FinVis: Applied Visual Analytics for Personal Financial Planning

Stephen Rudolph* Anya Savikhin† David S. Ebert *

*Purdue University Regional Visualization and Analytics Center (PURVAC)
†Purdue University Department of Economics

Abstract

FinVis is a visual analytics tool that allows the non-expert casual user to interpret the return, risk and correlation aspects of financial data and make personal finance decisions. This interactive exploratory tool helps the casual decision-maker quickly choose between various financial portfolio options and view possible outcomes. FinVis allows for exploration of inter-temporal data to analyze outcomes of short-term or long-term investment decisions. FinVis helps the user overcome cognitive limitations and understand the impact of correlation between financial instruments in order to reap the benefits of portfolio diversification. Because this software is accessible by non-expert users, decision-makers from the general population can benefit greatly from using FinVis in practical applications. We quantify the value of FinVis using experimental economics methods and find that subjects using the FinVis software make better financial portfolio decisions as compared to subjects using a tabular version with the same information. We also find that FinVis engages the user, which results in greater exploration of the dataset and increased learning as compared to a tabular display. Further, participants using FinVis reported increased confidence in financial decision-making and noted that they were likely to use this tool in practical application.

Keywords: Casual Information Visualization, visual analytics, personal finance, visualization of risk, economic decision-making.

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

1 Introduction

Financial planning is a challenging process in which the decision-maker must consider abstract and dynamic concepts such as risk and correlation of financial instruments. 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 [3, 14, 22, 23, 38]. Critical problems faced by individuals are finding the right investment and optimally allocating investments. Optimal asset allocation is often the most important decision for a portfolio's performance [3].

American workers are increasingly responsible for their own retirement; therefore, it is important to have a successful financial plan and to select a suitable portfolio of investments. However, a recent study found that less than 25% of individuals over the age of 50 succeeded at saving for retirement, often because they were unaware of fundamental economic concepts such as interest rate or inflation [24]. Here success at saving is defined as simply developing and following through with a financial plan. Researchers have called for the development of decision support systems to aid individuals in understanding financial planning [3]. Systems with textual feedback and graphs can improve decision making in simple tasks [3]. However, visual analytics tools are needed for complex decision-making involving long-term investment planning. Further, these tools must be accessible to the casual user. For this purpose we have developed FinVis, a visual analytics tool that allows the casual untrained user to easily assess and explore information about potential life-long impacts of many financial decisions simultaneously and interactively.

Our key contribution is a visual analytics tool, FinVis, that helps the individual improve decision-making by visualizing aggregate risk alongside a traditional wealth-time plot in a casual context for personal finance data. Since this software is accessible to non-expert users, general users can benefit greatly from using FinVis in practical applications. FinVis allows the user to evaluate potential long-term outcomes of multiple decisions.

The improved decision making that resulted from using FinVis in an laboratory setting suggests that the use of these techniques in practice could improve the ability of the general public to allocate finances in an appropriate manner. The economic experiment presented allows us to compare decisions made in a financial planning task for a group using FinVis versus a group using a tool with textual representations of the same data. Laboratory experiments such as this one are ideal for explaining decision-making and quantifying the value of visual analytics techniques [29]. We find that FinVis improves decision-making, learning, and exploration of the dataset, and increases users' confidence.

2 Related work in Visualization

FinVis builds on work from several key research areas, including visual analytics [29], financial visualization [4, 27, 33, 39], casual information visualization [28], temporal visualization [16], and visualization of risk [7, 30, 39]. While use of computer-assisted visualization techniques to show financial data goes back many years, these tools were designed for expert users.

FinVis can be described as a casual information visualization tool as it provides a simple and powerful visualization for the non-expert user. Here the casual, non-expert user is any individual who is not a professional in the field of finance. The goal of casual information visualization is to spread the benefits of visualization to the general public [11, 28, 34, 37]. One of the biggest challenges in making this transition is making the interface and visual metaphors simple and intuitive enough that the average user would require little training.

Visual analytics has previously been applied to economic decision-making problems, resulting in decisions that were closer to optimal [29]. Similar to this work, FinVis uses visual analytics techniques to visualize risk and uncertainty, and gives users the ability to explore information related to probable outcomes.

