An Experimental Study of Financial Portfolio Selection with Visual Analytics for Decision Support

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Abstract

We investigate the decision process as applied to the practical task of choosing a financial portfolio. We developed PortfolioCompare, an interactive visual analytic decision support tool that helps the consumer quickly create, compare and choose among several portfolios consisting of different financial instruments. PortfolioCompare facilitates the analysis of risk and return aspects of each portfolio considered. We investigate behavior in this task using an economic experiment in which the user actively creates and compares portfolios from a set of funds. We elicit risk preferences using a separate task and find that subjects using PortfolioCompare make decisions that are closer to their risk tolerance as compared to subjects presented with similar information in textual form. This finding suggests that PortfolioCompare helps understand risk aspects of portfolios. Portfolio selections are improved during the course of the decision process, suggesting that this tool is valuable for decision support.

Keywords: Economic decision-making, knowledge discovery, visualization for the masses, human-computer interaction, laboratory studies.

Index Terms: J.1 [Administrative Data Processing]: Financial (e.g., EFTS)—; I.6.8 [Types of Simulation]: Visual—

1 Introduction

Developing a financial plan and selecting a suitable portfolio of investments is a challenging analytical task in which the consumer must choose among many financial instruments with varying risk, return and correlation aspects. A recent study found that less than 25% of individuals have developed and followed through with a financial plan [25]. Further, the advice often given to the consumer is to "select a level of risk that you are comfortable with"; however, the fundamental question is whether the individual has a clear understanding of the risk level of different assets and whether he or she can choose a portfolio that is appropriate for his or her risk tolerance.

Empirical and laboratory research in economics and finance has shown that individuals often make sub-optimal decisions when choosing a financial portfolio due to cognitive limitations [2, 22, 23]. Known issues with representing probability and risk are that individuals may base decisions on subjective, rather than objective, probabilities and that perceptions of probabilities may not correspond to actual probabilities [16]. Related work suggests that visual representations of probabilities may be effective at combatting these issues [6, 8]. 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 individuals, and increased use of such services reduces the need for a personal financial advisor. However, online financial planning may result in an overload of information, giving the consumer instant access to a myriad of financial instruments with different risk and return attributes. The negative effect of information overload on cognition has been reported for decisions in domains such as healthcare, accounting and business [4, 11]. Providing support to consumers during the financial decision-making process is essential, and researchers have called for the development of decision support systems to fulfill this purpose [2].

We introduce a new interactive visual analytic decision support tool, PortfolioCompare, for personal financial planning [21]. While it is commonly acknowledged that portfolio selection is an important yet difficult problem, researchers have been slow in developing solutions for improving decision-making in this task. Information science theories like Task-Technology Fit [10] can explain the benefits from use of new technologies in complex decision making tasks. Our main contribution is to investigate decision-making when a new decision tool is introduced to the portfolio selection task and to quantify the effectiveness of this tool using rigorous experimental economics methods.

We use an economics experiment to investigate individual behavior during the portfolio selection task with and without PortfolioCompare. PortfolioCompare is an exploratory visual analytic decision support tool that we developed that allows the consumer to quickly create, compare and select among several investment portfolios consisting of different financial instruments. PortfolioCompare features two separate visual analytics displays which allow the individual to interactively analyze risk and return aspects of each portfolio considered in order to choose a portfolio that is appropriate for the decision-maker's risk tolerance (see Figure 1). In our experiment, the user actively creates and compares portfolios and chooses whether or not to use each of two visual analytics displays. The user's actual earnings are based both on the outcome of his or her final chosen portfolio, and also on the effectiveness of the decision process. We also investigate the risk preferences of individuals using a separate task and correlate risk preferences to the riskiness of the portfolio choice. Laboratory experiments such as this one are ideal for investigating decision-making in tasks involving visual analytics [31, 30].

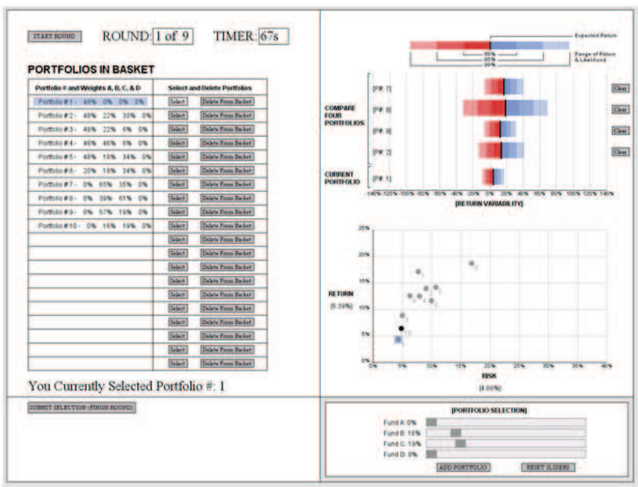

Figure 1: PortfolioCompare Decision Screen

We find that PortfolioCompare is effective at helping individuals understand risk aspects of portfolios, and use of this tool in practice could improve the ability of the general public to make suitable financial decisions. Decisions are improved during the course of the decision process, suggesting that interactive comparison of portfolios is valuable. It has been suggested that different individuals may vary in their ability to understand risk depending on the presentation format [16]. We collected the demographic characteristics of users and we pinpoint which users benefit most from the visual analytics tool.

