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Jack Gardner
Gettysburg College
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Keywords

mean-variance, portfolio choice, economics, dominance, Robust OLS, Fixed Effects

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Jack Gardner
Gettysburg College
gardjo02@gettysburg.edu

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I conduct a mean-variance portfolio choice economic experiment to evaluate how individuals' portfolio choices deviate from what modern portfolio theory considers optimal. The experimental framework is comprised of three treatments. In each treatment the portfolio selection task involves choosing between two risky assets with zero correlation among their payoffs and one risk free asset. Participants are tasked with completing thirty choice rounds in which they must allocate a constant experimental capital amount to the available asset options after which they are shown period-by-period state-realizations. I utilize the definition of dominance as described in Neugebauer (2004), and Baltussen and Post (2011), that states an asset is dominant if it is attractive in isolation – the asset with the higher Sharpe-ratio. The risky asset, A or B, that is dominant, and the return characteristics of the dominant asset vary over treatments 1, 2, and 3. I find that, relative to theoretically optimal allocation, subjects disproportionately allocate their experimental capital to asset A, the asset with higher expected return and variance, in all treatments, and forgo the benefits to diversification that asset B provides. In order to analyze subjects' allocation decisions across treatments, I utilize Robust OLS and Fixed Effects regression frameworks.

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Introduction:

Standard theories of finance assume humans are computational, rationally minded actors. Sharpe's (1964) research on portfolio allocation, embodied in the CAPM, shows that rational investors should choose a portfolio based on risk weighted return. Empirical evaluation of Sharpe's model is complicated by the uncertainty associated with the return and variance of real-world assets. The purpose of this paper is to evaluate Sharpe's model in an experimental setting where return characteristics can be tightly controlled.

Specifically, I examine how human decision-making deviates from optimality in a portfolio choice environment. Further, it is important to study the environment in which humans are prone to making sub-optimal choices and to exploit the behavioral fallacies humans exhibit while making investment choices. I add to the current body of literature by studying subjects' ability to properly diversify when a dominant asset is in their set of available asset options. Results from the three treatments showcase how subjects' allocation in relation to optimality is affected by changes in the position[1] of a dominant asset. Moreover, this analysis provides further evidence alongside a growing body of behavioral literature that showcases that humans are not the hyper rational actors that neoclassical economic theory describes.

It is important to distinguish the laboratory environment from a naturally occurring environment. In reality it is often impossible to observe data on a single subject over time, and it is often difficult to observe the returns an investor received on an investment choice as well as how the investor reacts to that return. Further, empirical studies of portfolio choice may analyze the decisions of investors at a firm or corporation level and, as a result, fail to measure the preferences of any individual investor but rather measure the choices that result from the action of many individuals with differing preferences (Kroll, Levy, Rapoport. 1988). The experimental laboratory creates an environment where it is possible to examine the behavioral biases humans exhibit while investing. Laboratory environments are described as simplistic or unrealistic as they cannot account for the number of factors that affect individuals'

[1] Position changes over the three portfolio choice treatments as the dominant asset changes from asset A to asset B.

investment choices in a naturally occurring setting, but some important benefits of the laboratory setting are described here: 1.) The ability to observe how an investor reacts to the return on an investment choice creates the opportunity to observe whether subjects exhibit decision making biases in an investment decision environment. 2.) Asset return distributions can be constructed to match the assumptions of underlying portfolio models. 3.) The estimation of investor risk preferences is made possible by observing a subject's choices over time along with how their wealth changes over time. Further, estimating subjects' degree of risk aversion is a necessary component in understanding their asset allocation choices.

The next section reviews previous authors' study of portfolio choice and decision-making behavior as well as differences in experimental framework across studies. Section III presents the mean-variance model, Section IV covers the experimental design and what the portfolio choice environment allows me to analyze that is relevant to understanding human behavior. Data from the experimental sessions are discussed in Section V. Section VI includes discussion on the econometric techniques employed in order to analyze allocation choices across treatments, and Section VII concludes.