Some initial work in financial visualization centered on the choice between 2D [19] and 3D [25] representations of the data. While the 3D format allows for more data dimensions to be shown, it adds complexity and can make comparisons between data points difficult, especially for a casual user. The 2D examples also allow for three dimensions of data, but with one axis over-plotted with two dimensions' worth of data. This method works well when one dimension is relatively small. Because the risk dimension can be plotted in terms of wealth and is of much smaller magnitude than net wealth, FinVis opts for the 2D approach.

*e-mail: {srudolph|anya|ebertd}@purdue.edu

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More recently, FINESSE [33], LifeLines [27], Performance Matrix visualization [39], an adaptation of the Bead system [4], and others [35] have refined both 2D and 3D techniques to ease some of the drawbacks originally present. These specific solutions are ideal for expert users. They use more complicated or denser representations of the data that would not be immediately understood by the general public.

2.1 Temporal Visualization

Of the many methods available for temporal visualization [1], only a few are appropriate for a casual user. Furthermore, personal financial data as a whole is not generally cyclic, which eliminates some of the remaining options [6, 36]. In most situations, wealth is accumulated over a certain time span and then depleted during retirement and FinVis makes no attempt to predict market cycles. Finally, we desire to show the individual contribution of each individual investment over time along with the aggregation of all investments, which brings us to ThemeRiver™[16] as the most applicable temporal example.

ThemeRiver™presents subject magnitude over time. FinVis parallels this; instead of visualizing theme magnitude, FinVis shows risk magnitude for financial decisions. Instead of branching from an axis, however, FinVis will follow the expected wealth curve. In this manner, a user may instantly see the impact of any decision. Another key distinction is that ThemeRiver™does not include a visualization of uncertainty, which is necessary for FinVis to emphasize the probable outcomes.

2.2 Visualization of Risk

Visualization of financial risk can take many forms. FundExplorer [7] and G-Sphere [15], for example, visualize the diversification of mutual funds and other assests. Generally, more diversified investments carry less risk because they are less dependent on any one sector of the economy. In this sense, these programs visualizes risk indirectly. They are useful personal finance tools for choosing carefully among very specific options in the present, but the scope of FinVis is much broader. FinVis is an exploratory tool that allows for short and long-term personal finance decision-making.

For direct visualizations of risk, bar charts and confidence intervals have been used to show investment standard deviations or other measures of risk and can be constructed using spreadsheet programs like Microsoft Excel [9, 12]. These techniques would be recognizable to most users, but, by themselves, fail to work for our purposes. Both methods are used to primarily show relative risk between different options. In FinVis, the user must be able to see the aggregate risk at any time, which is not possible with these paradigms.

To solve these issues, FinVis represents probability with partial transparency. The more likely a given outcome is, the more opaque it is. This will help focus the user on the most relevant outcomes. This technique has already been proposed to visualize expected financial wealth and risk simultaneously [30, 39]. As used previously, it can show the performance of one investment well, but does not scale in a useful manner. Combining these visual metaphors with those from ThemeRiver™by overlaying investments with magnitudes derived from their contribution to the aggregate risk on top of the risk gradient provides a useful visualization basis for FinVis as seen in Figure 1.

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 [10, 14] and in laboratory experiments [5, 23]. Computerized decision support systems are needed to improve decision-making in this task [3].

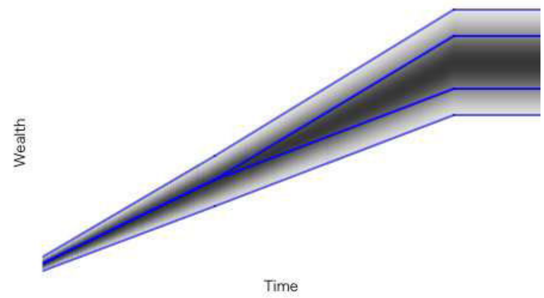


Figure 1: Aggregated risk gradient with investment risk contribution boundaries for two sample investments in blue.

3.1 Decision-Making under Uncertainty

The complexity of information encountered while making financial decisions may overwhelm the decision-maker, who does not have unlimited cognitive abilities and is therefore "boundedly rational" [13, 31]. "Bounded rationality," or the inability to make optimal decisions, is prevalent in many decision-making problems, including financial planning problems. Judgment and decision-making literature indicates that when available information is too complex and uncertain, individuals use heuristics or "rules of thumb" to make decisions [21, 38]. This kind of decision-making simplifies the cognitive process, but results in sub-optimal choices that are not in line with portfolio selection theory. Visual analytics reduces the complex cognitive work that is needed to perform decision-making tasks [32]. Savikhin et al. [29] recently found that individuals were able to make economic decisions that were significantly closer to the optimal while using an interactive visual analytics tool as compared to having this information in textual form. The implementation of FinVis in financial decision-making is a natural extension to this area of research. Economics experiments can be used to quantify the improvement in decision-making attributed to visualization. The use of laboratory experiments to understand decision-making is widespread in economics, and these have recently been implemented to quantify the value of visual analytics techniques for decision-making [29].