2 Visual Analytics for Decision Support

Visual analytics (VA) is the science of analytical reasoning supported by ineractive visual interfaces [21]. VA tools, which have already been implemented in fields such as medicine and the physical sciences, may reduce the complex cognitive work that is needed to perform decision-making tasks [36]. Humans have highly developed skills of perceptual sense making, which can be harnessed with new interactive visual technologies [21]. Visual presentations of information can be used to shift information processing to the perceptual system, therefore enlarging problem-solving capabilities [35]. In particular, graphical representations allow decision makers to quickly identify outliers, trends and patterns [24]. Information is more easily assessed and compared when it is presented in visual form [19]. Financial knowledge is directly correlated with success in investment planning [25]. We posit that the use of visual analytics tools may help individuals understand complex information, thereby increasing the chance of success with investment planning.

Several key visualization research areas are related to the study of portfolio selection, including visual analytics [31, 30], financial visualization [3, 28, 37, 40], casual information visualization [29], and visualization of risk [9, 32, 40]. While use of computer-assisted visualization techniques to show financial data goes back many years, these tools were designed for expert users. On the other hand, our tool is intended as a financial planning decision support tool for a non-expert consumer.

3 Related Work in Economics and Finance

Modern portfolio selection theory has been a significant topic for research since it was proposed by Markowitz over 50 years ago [26]. This theory suggests that rational investors should use diversification to optimize their portfolios by maximizing return for any given level of risk. Investors following this strategy should take into account standard deviations and correlations in order to choose assets optimally. However, individuals have cognitive limitations and cannot effectively use this strategy for financial planning, and this has been discovered in the field [12, 14] and in laboratory experiments [5, 23, 30].

The complexity of information encountered while making financial decisions may overwhelm the decision-maker, who has cognitive limitations and may not be able to interpret all the information of the problem correctly [13, 33]. The inability to make optimal decisions is prevalent in many decision-making problems, including financial planning problems. In related work, several visual analytics tools have been applied to economic problems and it was found that individuals were able to make decisions significantly closer to the optimal while using an interactive visual as compared to having this information in textual form [31, 30]. A difference between the current work and previous work in economic decision-making is that in FinVis [30] or the *Winner's Curse* problem [31] the individual uses the visual analytics tool to make one decision, while in PortfolioCompare the individual quickly creates several portfolios and compares among them. In addition, in the current work the individual is presented with two different visual analytics displays and can choose to use one or both.

Portfolio selection is an information search process in which the individual investigates different attributes of investments before selecting an appropriate portfolio. The information search process has been an active topic of investigation by economists since Stigler's [34] seminal paper on search with imperfect information. Our contribution to this literature is that we are able to document the search process with and without the visual analytics tool. The novel experimental design, which has not previously been employed in this context, incentivizes the user to choose a portfolio as soon as he or she finds one he or she is comfortable with, and then continue to improve selections until the final selection. This method allows us to measure the value of exploring the data using different tools.

A finding from economics is that individuals have difficulty interpreting risk aspects of uncertain choices [16]. Difficulty in interpreting risk may result in a choice that is not compatible with the risk tolerance of the individual. We mitigate this problem by introducing a decision-making tool that displays risk properties of portfolios in two different views, and allows the individual to choose which portfolios to compare in which view. By comparing the possible outcomes of portfolios with different risk aspects, the individual may be more able to select a portfolio that corresponds to his or her risk tolerance.

4 Theory Development

4.1 Economic Decision-Making Model

The optimal decision is one that maximizes the expected return at any level of risk, and this "efficient frontier" is calculated using the theoretical approach developed by Markowitz [26]. The rational decision-maker with unlimited cognitive capacity is expected to solve the following constrained minimization problem:

$$\begin{aligned} \textit{Minimize} \quad & P'\Omega P \\ \textit{Subject to the Constraints:} \quad & P'\Omega P = E \\ & P'1 = 1 \\ & P \geq 0 \end{aligned} \tag{1}$$

where Ω is the $n \times n$ variance-covariance matrix, P is a $n \times 1$ vector of investment expected returns, E is the vector of expected return of the portfolio and 1 is a vector of 1's.

It is commonly acknowledged in the literature that individuals have cognitive limitations, and therefore are constrained in their ability to correctly solve the minimization problem [13]. Under our model of constrained decision making, we assume that the decision-maker is unable to take correlations into account and instead believes that $\Omega = I$, where I is a square identity matrix with 1's down the main diagonal and 0's elsewhere. The constrained decision-maker thus solves the following minimization problem:

$$\begin{aligned} \textit{Minimize} \quad & P'IP \\ \textit{Subject to the Constraints:} \quad & P'IP = E \\ & P'1 = 1 \\ & P \geq 0 \end{aligned} \tag{2}$$

The solution to (2) will always result in an expected return that is equal to or less than the expected return in the solution to (1) for any level or risk. The impact of the visual analytic decision support tool is to augment the decision-maker's cognitive ability by removing the difficulty of interepreting Ω so that the constrained decision-maker can solve (1).