II

Literature Review:

Prior research relevant to this study has examined behavioral biases including overconfidence, ambiguity aversion, and sequential dependencies (Kroll et al. 1988). The research I present compares decisions against the normative theory of mean-variance analysis that describes the behavior an investor should follow while allocating capital among asset options (Fabozzi, Markowitz, Kolm, and Gupta, 2013). Portfolio theory provides a means to quantify the expected return and risk on a portfolio and introduces the ability to combine assets with varying risk and return characteristics in order to create a portfolio with a level of expected return corresponding to the individual assets within a portfolio but with a significantly lower amount of risk (Fabozzi et al. 2013).

Decision making under risk and uncertainty has been studied by several authors. Kahneman and Tversky (1979) criticize the ability of the Expected Utility Theory to describe decision making under risk and present an alternative choice theory, called Prospect Theory. They analyze subjects' responses to choice-problems regarding risky outcomes defined by probability. Results support the following deviations from Expected Utility Theory: 1.) People overweight outcomes with certainty relative to probable events (certainty effect). 2.) Subjects value changes in wealth rather the final outcome. 3.) Marginal utility of loss is greater in magnitude than the marginal utility of an increase in wealth.

The experimental design I present benefits from the work of Kroll et al. (1988). They design a portfolio selection task that involves subjects choosing between two risky assets with uncorrelated returns. In their design, subjects also have the option to borrow and lend at a risk-free rate of 3%. Ackert et al. (2015) analyze subject responses in a mean-variance context but differ from the experimental design of Kroll et al. (1988) and the experiments I present as the two risky assets in their experiment have perfectly negatively correlated payoffs. The mean-variance framework I implement differs from their 1988 study in that subjects have the option to allocate their capital endowment between the two risky asset options and the risk-free asset option whereas the framework of Kroll et al. (1988) requires that subjects allocate capital between one of the two risky assets with the option to utilize the risk-free borrowing and lending. Neugebauer (2004) and Baltussen and Post (2011) find that participants tend to disproportionally allocate to risky assets that are attractive in isolation but ignore dominated assets that offer a lower expected return but are attractive from a portfolio diversification perspective. The experimental design I implement involves three treatments, and the position of the dominant asset in the experimental portfolio varies across the three treatments. Further, the design I implement does not allow for borrowing or lending. The specific design characteristics for each treatment are discussed in detail in Section IV.

The objective of Kroll et al. (1988) and Ackert et al. (2015) is similar to the research I present in that these studies seek to identify the factors that compel individuals to hold inefficient portfolios and how subjects allocate capital between risky and riskless assets. Kroll et al. (1988) specify their goal to determine if the asset return distributions have the predicted effect on capital allocation. Further, they test whether initial capital size affects portfolio selection by conducting different experimental sessions with different initial amounts of wealth, and they analyze the effect of the ability to borrow and lend on allocation to the risky asset. The experimental findings of Kroll et al., (1988) study show that about 26% of all portfolios are mean-variance inefficient. Further, they observe a high number of switches in asset allocation choices between the two risky assets – a finding unsupportive of the mean-variance model. Their results also indicate that subjects exhibit sequential dependencies and that subjects' choices, with regard to optimality, do not improve as they make more allocation decisions. Ackert et al. (2015) find participants fail to properly balance risk and reward in their portfolios and that participants hold optimal portfolios when their payout is contingent on a single period and knowledge of payouts is unavailable until the end of the period. Additionally, they find the lack of feedback on allocation outcomes eliminates the behavioral bias resulting from misunderstanding of randomness.