3.2 Overcoming Cognitive Limitations

FinVis is a visual analytics tool that can help individuals overcome cognitive limitations and reduce the need for heuristics, improving decision-making. For example, when choosing between n financial instruments, individuals tend to follow the "framing and diversification" heuristic and allocate $1/n$ proportion of their wealth to each instrument, which is not always optimal [3, 14, 17]. FinVis reduces cognitive costs and reduces the need for this heuristic. Further, due to "ambiguity aversion," investors tend to choose an inappropriate default portfolio without considering options [3]. Choosing one's own portfolio helps the individual to identify with the portfolio and stick to an investment plan [10]. FinVis is an exploratory tool that mitigates these problems by allowing investors to quickly assess outcomes of possible portfolio options and choose an appropriate allocation. This allows individuals to move away from the default portfolio and successfully identify with their choice. Finally, some individuals tend to be overconfident compared to their abilities and after selecting a portfolio would prefer their own portfolio to that of an expert [10]. These "egocentric biases" can lead to serious misinvestments and financial crashes [10]. FinVis improves the choices of investors by helping them to diversify, thus reducing negative financial impact of untrained and overconfident investors. Other investors are not confident enough and fail to develop any plan [24]. Graphical representations increase confidence and accuracy [8], so that through use of FinVis, overconfident individuals may improve abilities and uncertain individuals may become more confident. Using FinVis helps individuals increase financial knowledge, which is directly correlated with success in investment planning [24].

4 Financial Model Implementation

We use the standard portfolio theory approach to calculate expected returns, standard deviations, and correlations [20]. The model uses historic investment return and standard deviation data values as input, as these are the best available predictors of future investments [20]. Standard deviation is used in this paper as a measure of risk, as is common in the financial field [26].

4.1 Liquid and Invested Assets

Net wealth can be broken up entirely into liquid assets and invested assets. FinVis tracks liquid wealth. When an investment is made, the principal used to make that investment is no longer available for further investment during that period.

When there is no risk associated with an investment, the principal is deducted from the liquid assets for the duration of the investment and subsequently, the principal and earnings are added back in to the available liquid assets. When risk is a factor, the earnings are no longer a single possible value. We could choose to be as optimistic or pessimistic about the return, but the most probable value will always be the interest without accounting for risk, which is what FinVis uses.

4.2 Interest

We use compound interest when calculating expected returns, using the following formula:

$$I = P(1+R)^T \tag{1}$$

In Equation 1 and subsequently in this paper, I is the interest or return on investment, P is the principal amount invested, R is the expected annual return rate, and T is the time elapsed in years since the initial investment was made. In the FinVis program, R is labeled as “APR” and displayed as a percentage and T is labeled as “Length.”

4.3 Risk

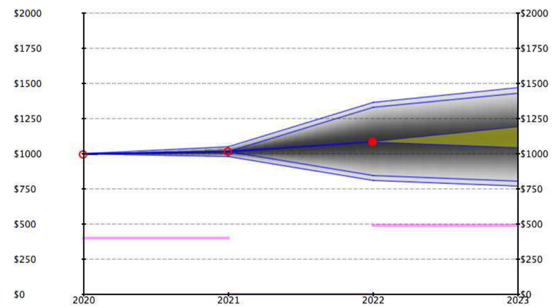
FinVis displays both individual risk and aggregate risk of investment allocation decisions. FinVis aims to help users improve diversification of portfolios; therefore, the risk discussed here is unsystematic risk, and does not include systematic risk (i.e., recessions, wars, and so forth) that cannot be diversified away. Risk is shown as two standard deviations above and below the expected return of the investment, and returns are normally distributed. FinVis displays both individual risk (from each investment choice) and the aggregate risk (from the entire portfolio), which results in approximately a 95% confidence interval and gives the user a very good idea of the most probable earnings. To account for risk, we modify Equation 1 by either adding or subtracting two standard deviations (2σ) to the return. The resulting formula is:

$$I = P(1+R \pm 2\sigma)^T \tag{2}$$

The aggregate risk of n investments also depends on their correlations. For example, when investments are perfectly correlated, no reduction in risk results from diversification. When those investments are perfectly negatively correlated, one is the complement of the other, and all risk can be eliminated. In order to show the

	Principal	Year ▼	Type	Length	σ	APR
1	$600	2020	A	1	3	3
2	$1018	2021	C	1	12	7
3	$600	2022	B	1	6	5

(a) Table of Investments, σ Indicates the Standard Deviation of the APR (R, displayed as a percentage).