4.2 Design Guidelines

We apply the design-science methodology to the construction of PortfolioCompare [17]. The aim of design-science research is to develop a technology-based solution to solve a relevant applied problem: in this case, we develop PortfolioCompare to aid decision-makers in the portfolio selection process. We then proceed by using our economics experiment to rigorously quantify the utility and quality of PortfolioCompare.

We rely on a basic variant of the existing Task-Technology Fit model (TTF) to explain the ability of PortfolioCompare to support the portfolio selection task [15]. 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 by Figure 2. The improvement in individual performance between users who choose decision path (2) relative to path (1) represents the value-added of the visual analytic tool.

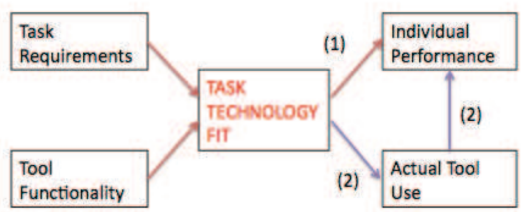

Figure 2: Basic TTF Model

5 The PortfolioCompare Environment

5.1 Financial Model Implementation

We use artificially generated return and standard deviation in the laboratory experiment, but historic investment return and standard deviation could be used in practical application as the best available predictors of future outcomes [20]. PortfolioCompare displays the aggregate risk of each portfolio (see Figure 1). The goal of PortfolioCompare is to help users quickly compare risk aspects of different portfolios; therefore, the risk discussed here is unsystematic risk, and does not include systematic risk which cannot be diversified away (i.e., recessions, wars, etc.). Standard deviation is used in this paper as a measure of risk, as is common in the financial field [26]. Risk is shown as one, two, three and four standard deviations above and below the expected return of the investment. We also account for change in risk due to correlations between investments, using the straighforward calculations for expected return, risk and correlation as explained in financial textbooks [20].

5.2 Visual & Interactive Implementation

The user of PortfolioCompare employs interactive slider bars to create portfolios and has the option to view portfolios in two different visual analytic displays. Portfolios are not available at the beginning of the decision task until they are created by the user. The different interactive visual tools of PortfolioCompare work in unison to give the user a holistic view of all portfolios being considered.

All portfolios currently being considered are listed on the left in what we term the "Basket of Portfolios." Users add portfolios comprised of different investment options using a slider interface (Figure 3). There are four sliders each representing different investment options labelled Funds A, B, C and D. Users can allocate up to 100% of their endowment into any or all of the available funds. The user can add up to 20 portfolios at a time to the consideration "basket," and adding a portfolio to this "basket" automatically activates the *Risk/Return* display. The secondary display is the *Return Variability* display, and the user can select any portfolio in the "basket" to visually compare expected return and risk aspects of up to 4 portfolios at a time in this display.

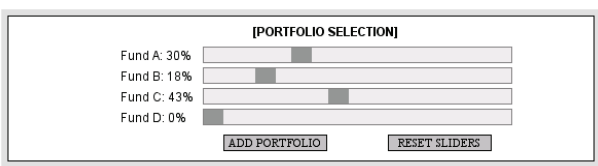

Figure 3: User Input Sliders

5.3 Risk/Return Display

As the portfolio is being created for addition to the "basket," the portfolio's risk and return characteristics are continuously visualized in the *Risk/Return* display (see Figure 4). As investment proportions are modified, a dot representing the portfolio appears and moves in a 2-D display similar to a scatterplot in which the horizontal axis represents risk and the vertical axis represents return. The dot also features a trail as a visual cue to help the user quickly see if the portfolio is decreasing or increasing in risk or return as the investment proportions change. A number of studies have shown that motion can express relationships, and that motion increases perceptions of causality [27, 38]. In our display, changing proportions of investments using the sliders changes the risk and return aspects of the portfolio. When the portfolio is added to the consideration "basket," the dot becomes static and is given an ID number. Creating additional portfolios allows the user to quickly compare and identify several salient portfolios such as portfolios with highest return or risk, or lowest return or risk. The display also allows the user to compare return and risk of all portfolios in the consideration "basket" and select the highest return portfolio for each level of risk. According to Clevelands graphics elements hierarchy, position along a common scale is one of the best ways to display this type of data [39]. The *Risk/Return* display makes use of spatial proximity, a powerful perceptual organizing system and one of the simplest and most powerful ways to emphasize relationships between different data entities [38].

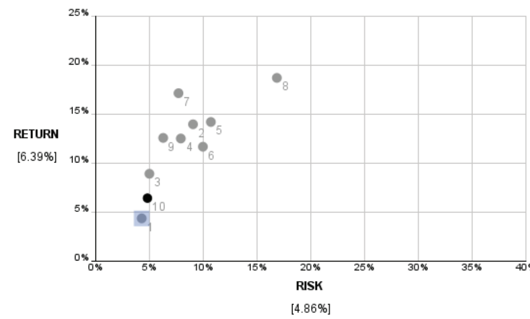

Figure 4: Risk/Return Display

5.4 Return Variability Display

The second display, the *Return Variability* display (see the top right of Figure 1) allows the user to select a portfolio in the "basket" of portfolios under consideration and visually compare the variability of expected return. In addition, the *Risk/Return* display connects to the Return Variability display through a rollover effect intended to help users analyze return variability and assess the likely outcome from investing in the considered portfolio. Clicking on any portfolio in the "basket" displays this portfolio in the *Risk Variability* display in a distribution bar. The distribution bars are displayed with the blue bar representing potential upside risk and the red bar representing potential downside risk. Similar to [30], transparency is used to represent different levels of risk. The level of transparency represents the return falling within the 68%, 95%, 99% probability. Users can interactively add and remove portfolios to the *Return Variability* display at any time.

