-axis on the left side represents the total amount of money invested, while the y-axis on the right side represents all possible outcomes in a period of time. Darker gradient translates to a more likely outcome, while lighter gradient translates to a less likely outcome. The scenarios on the right and middle include more than one fund in the portfolio, while the scenario on the left shows the impact of only one fund. FinVis also allows subjects to 'sample' possible outcomes. When a possible outcome is 'sampled,' an indicator is displayed at a random point on the right y-axis. Outcomes are sampled randomly from the underlying distribution.

We found that individuals using FinVis are more likely to create portfolios that are closer to the Markowitz efficient frontier; that is, portfolios selected using FinVis have a greater return for any level of risk compared to portfolios selected when information is presented in textual form (Markowitz 1952; Rudolph et al. 2009). Moreover, individuals using FinVis display greater confidence compared to individuals using the textual representation and are more likely to make a choice that is closer to their risk preferences (Rudolph et al. 2009). In a follow-up paper that used a laboratory experiment, we also found that how possible outcomes are visualized is important. Visualizations of both upward and downward risk (as in FinVis) or only downward risk increased user confidence and exploration of the data more than visualizations of only upward risk (Savikhin and Ebert 2012).

A later version of FinVis that was created in 2010–2011, which includes an audio/video tutorial to improve usability, is currently being tested using a computerized survey. We will compare the pre- and post-survey responses to financial

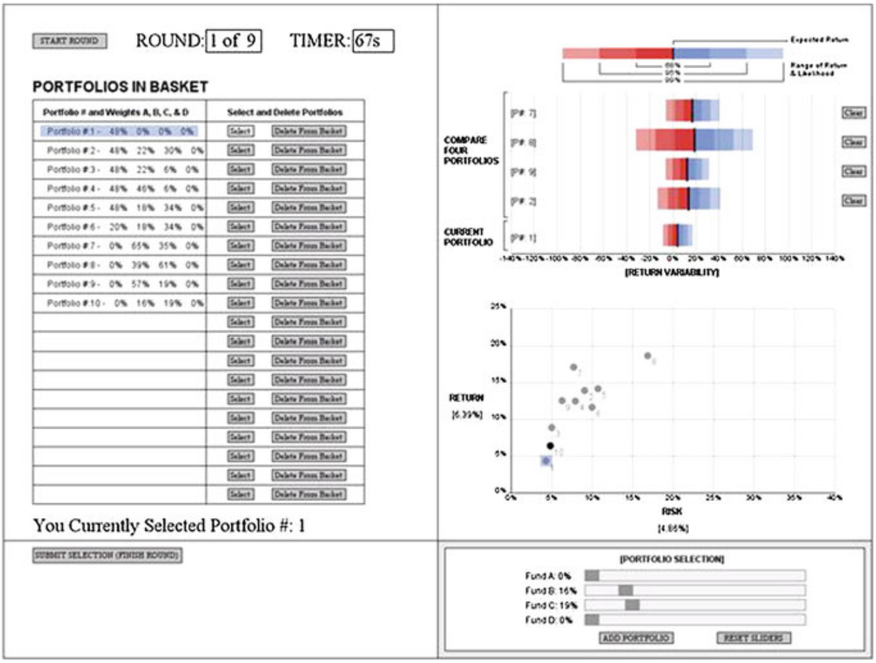


Fig. 5.5 PortfolioCompare screen

literacy questions for participants who used FinVis, compared to participants who received the same information in a static brochure. We will also examine retention of knowledge by conducting another survey six months following the initial intervention.

In another project aimed at helping individuals build a financial portfolio, we introduced PortfolioCompare, a tool allowing the user to create several different portfolios and quickly select one that is optimal, see Fig. 5.5 (Savikhin et al. 2011). PortfolioCompare compares potential portfolios based on expected risk and return using two different views, the Return Variability view and the Risk/Return scatter plot. Using the decision process methodology in the experiment to evaluate PortfolioCompare, we found that PortfolioCompare helped the user select a portfolio that was closer to his or her risk preferences compared to receiving the same information in textual form. The exploratory nature of PortfolioCompare was useful to subjects, as subjects continued to improve their selections during the decision-making process.