(b) Visualization of investments listed above.

Figure 2: Corresponding displays of three investments in three different years.

value of investment diversification, we must account for the change in risk due to correlations.

The aggregate risk is defined as:

$$\sigma_{aggregate} = \sqrt{\sum_{i=0}^{n} \sum_{j=0}^{n} w_i w_j \sigma_i \sigma_j c_{i,j}} \tag{3}$$

Where w_i represents the ratio of the i^{th} investment’s principal to the sum of all principals and $c_{i,j}$ is the correlation between the i^{th} and j^{th} investments as a value between -1 (perfectly negatively correlated) and 1 (perfectly correlated).

5 Visual & Interactive Implementation

5.1 Investment Display & Modification

Each investment is simultaneously shown in two ways: in the table of all investments (Figure 2(a)) and in the plot window (Figure 2(b)). In the table, the details of each investment are enumerated and each field is sortable. This display allows the user to quickly see which investments have the lowest risk or highest principal, for example. A corresponding visualization marks each investment as either a ring when unselected or disc when selected. Each marker is placed at the start year of each investment and at the expected net wealth value for that year.

Once an investment has been selected from the investments table, its properties are shown in the modification panel. Figure 3 shows the panel for the investments in Figure 2 where the selected investment is of Type B. The investment option, principal, and start year are all editable and may be altered as many times as the user wishes. For the user study, where all investment options are pre-defined, the remaining properties are derived from those three. Changes to investment properties immediately update the visualization to allow for quick exploration.

There are two buttons available between the investment list and modification panel, labeled as “+” and “-”. The former allows the user to add a new investment, which is immediately selected. The latter removes the currently selected investment and selects the next one, if there are any left.

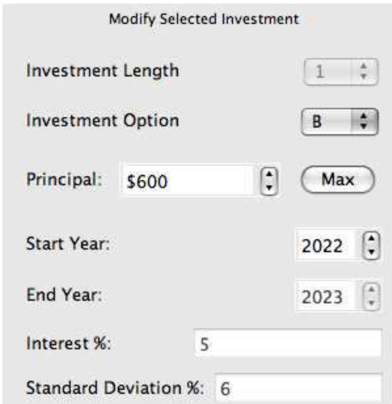


Figure 3: Modification Panel

5.2 Visualizing Risk

Risk is shown in two distinct ways. First, the aggregate risk (within two standard deviations) is displayed as a Gaussian gradient where darker parts of the gradient represent more probable outcomes. Since exactly two standard deviations from the mean are always displayed, the range of intensity values can be precomputed and converted to a linear scale.

The risk is also displayed on a per-investment basis so that the user can ascertain each investment's contribution to the aggregate risk. Thus, the aggregate risk is divided by linear blue borders as seen in Figure 2(b). Subsequent investments have their risk contribution displayed closer to the center. The most recent contribution is in the middle and the least recent has its optimistic range at the top and its pessimistic on the bottom. Here, optimistic refers to the positive two standard deviations' worth of risk, and pessimistic, the negative.

We provide a formula that satisfies the two necessary conditions for defining the aggregate risk: the sum of all individual risk must equal the aggregate risk and the proportions must account for the principal. Larger investments must take up a correspondingly greater share of the aggregate risk. The formula we derived to satisfy both of these conditions is shown in Equation 4.

$$\hat{\sigma}_i = \frac{\sqrt{(\sigma_i / \sum_{j=1}^{n} \sigma_j) w_i}}{\sigma_{aggregate}} \tag{4}$$

where σ_i is the unadjusted standard deviation of the investment we are calculating the individual risk for and $\hat{\sigma}_i$ is the effective standard deviation accounting for covariance between investments made in the same year.

5.3 Showing Context

To show the amount remaining to invest, the liquid assets, a partially transparent purple line is plotted on top of the chart[1], as seen in Figure 2(b) for the investment choices listed in Figure 2(a).