5.5 Baseline Version

Figure 5 shows the screen of the non-visual version of PortfolioCompare that was developed to be used in our laboratory experiment. The baseline version presents the same key information of the two visual displays in textual form. We retain interactivity and the user input sliders, but replace the *Risk/Return* display and the *Return Variability* display with textual information. While PortfolioCompare allows the user to quickly compare risk and return visually, the baseline version requires the user to view numbers and compute differences in risk and return in working memory.

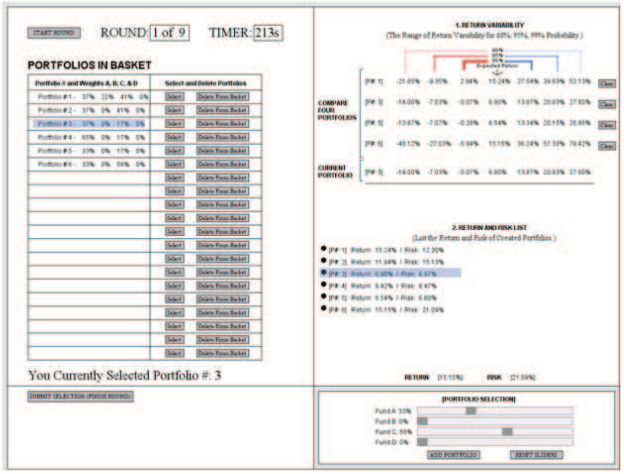

Figure 5: Baseline Version of PortfolioCompare

6 EXPERIMENTAL DESIGN

6.1 Anticipated Findings

We designed the laboratory experiment to address several research questions about the decision-making process with applied visual analytics tools. Laboratory experiments are ideal for initial studies of the decision-making process in complex tasks such as this one because the environment is controlled and we can rely on experimental variation to quantify the value of the different support tools. Our anticipated findings are outlined below:

1. By allowing the user to compare portfolios with different risk levels, PortfolioCompare will help select a portfolio with a risk profile that is appropriate for the user's (separately elicited) risk tolerance

2. By visualizing the risk and return tradeoffs of each choice, PortfolioCompare will improve financial decision-making, helping select portfolios with a higher return at any risk level.

3. PortfolioCompare will reduce the cognitive load and increase the value of information search by allowing the user to quickly create, compare and select among portfolios.

6.2 Experimental Setup

Non-expert students from Purdue University volunteered to participate in the study. Experiments were conducted at the Vernon Smith Experimental Economics Lab using standard laboratory protocols. Subjects earned between $17 and $27 in the experiment, where their earnings depended on their portfolio selections. Subjects whose final and intermediate portfolio choices resulted in higher experiment earnings earned a greater amount of money as compared to subjects whose final and intermediate portfolio selections resulted in lower experiment earnings.

We used a between subjects design, with 19 subjects participating in the treatment using the visual version of PortfolioCompare (V) and 20 different subjects participating in the baseline treatment (B) using a non-visual version of PortfolioCompare[1]. The information and training was the same in both treatments.

As in previous experimental work [23], we provided subjects with four generic investments, A, B, C, and D with returns and standard deviations of 9%, 15%, 21%, 6% and 9%, 18%, 36%, 0%, respectively. Future versions of PortfolioCompare could scale to any number of investments. The correlation between B and C was -0.8, while all other correlations between investments were 0. Correlation between i and j, $\rho_{i,j}$, is defined as:

$$\rho_{i,j} = \frac{\sigma_{i,j}}{\sigma_i \sigma_j} \tag{3}$$

where σ_i is the standard deviation of investment i, σ_j is the standard deviation of investment j, and $\sigma_{i,j}$ is the covariance between i and j. Covariance is the extent to which the investments covary, and is defined as:

$$\sigma_{i,j} = \sum_{k=1}^{m} \left[R_{i,k} - E(R_i)\right] \left[R_{j,k} - E(R_j)\right] \tag{4}$$

where $R_{i,k}$ is one possible return on security i, $E(R_i)$ is the expected value on security i, and m is the number of likely outcomes for a security for the period.

Each subject received a $5 U.S. dollar endowment at the start of each round, and were able to allocate proportions of this endowment to any (or all) of the four funds. Each round lasted up to 5 minutes, during which the individual created, compared, and selected a final portfolio choice. In order to allow for learning of both the tool and task, the same decision task was repeated for 9 rounds. Subjects could create portfolios by moving the sliders representing the proportion of investments A, B, C or D they wished to allocate to each portfolio and then adding these to their consideration "basket." All the portfolios in the "basket" were visualized in the *Risk/Return* display in the V treatment (or risk and return values were listed for these portfolios in the B treatment). Subjects could additionally select up to four portfolios at a time to compare in the *Risk Variability* display. In the V treatment, this display included visual cues consisting of red possible loss and blue possible gain bars, while in the B treatment this display included a series of numbers representing the riskiness of each portfolio.