Another major focus of our work is the study of auction market bubbles and overbidding relative to the underlying value in auctions. An asset bubble occurs when assets are traded above their fundamental value in the market. This research builds on our work on a known economic problem, known as the Winner's Curse,

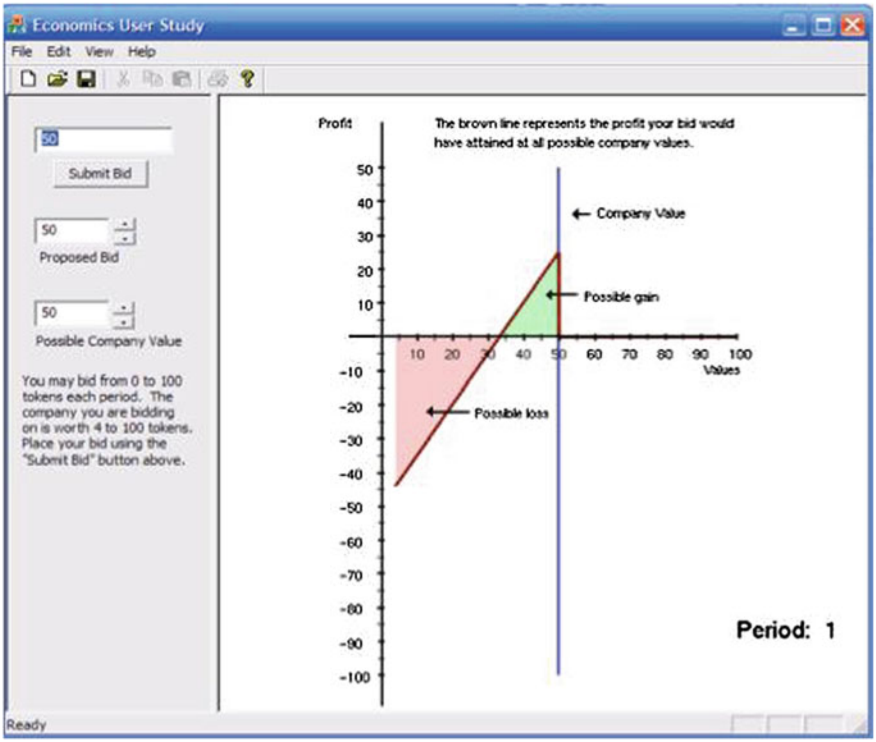


Fig. 5.6 Winner's curse VA tool

when individual or organizational behaviour deviates from the optimal (Savikhin et al. 2008). The Winner's Curse was first discovered by petroleum engineers in the 1970s who claimed that oil companies suffered persistent losses because of overbidding on projects (Capen et al. 1971). We investigated the impact of a VA tool we developed on bidding in a two-person experimental task called the 'acquiring a company' task. In this task, participants bid on a company, the value of which is uniformly distributed and randomly determined by the computer but unknown to the subjects (Samuelson and Bazerman 1985). The VA tool allows the subject to view all possible outcomes of every proposed bid and sample probable company values from the distribution (see Fig. 5.6). We found that individuals were able to reduce the Winner's Curse and bid closer to the optimal when using the VA tool as compared to receiving the same information in textual format. The next step is to develop VA tools targeted at reducing asset market bubbles in common value auctions. The direct application of this line of research is to stock market bubbles.

5.5 Research Challenges

5.5.1 *Problems in Economics and Information Management*

This is a nascent area of research, and additional work is needed to develop and rigorously evaluate appropriate VA tools for financial decision-making and risk management. Through rigorous evaluation of the effect of information presentation on actual financial choices, we will develop a thorough understanding of best practices for presenting complex information sets and, in turn, improve consumer welfare.

Behavioural economists have had difficulty determining the underlying reason why individuals make suboptimal decisions. For example, in the acquiring a company task, suboptimal overbidding is blamed either on bounded rationality or on a 'utility of winning'[3] not accounted for in the original decision-making model. Testing whether mistakes are reduced through VA can also shed light on whether individuals make suboptimal decisions because they are boundedly rational or because they have different preferences than assumed by the model. A reduction in cognitive load will also allow individuals to make decisions that are in line with their preferences, and enable economists to more accurately measure those preferences.