In addition to the selected investment being highlighted in the table of investments (Figures 2(a), 4(a)), it is also shown as a yellow highlight over the selected investment's risk contribution (Figures 2(b), 4(c)), which is the area between its upper and lower boundaries. The user focuses on the highlighted section to easily see changes as they modify the selected investment.

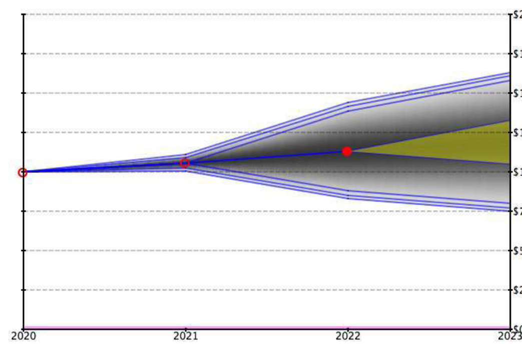
[1]The liquid assets were originally displayed slightly differently to eliminate zero order discontinuities; however, to avoid ambiguities, the presented version of FinVis uses a discontinuous function.

	Principal	Year ▼	Type	Length	σ	APR
1	$500	2020	B	1	6	5
2	$500	2020	C	1	12	7
3	$1060	2021	C	1	12	7
4	$1134	2022	B	1	6	5

(a) Investment Table

	Year ▼	Expected Net Wealth	-2σ	+2σ	Funds Available
1	2020	$1000	$1000	$1000	$0
2	2021	$1060	$1021	$1099	$0
3	2022	$1134	$841	$1427	$0
4	2023	$1190	$761	$1619	$1190

(b) Baseline Version



(c) Full FinVis Version

Figure 4: Both treatments showing the investments listed above.

5.4 Baseline Version

A baseline tabular version of the program was made to be used in our laboratory experiment. The baseline version presents the same key information, including aggregate risk, expected wealth, and liquid assets in sortable columns with one row per decision year (Figure 4(b)). The only difference between the baseline program and FinVis is that the latter also includes visual information of context, risk gradient, and risk boundaries for each individual investment, which are derived from the key information. This additional information would be impractical to present in tabular form and thus must be presented visually. Both versions have identical controls, capabilities, and investment list displays. A comparison between versions is shown in Figure 4.

6 Experimental Design

6.1 Anticipated Findings

We conjecture that FinVis can help decision-makers in a number of ways, and we directly tested each of our predictions using a laboratory experiment. Our laboratory experiment consisted of a treatment with subjects making decisions using the FinVis visual analytics application, and a separate baseline treatment with subjects making decisions using an application with the same information in tabular form. Our expected findings were:

1. FinVis is a useful visual analytics application that can improve decision-making by helping subjects choose optimal allocations that maximize return and minimize risk.

2. FinVis engages subjects and subjects using FinVis will choose to explore the dataset more than their counterparts using the baseline application. This should lead to greater learning over time in the FinVis treatment as compared to the baseline.

3. FinVis will increase the confidence of participants in decision-making in the experiment and also in practical application. Increased confidence is positively correlated with the ability to follow through with a financial plan [24].

6.2 Experimental Setup

Inexperienced undergraduate students from Purdue University volunteered to participate in the study; 27 subjects in total volunteered [2]. Experiments were conducted at the Vernon Smith Experimental Economics Lab using standard laboratory protocols. Subjects earned between \$9 and \$18 in the experiment, where their earnings depended on their choice of investment portfolio. Subjects whose portfolio choices resulted in higher experiment earnings earned a greater amount in the experiment as compared to subjects whose portfolio choices resulted in lower experiment earnings; thus, there was a high incentive to make good decisions that maximized return and minimized risk.

We used a between subjects design, with 13 subjects participating in the treatment using FinVis (FV) and 13 different subjects participating in the baseline treatment (B) using a tabular display with the same information. The information and training was the same in both treatments. Self-reported academic majors included business, engineering, information technology, science, and health sciences. It is possible that business majors would be likely to perform better in this experiment and that this could account for the improved performance in FV; however, over half of participants in B were business majors, while less than one third of participants in FV were business majors. About 60% of participants were male and 40% were female, with the same proportion in each treatment. The average age of participants was 21, and most participants were between age 18 and 23, with the same approximate ages in both treatments. None of the demographic characteristics had a statistically significant effect on subjects' decisions.