We used a variation of the choice process methodology [7] to elicit data on the decision-making process. Subjects were instructed to select a portfolio as soon as they created and added an appropriate portfolio to the "basket". Subjects were further instructed to continue during the round by selecting any portfolio they created that they knew was better than the currently selected portfolio. Subjects' earnings were equal to

[1]Originally 20 subjects participated in treatment V, but data on one subject was lost due to a technical error.

the outcome of the final portfolio selected, plus 20% of the outcome of a portfolio selected at a random time. At the end of the round, a random time was selected from a uniform distribution ranging from 0 seconds to 300 seconds, and the outcome of the portfolio the subject had selected at that random time was multiplied by 0.2 and included in the final earnings output presented to the user. If the subject finished the round prior to the 5 minutes allocated to the round, and the random time selected was greater than the amount of time spent in that round, the final portfolio choice was also the randomly selected portfolio choice. In this way, subjects were incentivised to always make utility-improving decisions, because selecting a portfolio that is not preferred to the currently selected portfolio would result in a sub-optimal outcome. This setup incentivized subjects to make several, rather than one, portfolio choices in each round.

Adding a portfolio to the "basket" is different from selecting a portfolio. While adding the portfolio to the "basket" allows the user to view the portfolio's risk and return characteristics in any or both of the displays, it does not affect earnings. Any portfolio in the "basket" can be selected as the current selection, but adding the portfolio to the "basket" does not automatically select it. In this way, we are able to track all the portfolios currently under consideration by the user, and also track which of those is most preferred at any time during the decision-making round.

After each round, an outcome for the final selected portfolio and the portfolio selected at the random time was generated by the program according to the resulting Gaussian distribution of the portfolio selections and reported to the subject. In order to control for the possibility that the additional information about the outcome of the randomly selected portfolio would inadvertantly influence behavior, we did not provide any information about the randomly selected time or about which portfolio had been selected at that time, and simply added the outcome of the randomly selected portfolio to earnings. At the end of the experiment, random numbers were drawn to determine which round was to be paid. As is common practice in economics experiments, only 2 rounds were paid at random, and because the selected rounds were not announced in advance, subjects were asked to pay attention to the choice they make in every round [18].

The program recorded all user events, including when portfolios were added or removed from the "basket," when portfolios were selected, when portfolios were viewed in the *Risk Variability* display, and the time taken to perform any of these actions. These data allow us to investigate the decision process in detail.

At the end of the experiment subjects were also asked to rate their confidence during the experiment and the likelihood that they would use this screen to make decisions in practice rated on a 7-point Likert scale.

6.3 Training

Before the beginning of the experiment, subjects also received a training on completing one round of the decision process. Subjects participating in B received a training on using the textual version of the tool, while subjects participating in V received the visual version of the tool. The training took approximately 40 minutes, and included descriptions of the program and a tutorial. During the tutorial, subjects inputted a set of portfolios during one round of decision-making. In order to reduce the likelihood of introducing bias, subjects were made aware that the set of portfolios was randomly selected prior to the experiment.

A simple quiz was administered in which subjects were asked to answer several questions about the instructions to guage subjects' basic understanding. Unlike previous work in applied visual analytics for economic decision-making tasks, which has excluded subjects who did not understand graph reading from participating [31, 30], we allowed all subjects, regardless of cognitive ability, to participate. Subjects who did not answer quiz questions correctly were provided the answer and an explanation at the end of the quiz. Thus, we are able to make broader judgements about which users benefit most from the tool. Number of questions correct on the quiz was later correlated with performance in the task, and no statistically significant correlation was observed. This suggests that the explanations during the quiz cleared up confusion about use of the interface.

6.4 Risk Elicitation Task

After the experiment, we also asked a risk preference question commonly used to elicit subjective risk tolerance - this question asked subjects to decide whether they would take a series of hypothetical gambles to increase or decrease their income [1][2]. We used the data gathered from this question to categorize subjects based on risk tolerance and compare the risk tolerance elicited using the subjective task to the level of risk taken on by subjects in their portfolio choices during the experiment.

7 Results

The experimental evaluation of PortfolioCompare supports anticipated findings (1) and (3), but does not support antici-

[2]The risk elicitation task, developed by Barsky et al. [1] consisted of three separate questions. The first question was: "Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50-50 chance it will double your (family) income and a 50-50 chance that it will cut your (family) income by a third. Would you take the new job?" Depending on the answer to this question, subjects were then asked one of two questions; if yes, "Suppose the chances are 50-50 that it would double your (family) income, and 50-50 that it would cut it in half. Would you still take the new job?", and if no, "Suppose the chances were 50-50 that it would double your (family) income and 50-50 that it would cut it by 20 percent. Would you then take the new job?" Subjects who answered that they would not take the new job in any of these cases were classified as more risk averse, while subjects who answered that they would take the new job in any of these circumstances were classified as less risk averse

pated finding (2). That is, we found that PortfolioCompare helped the user to select a portfolio with a more appropriate risk profile for his or her risk tolerance, and that PortfolioCompare reduced cognitive load as measured by the time spent on the task. However, PortfolioCompare did not improve efficiency because efficiency of choices in both treatments was high (above 90%). In addition, we found that men tend to perform better in this task than women, but the gap in performance was reduced with PortfolioCompare.