Overestimating how closely one's decisions resemble the optimal choice is a violation of standard finance theory documented in experimental literature known as overconfidence. Dittrich et al. (2001) take an experimental approach to test overconfidence in investment decisions by allowing participants the ability to choose an alternative investment choice in place of their own. Their findings provide evidence to support the fact that overconfidence increases with deviation from optimal choices as well as task complexity and decreases with uncertainty. In a six-year study on the diversification choices of 60,000 individual investors at a large U.S. brokerage firm, Goetzmann and Kumar (2008) find that under-diversification among individual investors is related to investment choices characterized by trend-following behavior and over-confidence. In order to accurately draw these conclusions, they measure the covariance structure of investors' portfolios and analyze diversification in terms of holding more than one security as well as the presence of imperfectly correlated stocks in investors' portfolios. Empirical studies of individual portfolio choices in naturally occurring environments support results in the experimental setting in that investors fail to properly diversify (Ackert et al. 2015).

The experimental environment provides an opportunity to observe ambiguity aversion as the probability of an event occurring in a natural environment is rarely known. Charness and Gneezy (2010) analyze how portfolio choice depends on three behavioral phenomena: ambiguity aversion, the illusion of control, and myopic loss aversion. They find that when experiment participants are asked to pay to decrease ambiguity, increase control, or obtain more frequent feedback on investment choices, participants' investment choices do not change as a result of the level of ambiguity, preference for control is nonexistent, and that participants were willing to pay to have more frequent opportunities to change their investment choices. Ahn et al. (2007) analyze ambiguity aversion using data from a portfolio choice experiment. In their experimental design, subjects allocate their endowment between three assets and each asset produces an equal payout in one of three possible states. One asset payout occurs with a known probability, the other two occur with unknown probability. Their findings show that subjects exhibit considerable heterogeneity in ambiguity aversion. Ahn et al. (2007) fail to reject the null hypothesis of the Subjective Expected Utility theory for the majority of their experiment participants. Now, it is relevant to discuss the framework of the mean-variance model and outline its assumptions.

III

Mean Variance Model:[2]

$$R_t = \sum_{i=1}^{I} w_i r_i \tag{1}$$

The mean-variance framework assumes that investors are risk averse and desire to maximize the expected utility of wealth. Equation (1) describes the total return, R, over a time period, t, from individual assets, i, with individual returns, r, and weights, w. The mean-variance portfolio choice model provides a solution to the investor's problem. The model is constructed to create the optimal balance of risk and reward, measured by expected return and variance (or standard deviation) associated to the random normal distribution specific to each asset option. Further, the MV model assumes that one capital allocation choice is preferable over another if the expected return of the allocation is greater and its variance lower.

$$E_A w \geq E_B w \tag{2}$$

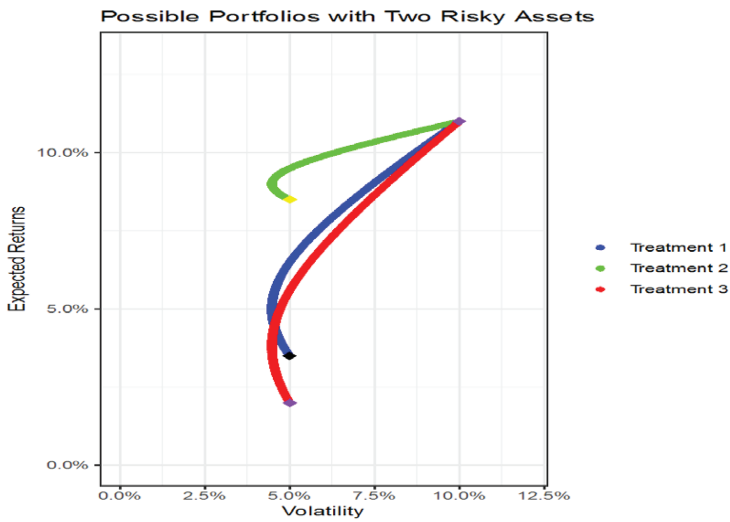
$$Var_A(w) \leq Var_B(w) \tag{3}$$

Equations (2) and (3) describes these preferences where $E_A w$ and $E_B w$ are the expected excess returns on the allocations A and B, respectively, and $Var_A w$ and $Var_B w$ are the variances corresponding to each allocation.