Many decision-making problems in finance and risk management would benefit from evaluation and application of VA decision support. One key area for study is the origin and suppression of asset market bubbles. History contains many instances of bubble behaviour when speculative trade in financial assets or commodities creates a period of rapidly increasing prices, followed by abrupt collapse. Speculative bubbles are cause for concern in real world application as evidenced by the recent US housing bubble of 2006–2007 and dot-com bubble of 1995–2000 (see Lybeck 2011 for a history of the housing bubble and comparison to other bubbles), but there is no widely accepted theory to explain their development. This behaviour has been documented in over 72 laboratory experiments in the past 15 years (Porter and Smith 2003). Dufwenberg et al. (2005) found that bubbles can be substantially reduced or eliminated with a few experienced traders in the market. Johansen and Sornette (1999) also suggest that agents trading in asset markets are limited in the amount of information they have and are therefore boundedly rational. Previous experiments have shown that even when subjects have the fundamental price of an asset, bubbles develop and persist (Hommes et al. 2008). It appears this is a function of subjects' expectations: if asset prices were increasing in the past, subjects expect they will continue to increase; if they were

[3] According to the 'utility of winning' hypothesis, individuals gain utility not just from acquiring an item but also from the act of winning itself. See Sheremeta (2010) and Parco et al. (2005) for examples of utility of winning in experiments with a lottery contest.

decreasing in the past, they are expected to continue to decrease (Hommes et al. 2008). This belief may be similar to subjects' inability to understand probability in the acquiring a company game. An effective VA decision-making tool would be useful in practical application to mitigate future speculative bubbles. This would have the effect of decreasing uncertainty in the stock market and preventing stock market crashes.

Other key areas for study are helping individuals understand compound interest and selection of appropriate levels of debt, as well as how to process the risk of certain events in order to determine the optimal level of insurance. Reducing certain cognitive biases across all of these economic and financial challenges is also of interest. In general, helping individuals better process information and understand risk can benefit consumers, organizations, and policymakers.

Design of collaborative visualization tools has been identified as a challenge in visualization research (Thomas and Cook 2005). Yet, the impact of VA on collaborative financial decision-making environments is not well understood. Collaborative capabilities are necessary for work teams (Heer and Agrawala 2008; Benbunan-Fich et al. 2003). Groups can learn faster and may act more rationally on average than individuals (Kocher and Sutter 2005; Bornstein and Yaniv 1998). This improvement may come from diversity of opinions (Casari et al. 2008). Economists have also documented that groups face coordination problems, which are eliminated through communication (Zhang 2009). However, giving more information (in textual form) may cause both individuals and groups to deviate further from the optimal, with a more pronounced effect for groups (Cox and Hayne 2006). This suggests that providing VA support to group decision-makers is even more important than providing it to individuals.

5.5.2 Moving Knowledge into Practice

Until recently, individuals and households relied on face-to-face contact with a financial advisor to develop a financial or retirement plan. Online financial services are becoming more popular, especially among younger adults, and increased use of online services reduces interactions with financial advisors, However, online financial planning may result in overload of information, giving the consumer instant access to an overwhelming number of financial instruments with different risk and return attributes. Providing support to consumers during the financial decision-making process is thus essential. VA systems can be applied to these challenges and used as a helpful tool for financial advisors to explain difficult concepts to clients. Furthermore, VA-based support can be easily disseminated via the Web.

VA support is also necessary for organizations that process large amounts of data and often make decisions as a team. More research is needed on the effect of decision-making in collaborative environments.

We have applied VA practices that enable users to interactively discover information from large information sets to the financial decision-making process. Using experiments, we found evidence that VA reduces the cost of obtaining information, improves decisions, and increases confidence of users in a range of different decision tasks involving risk. We now have evidence that appropriate VA will increase the welfare and well-being of consumers by improving choice and increasing confidence. The next step is to incorporate VA tools into practice. Researchers should continue to investigate the impact of VA on real-world decision-making processes and outcomes, and explore effective avenues for encouraging consumers to use VA tools in their decision-making. The future of applied VA for financial decision-making and risk management is potentially bright, but must involve an interdisciplinary team of behavioural economists, VA researchers, and cognitive scientists in order to advance understanding in this area.

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