7.1 Risk Preferences and Risk of Portfolio

We find support for our conjecture that individuals using the visual version of PortfolioCompare would make decisions that are more appropriate for their risk tolerance. We calculated the riskiness of each subject's final selected portfolio in each round by taking into account the standard deviations and correlations of the investments allocated to this portfolio, and correlated the riskiness with the risk aversion measure from the separately administered risk elicitation task. Riskiness of portfolios chosen in each treatment ranged from a standard deviation of 0% (no risk - either selecting no investment or selecting investment D) to 21% (maximum risk - selecting only investment C). Answers to the risk aversion task were coded from 0 to 3, with 0 being risk loving (8% of subjects) and 3 being most risk averse (31% of subjects). 5% of subjects were classified as 1, and 56% were classified as 2. We did not find statistically significant differences in risk aversion across the two treatment groups.

We find that riskiness of the final portfolio choice and risk aversion are negatively and significantly correlated for subjects in the V treatment (Spearman's *rho* = -0.72 with *p*-value = 0.00), suggesting that more risk averse subjects select less risky portfolios. On the other hand, we find no significant correlation between final portfolio choice and risk aversion for subjects in the B treatment (Spearman's *rho* = -0.03 with *p*-value = 0.96). We used the average riskiness of the final portfolio chosen across all of rounds 1 through 9 for this analysis. When analyzing each period choice separately, we have negative correlation for all rounds, and 5 out of 9 of these are significant at the 5% level for the V treatment, but we do not have any statistically significant correlations in the B treatment (all *p*-values above 0.53).

At the end of the experiment, we asked subjects to describe their selection strategy via an open-ended questionnaire, and we classify subjects' strategies into "best return to risk", "minimize risk", "maximize return" or "consider an equal proportion of both risk and return." Some subjects noted having used more than one strategy. Two experimenters separately categorized the strategies. Based on this classification, the proportion of each strategy used is roughly equivalent across treatments, suggesting that the visual tool did not fundamentally change the approach used by subjects to make the decision. The strategy reported most often was to find the "best return to risk" (75% reported using this strategy in B, and 79% reported using this strategy in V).

Table 1: Summary of Final Portfolios Chosen.

Treat.		Mean	St. Dev.	Min.	Max.
B	*Risk*	0.10	0.83	0	0.36
	Return	0.15	0.03	0.06	0.21
	Efficiency	0.94	0.10	0.55	1.00
V	*Risk*	0.09	0.68	0	0.36
	Return	0.15	0.04	0	0.21
	Efficiency	0.92	0.14	0.00	1.00

7.2 Risk, Return and Efficiency of the Selected Portfolio

The theoretical benchmark is calculated using Markowitz' "efficient frontier" model [26]. Note that while the calculation of the efficient frontier is purposely simplified in this experiment using artificial data, the efficient frontier is more difficult to calculate with data in practice. Thus, since it would not be relevant to practical application, we do not incorporate an automatic visualization of the optimal in the experiment. The efficient frontier was created by varying E so that each data point on the frontier corresponds to a vector of investment proportions. Figure 6 shows this theoretical benchmark overlaid with a scatter plot of all expected returns and risk properties of actual portfolio choices of subjects in each treatment for all rounds.

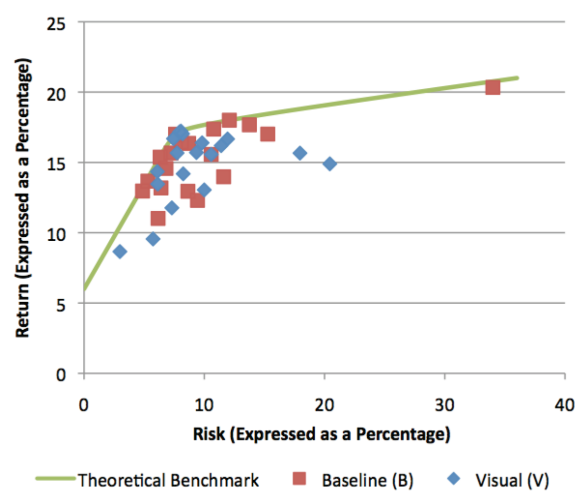

Figure 6: Return and Risk of Actual Portfolios Relative to Markowitz Benchmark

We do not find significant differences in the risk, return or efficiency of the portfolio chosen between the B and V treatments We used the approach in [30] by conducting an unpaired independent sample t-test separately for each round, and do not find any statistically significant differences in portfolio choices between the two groups.[3]

We also developed an efficiency measure of each portfolio choice, which was calculated by finding the fraction of expected return of the chosen portfolio relative to the Markowitz benchmark for any level of risk. We find similar efficiency across treatments: the efficiency in V is 0.92

[3] p-values for risk and return in all of the rounds were above 0.05.

and the efficiency in B is 0.94, averaged across subjects and periods (see Table 1). The difference between efficiency in B and V is not statistically significantly different using a non-parametric Wilcoxon-Mann-Whitney test (p-value = 0.36).