[2] Discussion of the mean variance model in this section follows that of Kroll, Levy, Rapoport. (1988)

Portfolio theory underlying the mean-variance portfolio choice experiment involves the study of the capital allocation line and the opportunity set of risky assets. The opportunity set of risky assets shows all combinations of portfolio expected return and standard deviation constructed from available assets. In the case of Figure I, the opportunity sets of risky assets A and B for treatments 1, 2, and 3 are shown. Portfolio theory suggests the optimal portfolio choice is the point along the opportunity set of risky assets where risk adjusted return is maximized. The tangency point that produces the highest slope on each of these opportunity sets denotes the optimal portfolio and is the point at which the Sharpe ratio of the two-asset portfolio is maximized.

Figure I: The Opportunity Set of Risky Assets



[3]

In order to solve the investor's problem of maximizing expected utility from wealth, portfolio theory provides a solution for the weights of the two risky assets in the optimal risky portfolio. The weights[4] of the risky assets are calculated in equation (4).

[3] Zimmermann, David. "A Gentle Introduction to Finance Using R: Efficient Frontier and CAPM – Part 1." Data Shenanigans. October 13, 2016. Accessed April 5, 2019. https://datashenanigan.wordpress.com/2016/05/24/a-gentle-introduction-to-finance-using-r-efficient-frontier-and-capm-part-1/.

[4] Bodie, Zvi, Alex Kane, and Alan J. Marcus. *Investments*. McGraw-Hill Irwin, 2014. Pp 217. Equation (7.13)

$$w_A = \frac{E(R_A)\sigma^2{}_B - E(R_B)Cov(R_A,R_B)}{E(R_A)\sigma^2{}_B + E(R_B)\sigma^2{}_A - [E(R_A)+E(R_B)]Cov(R_A,R_B)} \quad (4)$$

$$w_B = 1 - w_A$$

IV
Experimental Design:

Participants receive a set of instructions (see Appendix) describing the nature of the capital allocation problem and are made aware of the risk and reward characteristics of the asset options and experiment payoff structure. In treatments one, two, and three, subjects are tasked with completing a series of 30 choice rounds during which they allocate their working-capital among two risky assets, option A and option B, as well as the risk-free asset, option C, which carries a fixed return value of 1%. In treatment 1, option A has an expected gross return value of 11% and a standard deviation of 10%, option B has an expected gross return of 3.5% and a standard deviation of 5%. In treatment 2, the risk-reward characteristics of options A and C remain unchanged, but option B now carries an expected gross return of 8.5% and a standard deviation of 5%. In treatment 3, the return characteristics for options A and C again remain unchanged, but option B carries an expected gross return of 2% and a standard deviation of 5%. As mentioned earlier, the payoffs of the two risky asset options are uncorrelated in all three treatments. Inputting these asset return characteristics into equation (4) allows me to see the optimal allocation weights for option A and B across the three treatments. In treatment 1, options A and B are equally attractive from a portfolio diversification perspective and portfolio theory suggests participants should allocate their capital to these risky assets in equal proportion. In treatment 2, asset B is dominant, and portfolio theory suggests participants should allocate 25% of the capital they will invest in risky assets to option A and 75% to option B. In treatment 3, the dominant asset is option A. Portfolio theory suggests participants should allocate 71.4% of the capital to be allocated to risky assets to option A and 28.6% to option B. These optimal allocation proportions are reiterated in Section VI.

This portfolio choice experiment is administered through Z-Tree (Zurich Toolbox for Readymade Economic Experiments) software[5]. After reviewing instructions and payoff structure, subjects click through a series of screens that display random-normal computer-generated draws specific to the risk-reward characteristics of asset options A and B in each treatment. I do this in order to provide subjects with a baseline understanding of random-normal draws and to enforce the fact that with higher expected return comes higher risk. Upon completion of these 'draw' screens, subjects continue to the capital allocation choice problem. Participants have access to 50 experimental dollars (ED) in working capital at the beginning of every choice round over all three treatments. Participants then enter the amount of experimental capital they choose to allocate to each asset, knowing the total allocation amount between the asset options must be equal to the available working capital of 50 ED. After option allocation amounts are specified, the computer-generated draw specific to the random normal distribution of each asset option is applied to each asset allocation. Any returns, positive or negative, are applied to the subjects total ED account. At the end of each choice round, subjects have the opportunity to observe their updated account, the draw (percent return) they received on option A and option B, as well as the return on their allocation to each asset option.