While FinVis is capable of allowing an arbitrary number of investments, we provided subjects with four generic investments, A, B, C, and D with returns and standard deviations of 3%, 5%, 7%, 2% and 3%, 6%, 12%, 0%, respectively to align with previous work [23]. 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:

$$\rho_{i,j} = \frac{\sigma_{i,j}}{\sigma_i \sigma_j} \tag{5}$$

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:

$$\sigma_{i,j} = \sum_{k=1}^{m} \left[R_{i,k} - E(R_i)\right] \left[R_{j,k} - E(R_j)\right] \tag{6}$$

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.

[2] 1/27 subjects did not successfully complete the pre-experiment task and did not participate in the full experiment

Each subject had 3 years (2020, 2021, and 2022) in which to make allocation decisions. We chose years far in the future in an attempt to keep the current financial situation from influencing the controlled laboratory experiment. Three decision years were used because this gives subjects the opportunity to plan for the future. While we could have allowed decisions further into the future in order to make the experiment more akin to a retirement planning task, we feel that this would have complicated the experiment without providing further information about decision-making. In order to allow for learning, the decision task was repeated for 6 periods; thus, subjects made decisions in 3 decision years and this was repeated for 6 different periods. After each period, an outcome was randomly selected according to the resulting Gaussian distribution at the end of the final decision year and reported to the subject. At the end of the experiment, random numbers were drawn to determine which period was to be paid. Only 2 periods were paid, which is a common practice in economic experiments [18]. Subjects received a \$1,000 experimental dollar endowment at the start of each period, and were paid for the profit earned after returning the initial endowment to the experimenter. Experimental dollars were converted to U.S. dollars at the rate of \$100 experimental dollars to \$1 U.S. dollar.

Subjects could make any number of decisions for each year when choosing to allocate the \$1,000 experimental dollar endowment. For example, subjects could either make one decision in each year and allocate the full endowment to one of the four investments, or subjects could make multiple decisions in each year, allocating fractions of the endowment to any or all of the investment choices. Subjects were told that they could add, remove, or modify investment decisions as many times as they desired, and subjects moved through the experiment at their own pace. The program recorded both the final choices made, the time taken for each period, and the number of times investments were added, removed, or edited. These latter measurements help us understand to what extent exploration of the dataset occurred.

6.3 Training, Risk and Confidence Elicitation

Before the beginning of the experiment, subjects also received a short training on reading the information screen presented by FinVis. Subjects participating in the baseline treatment received a short training on reading the tabular information screen. The training took approximately 30 minutes for both treatments, and included descriptions of the components of the program and a tutorial.

A simple quiz was administered in which subjects were given a static information screen similar to the one presented in each treatment and asked to answer 3 questions about the screen to gauge subjects' basic understanding. This quiz was not difficult and did not require exploration of data. Subjects who did not answer all questions correctly were asked to leave and did not participate in the experiment. This minimal requirement ensured that only subjects who paid attention to instructions and knew how to read a table or a graph participated in the experiment. Fourteen subjects participated in the FinVis treatment, and 13/14 completed the quiz successfully. Thirteen subjects participated in the baseline treatment, and 13/13 completed the quiz successfully.

Prior to the experiment, we elicited subjects' objective risk preferences using a simple lottery task commonly used in economics experiments [18]. Fifteen lottery choices were presented and subjects were asked their preference for the safe option versus the gamble. In this task, subjects often choose the safe option in lotteries with a greater chance of loss and choose the gamble in lotteries with a lower chance of loss. Subjects who choose the safe option more often are considered risk averse, while subjects who choose the gamble more often are considered risk loving. At the end of the experiment, one of the lotteries was selected for payment - subjects earned between \$0 and \$3 in this task. We also asked a risk

Table 1: Means and Standard Deviations of Allocation Decisions.

Treatment		A	B	C	D
Baseline (B)	*mean*	0.17	0.22	0.48	0.11
	st dev	0.23	0.30	0.40	0.17
FinVis (FV)	*mean*	0.05	0.23	0.62	0.06
	st dev	0.13	0.24	0.33	0.15

preference question commonly used in behavioral finance to elicit subjective risk tolerance - this question asked subjects to decide whether they would take a gamble to increase or decrease their income [2]. It is useful to compare risk preferences to decisions in the experiment in order to control for risk preferences when analyzing decisions.