This is in contrast to [30], who also found similar risk profiles of portfolios, but statistically significant differences in returns, suggesting greater efficiency when using a visual analytics tool (FinVis). We believe efficiency is not significantly different across groups for several reasons. First, we have simplified the decision problem so that efficiency is already quite high in the baseline treatment, which does not leave much room for improvement. For example, efficiency is high relative to the efficiency found in [30], who used a similar investment list but complicated the problem by allowing for three investment years in each round[4]. Complicating the problem by increasing the number of decisions made in each round may allow us to see greater differences between the visual version of PortfolioCompare and the textual version of PortfolioCompare. Second, the textual version of PortfolioCompare also included interaction in the form of choosing many different porftolios, as well as a visual slider input screen for adding portfolios, which could have been beneficial for decision-making and could have contributed to the high efficiency in both treatments. Reducing the visual input screen to a simple user input or reducing interaction capability in the B treatment may highlight the value of the visual version of PortfolioCompare, and this could be considered in future work. Finally, we consider the presence of learning across rounds. We do find that efficiency is higher in later rounds. To investigate this result, we conducted a random-effects panel regression analysis, regressing the inverse of round and treatment dummy variable on efficiency. We find that subjects learn across rounds, and this result is statistically significant (Coefficient = -0.05; p-value ¡ 0.01).

7.3 Cognitive Load and Decision Process

Cognitive load is a construct in psychology representing the burden that performing a task imposes on the decision-maker's cognitive system (paas::1994). Relevant measures for cognitive load are performance and time spent. While performance (efficiency) is the same across treatments, we do find a difference in time spent. Time taken to explore between the first portfolio selected and the final portfolio selected in each round decreases from an average of 141 (129) seconds in the first five rounds of B (V) to 79 (79) in the last four rounds of B (V). This suggests that creating new portfolios and comparing them was valuable to the user, but that over rounds as exploration continued, the value decreased. This also suggests that cognitive load was decreased with PortfolioCompare.

The decision-maker proceeds through each round by making a series of consecutive portfolio selections. Table 2 displays summary statistics for the number of selections made by subjects in each round. Earnings depended on the selected portfolio at all times during the decision process; therefore, any change in beliefs about the optimal portfolio should be followed by a change in the currently selected portfolio. We find that selections were updated more often in V: subjects made 6 intermediate selections on average in V, and only 4 intermediate selections in B. Adding portfolios to the "basket" resulted in a richer comparison of portfolios in the *Risk/Return* display but did not directly affect earnings. Adding portfolios to the *Return Variability* display also resulted in richer comparisons but did not directly affect earnings.

Table 2: Summary of Selections, Basket Additions, and Distribution Additions.

Treat.		Mean	St. Dev.	Min.	Max.
(B)	*Selection*	3.82	4.14	1	24
	Basket	7.08	5.57	1	17
	Variability	2.38	3.05	0	17
(V)	*Selection*	5.84	7.37	1	43
	Basket	6.91	4.45	1	21
	Variability	1.46	1.99	0	8

Because intermediate portfolio selections were incentivized, selections over time should track the subjects' beliefs about the best portfolio at any time. Therefore, we track the efficiency of currently selected portfolios during the decision-making process to investigate whether performance improves during information search. We found that the final portfolio selected after some exploration of the data is statistically significantly more efficient relative to the initial portfolio chosen. The change in efficiency from the initial selection to the final selection is greater in the V treatment (3.99%) than in the B treatment (2.99%). Also, the difference in efficiency in early rounds is greater than the difference in efficiency in later rounds. In the first five rounds, the difference in efficiency is 4.83% in the B treatment and 6.78% in the V treatment, while in the last four rounds the difference in efficiency is only 0.67% in the B treatment and 0.51% in the V treatment.

We also measured the value of the two separate visual analytics displays featured in PortfolioCompare by finding the degree of association between the amount of times each display was utilized and the final efficiency. We investigated the effect of the *Risk/Return* display by analyzing whether a greater number of investments in the "basket" increase efficiency of the final portfolio task. We also quantified the value of the additional *Risk Variability* display by documenting whether increased use of this display leads to greater efficiency of final portfolio choices. We conducted separate tobit censored regressions (left censored at 0 and right censored at 100% with subject dummies) for each treatment with efficiency of the final choice as the dependent variable with independent variables of the number of times investments were added to the "basket", the number of times investments were added to the *Risk Variability* display, the number of times selections were made, the time spent on

[4][30] found an efficiency of 69% in the baseline treatment and 80% in the visual FinVis treatment.

Table 3: B - Treatment Effect Regression.

	Coeff.	Standard Error	p-value
Add to Basket	0.43	0.05	<0.01
Add Distribution	-0.80	0.08	<0.01
Select	0.07	0.06	0.28
Time	-0.01	0.00	<0.01
Round Trend	0.08	0.06	0.17

Table 4: V - Treatment Effect Regression.

	Coeff.	Standard Error	p-value
Add to Basket	0.73	0.64	0.26
Add Distribution	-1.96	0.64	<0.01
Select	-0.17	0.29	0.56
Time	-0.01	0.02	0.71
Round Trend	-0.12	0.61	0.84

the task, and the round trend variable, and the results are reported in Tables 3 and 4.