Upon completion of the 30 choice rounds, subjects are then instructed to complete the Holt-Laury (2002) questionnaire that tasks participants with choosing a series of paired lottery choices. In this questionnaire, subjects choose between options A and B (different than risky assets A and B) ten times. Each option carries with it the probability for low payout as well as the probability for high payout. As subjects make their decisions, they are aware that only one of their choices will be selected at random to determine their earnings from the questionnaire. The expected payouts on options A and B change over the ten paired decisions. As a result, measuring the point at which subjects switch from choosing option A to option B provides a measure of subject risk preference. Upon completion of the treatment, subjects'

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[5] Fischbacher, Urs. "z-Tree: Zurich toolbox for ready-made economic experiments." *Experimental economics* 10, no. 2 (2007): 171-178.

total experimental dollar account, the returns they receive from their working capital allocation, is converted to U.S.D. at a rate of 4ED:1U.S.D.

V

Data:

The data set generated from 48 subjects over all treatments produces 1,440 observations over the course of thirty choice rounds. Data is recorded in the Z-Tree experimental toolbox (Fischbacher, 2007) on each subject over the course of their thirty decision rounds and the Holt-Laury (2002) questionnaire. I seek to observe how subjects' capital allocations deviates from optimal allocation proportions according to the mean-variance portfolio framework. I measure the amount subjects allocate to the two risky assets, option A and option B, as well as subjects' allocations to the risk-free asset, option C. The computer-generated draws corresponding to the random-normal distribution specific to each asset option are also recorded.

Although a subject is not required to allocate experimental capital to each risky asset during a decision round, the return received on each asset option is presented to subjects. The return on the allocation to an asset provides subjects with a means to easily understand how their allocation choice affect their total ED account. It is important for participants to see how their working capital changes across periods due to the fact that participants may have some expectation with regard to the return they believe they should receive over the course of thirty choice rounds. The presence of this expectation may cause participants to alter their allocation among the two risky assets and risk-free asset such that their portfolio in a given round takes on more or less risk in order to achieve a desired benchmark return. Measuring these variables and providing subjects the opportunity to observe the outcomes of their decision upon completion of a choice round increases subjects understanding of the risk reward characteristics specific to each asset option and how volatility in asset returns impacts working capital.

The number of times a subject chose option B, the risky choice of the two options, in the Holt-Laury (2002) questionnaire is recorded as a measure of risk preference. However, some experiment subjects exhibit behavior that implies misunderstanding of paired choice problem in that they choose option A some number of times, choose option B, and then switch back choice A. I measure the number of times a participant chose A as their last selection of this option, and subtract this amount from ten, the total number of choices, to calculate the number of times they chose risky option B.

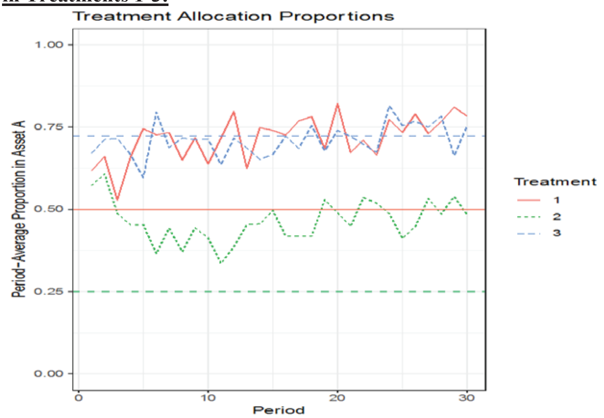
VI
Results:

This section provides analysis on subjects' asset allocation choice over the three treatments in this framework. Table I shows optimal allocation amounts by treatment. Figure II displays the average proportion of risky asset capital that subjects allocated to asset A. Table II provides Z-scores on the average proportion of ED that subjects allocated to asset A by treatment, and Table III provides Z-scores over specific periods in order to investigate learning and end-game effects.