At the end of every period before the outcome was known, we also asked subjects how confident they were that their decision was the best one. This is commonly elicited in the finance literature [8] and is important for quantifying the possible increase in confidence from using FinVis. This also helps us to gauge how confidence may change over time in either treatment. Finally, at the end of the experiment subjects were also asked to rate the usefulness of the information screen and the likelihood that they would use this screen to make decisions in practice. Subjects were also asked to report on their confidence in their overall decisions and in their decision-making abilities in financial planning. Confidence and usefulness were rated on an 8-point scale, while likelihood for future use and decision-making abilities were rated on a 3-point scale.

7 Results

Experiment results confirmed our conjecture that FinVis improves decision-making. Allocations in the FinVis treatment (FV) resulted in statistically significantly greater expected returns for the same level of risk as compared to allocations in the baseline treatment (B). The FV group explored the dataset at almost double the rate of the B group, and significant learning occurred in the FV group but not in the B group. Post-experiment questionnaires showed that subjects in the FV group were more confident making decisions. Also, all subjects in the FV group reported that they were likely to use FinVis in practical application, as compared to slightly over half of the B group.

Subjects did not differ statistically significantly in their risk preferences, and this was confirmed using an unpaired independent sample t-test for both the objective and subjective risk elicitation tasks. This suggests that the two treatments are comparable in this regard. Table 1 summarizes the means and standard deviations of all subjects' allocation decisions in all periods for funds A, B, C and D in each treatment. We used the proportion of total money invested averaged across all 3 decision years for this calculation.

7.1 Finding One: Improved Decision-Making

The optimal decision is one which maximizes the expected return at any level of risk, and this "efficient frontier" was calculated using the theoretical approach developed by Markowitz [26]. We solved the following constrained minimization problem:

$$\begin{aligned} &\textit{Minimize} && P'\Omega P \qquad (7)\\ &\textit{Subject to the Constraints:} && P'\Omega P = E\\ & && P'1 = 1\\ & && P \geq 0 \end{aligned}$$

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. The efficient frontier is created by varying E so that each data point on the frontier corresponds to a vector of investment proportions. Figure 5 shows this

Table 2: t-tests of Expected Return and Standard Deviation

Period	Return p-value, H_a *return FV > return B*	Risk p-value, H_0 *risk FV = risk B*
1	0.44	0.68
2	0.23	0.53
3	0.14	0.37
4	0.05	0.38
5	0.03	0.61
6	0.02	0.67

theoretical benchmark overlaid with a scatter plot of all expected returns and risk properties of actual portfolio choices of subjects in each treatment for periods 3 through 6[3]. We derived the return and risk properties of the portfolio allocation choices for each period by calculating the expected return and standard deviation of the chosen portfolio in each year and then taking the average across three years. Subjects in FV outperformed subjects in B in making decisions that were closer to the efficient frontier. We analyzed the expected return and risk of portfolio choices in FV versus B using an unpaired independent sample t-test, and the results are summarized in Table 2. For each t-test, we report p-values for (H_a: expected return of FV > expected return of B) and (H_0: risk of FV = risk of B). Accounting for learning in the first few periods, subjects in the FV treatment chose portfolio allocations with statistically significantly greater returns as compared to subjects in the B treatment. Risk of chosen allocations was not statistically significantly different between treatments.

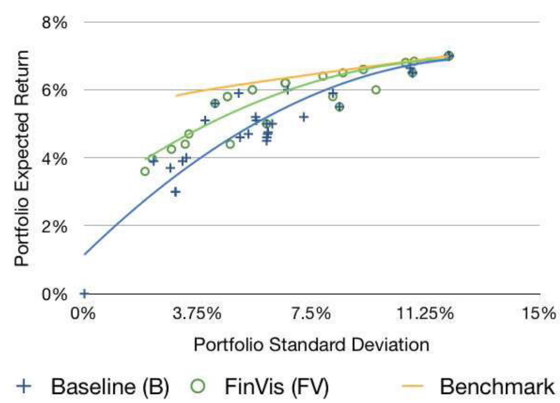


Figure 5: Theoretical vs. Actual Return & Risk

We found that subjects were less likely to resort to using the *1/n* heuristic when using FinVis. Subjects did not use this heuristic often in either treatment, perhaps because the baseline tool also mitigated the need for this heuristic. We calculated the number of decisions in which subjects appeared to be using this heuristic by counting the number of times that allocation choices for all of A, B, C and D were 'close' to $\frac{1}{4}$ using the open interval from 20% to 30% of the total invested. Across all periods and treatments, this occurred only 2 times in B and 1 time in FV. We extended our measure to include the open interval from 14% to 36% and found that such decisions occurred 10 times in B and only 4 times in FV.