We find that adding portfolios to the "basket" and viewing them in the *Risk/Return* display increased efficiency of the final portfolio selected, and this was statistically significant for the B treatment. However, adding portfolios to the *Return Variability* display decreased efficiency of the final portfolio selected, and this was statistically significant for both treatments. This may be explained by the fact that individuals who understood the *Risk/Return* display did not require the additional display, while those individuals who had difficulty with the first display also attempted to use the second display but did not perform as well as the former subjects. Spending more time deliberating is negatively correlated with efficiency in the B treatment, but this coefficient is not statistically significant in the V treatment. This may suggest that while some time was needed, individuals spending more time were also those who were confused.

We also consider whether individuals who were more likely to utilize the *Risk/Return* display were also more likely to utilize the *Return Variability* display. We added the total number of times that an individual added a portfolio to his or her "basket" and the total number of times that an individual added a portfolio to the *Return Variability* display over all 9 rounds. We find that the use of each display is positively correlated, and this is statistically significant for the B treatment but not for the V treatment (Spearman's *rho* = 0.24 with p-value 0.01 in the B treatment, and Spearman's *rho* = 0.27 with p-value 0.27 for the V treatment). This suggests that some individuals are more likely to explore the data than others, but this link is more tenuous for the V treatment.

7.4 Subject Characteristics

While laboratory experiments on decision-making with student subjects are usually considered generalizable to other populations, we believe that this group would particularly benefit from a decision support system such as PortfolioCompare. Students who participated in the experiment will be entering the job market in the next few years and will be making decisions about investing in company-sponsored plans for the first time. This is a group who may not be trained in financial decision-making, and would most benefit from the simplification of using a tool like PortfolioCompare.

We elicited information from subjects about age, gender, and major. 67% of participants were male and 33% were female. Self-reported academic majors included arts (13% of participants), business/economics (25%), engineering (26%), information technology (13%), medicine, nursing and health sciences (3%), or other science (20%). The average age of participants was 23, and all participants were between age 20 and 33. 15% of subjects were graduate students, and the rest were undergraduate students. Subjects were randomly assigned to treatments, and both treatments contained a representative sample of these participants. Women and men were not statistically significantly different based on age, major, or any of the other characteristics we elicited.

We find that the visual version of PortfolioCompare reduces the gap in performance between men and women. In the B treatment, a statistically significant gap exists between the efficiency of the final portfolio selected by men and the final portfolio selected by women (the efficiency of the portfolio selected by women is 89% on average, while the efficiency of the portfolio selected by men is 98% on average.) On the other hand, men and women perform equally well in the V treatment (the efficiency of the portfolio selected by men in the V treatment is 94%, which is not statistically significantly different from efficiency of the portfolio selected by men in the B treatment, and the efficiency of the portfolio selected by women in the V treatment is 91%)[5].

We conducted a non-parametric t-test and find that the difference in efficiency between women is statistically significant in the B treatment (p-value=0.02) but not in the V treatment (p-value=0.86). This provides some preliminary evidence that women would be most impacted by use of this tool. Figure 7 displays the efficiency in performance of men as compared to women in both treatments. Note that the performance is volatile because we have a limited subject pool.

We did not find statistically significant differences in the impact of PortfolioCompare for any of the other elicited characteristics, and women did not have any confounding characteristics which we elicited that would impact the difference in performance. Familiarity with the financial markets did not have an effect on performance for either men or women, suggesting that benefits of decision support tools may be gleaned even without high levels of financial literacy.

8 Conclusions and Future Work

We developed a visual analytics decision support tool that allows the consumer to make improved personal finance decisions. An experiment was conducted and we found that subjects using the visual verson of PortfolioCompare were able

[5]For this analysis, we use only rounds 2-9 because we consider that participants are still learning in round 1.

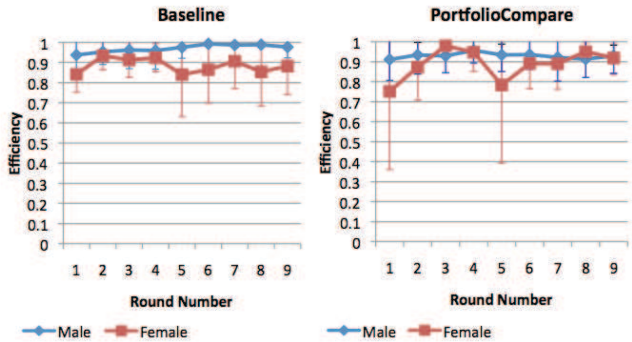

Figure 7: Performance of Women and Men over Rounds

to choose portfolios that were more in line with their risk preferences as compared to subjects using the textual version of PortfolioCompare. The exploratory nature of PortfolioCompare was useful for subjects, as subjects continued to improve their selections during the decision-making process within each round. Finally, we introduce the possibility that PortfolioCompare can reduce the gap in performance between women and men for selecting an investment portfolio.

Our ultimate objective is to extend PortfolioCompare for use in practical applications, which can be achieved through a few additions to the system. Extensions of this work include triangulating the interaction logs with additional analysis such as paired-analytics sessions and "think aloud" protocol analysis. A limitation of our results about the gap between men and women is that not enough students participated in the study to make robust conclusions. Future work includes increasing the number of subjects participating in each treatment in order to generate robust conclusions about the difference in impact on men versus women.

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