7.2 Finding Two: Greater Exploration and Learning through Visual Analytics

We were also able to test the exploratory nature of FinVis by comparing the amount of time and exploration spent in each treatment.

[3] Subjects are still learning in periods 1-3, so these are not plotted.

Table 3: p-values for H_a: exploration FV > exploration B.

Period	*# modifications FV > # modifications B*	*# added FV > # added B*	*# removed FV > # removed B*
1	0.02	0.40	0.28
2	0.01	0.03	0.02
3	0.00	0.03	0.02
4	0.01	0.11	0.08
5	0.05	0.17	0.14
6	0.40	0.72	0.76

We recorded the number of times an investment was added, removed, or modified during each period. Modification of an investment included actions such as changing the type, principal, or start year of the investment. Investments were modified an average of 107 times per period in FV and 55 times per period in B. Investments were removed an average of 6 times per period in FV and 4 times per period in B, and added 13 times per period in FV and 11 times per period in B.

We used an independent sample t-test for each period and found that subjects in FV modified investments more than subjects in B, and this was statistically significant in almost all periods. Further, the FV group removed and added investments at a greater rate, and this was statistically significant in half of the periods. Table 3 summarizes the resulting p-values. It is unclear why results in period 6 reflects reduced exploration in FV, but it is possible that subjects have explored sufficiently by this point. While the FV group explored the decision space more, both groups ended with a similar number of investments at the end of each period (a mean of 7 and standard deviation of 3). In half of the periods, subjects in FV spent statistically significantly more time for each portfolio allocation decision, while in the remaining half of the periods subjects in FV did not spend a statistically significantly different amount of time for each decision. On average, subjects in FV spent 7 minutes on each period, and subjects in B spent 5 minutes. These results suggest that the FinVis tool improves the amount of exploration, which can help reduce the "ambiguity aversion" bias. Increased exploration may be a contributing factor to greater learning over time in FV and compared to B.

7.3 Finding Three: Increased Confidence and Perception of Usefulness

Confidence was elicited at the end of each period using an 8-point scale from 'least confident' (0) to 'most confident' (7). Average confidence levels were 3.6 for the B group and 4.1 for the FV group. Subjects were also asked to report their overall confidence at the very end of the experiment: the average confidence level of the FV group was 4 while the average confidence level of the B group was 3.5. The median confidence was 4 for both groups. The confidence elicitation is not ideal because this is a between-subjects design; therefore, we cannot compare the same subject's confidence across treatments. For this reason, we also asked subjects if after completing the experiment they were more, less, or equally confident in their abilities to understand financial planning. 85% of subjects in B reported that they were equally confident, while 15% reported that they were less confident. In contrast, 23% of subjects in FV were *more* confident, 62% were equally confident, and 15% were less confident. We conclude that some improvement in confidence does occur with the use of FinVis. The greater confidence of the FV group is an important result, because individuals who are not confident would be less likely to be able to develop a financial plan in practical application [24].

We also asked subjects how likely they are to use a system such as the one presented to them to plan investment decisions in practice. 38% of B subjects reported that they were "not very likely" to use the baseline program, 46% of B subjects were "somewhat likely", and only 15% of B subjects were "very likely" to use it. In contrast, 61% of FV subjects were "somewhat likely" and 39% of FV subjects were "very likely" to use the FinVis program. This result suggests that FinVis would be more widely adopted by the general public.

8 Conclusions and Future Work

We developed a visual analytics tool that allows the non-expert user to make improved personal finance decisions. A laboratory experiment was conducted and we found that subjects in the treatment using the FinVis program outperformed subjects using a modified version with the same information in tabular form, and this result was statistically significant. FinVis helped subjects learn to overcome decision biases that are common in economics, and improved subjects' confidence. This is a meaningful result, suggesting that visual analytics lowers the cognitive cost and allows subjects to analyze decisions without resorting to suboptimal "rules of thumb".

8.1 Future Work

The current version of FinVis is necessarily simple in order to establish a baseline for future extensions. Our ultimate objective is to extend FinVis for use in practical applications, which can be achieved through a few additions to the system. These include adapting the system to allow easy addition of investments of any duration or characteristics. The existing financial model does not account for many possible factors like periodic trends, inflation and transaction costs, which could be incorporated to improve the predictive power of FinVis. Alternative visual analytics tools can also be developed, and experimental methods can be used to compare their value to that of FinVis.

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