Table I: Optimal portfolio weights by treatment:

Treatment	1(%)	2(%)	3(%)
Weight A*	0.5	25	71.4
Weight B*	0.5	75	28.6

Figure II Average Proportion Allocated to Asset A in Relation to Optimality Over Choice Rounds in Treatments 1-3:



The proportion of capital allocated to asset A is computed as: $\frac{(Capital\ Allocated\ to\ option\ A)}{(Working\ Capital - Capital\ Allocated\ to\ option\ C)}$.

Table II: Proportion of risky asset capital allocated to option A in all choice rounds.

Treatment	Periods 1-30: Average Proportion Allocated to Option A.	Z-Score (Optimal Hypothesis)
1	0.7185	19.14838
2	0.4662	25.26242
3	0.7189	-0.5591691

In order to investigate the effects of learning as well as the effects of nearing the end of the 30 choice-rounds, I compute the proportion of risky asset capital participants allocated to option A in periods 1-10, and periods 11-20 to investigate the effects of learning, and then compute the proportion allocated to option A in periods 1-25, and periods 26-30 to investigate end-game effects. I do this under the hypothesis that the proportion allocated to option A is equal to the mean-variance optimal solution as well as the hypothesis that the proportion is equal to the average proportion allocated to option A across the three treatments.

Table III: Investigating Learning and End-Game Effects Across Treatments.

Treatment 1	Average Proportion Allocated to Option A.	Z-Score (Optimal Hypothesis)	Z-Score (Treatment Average Hypothesis)	Treatment 2	Average Proportion Allocated to Option A.	Z-Score (Optimal Hypothesis)	Z-Score (Treatment Average Hypothesis)	Treatment 3	Average Proportion Allocated to Option A.	Z-Score (Optimal Hypothesis)	Z-Score (Treatment Average Hypothesis)
Periods 1-10 (Learning)	0.6670457	8.451919	-3.111447	Periods 1-10 (Learning)	0.4609639	14.23203	-0.1168133	Periods 1-10 (Learning)	0.6984624	-1.616564	-0.702652
Periods 11-20 (Learning)	0.7404305	12.16493	1.462858	Periods 11-20 (Learning)	0.4399363	12.81347	-1.186512	Periods 11-20 (Learning)	0.6935194	-1.929463	-1.006257
Periods 1-25 (End-Game Effects)	0.7051714	16.41371	-1.162058	Periods 1-25 (End-Game Effects)	0.4700052	22.01661	-0.551331	Periods 1-25 (End-Game Effects)	0.7188648	-2.075855	-0.6450944
Periods 26-30 (End-Game Effects)	0.7759155	9.871451	2.59844	Periods 26-30 (End-Game Effects)	0.4975323	11.80798	1.232814	Periods 26-30 (End-Game Effects)	0.7431151	0.8556082	1.442475

In treatment 1, where optimal allocation is defined as placing an equal proportion of ED in option A and B, I see that subjects allocated a higher proportion of their experimental capital to option A in rounds 11-20 than they did in rounds 1-10. To calculate the Z-statistics in Table III, under the optimal hypothesis, I conduct a proportional Z-test on the average proportion of capital subjects allocate to option A out of the total capital they allocate to risky assets against the mean-variance optimal solution. Further, I conduct a Z-test on the average proportion of capital that subjects allocated to option A in the specific rounds noted above against the average proportion that subjects allocated to option A over all choice rounds. As these allocation proportions are significantly different, according to the Z-statistics above, from the optimal allocation hypothesis as well as the treatment average allocation hypothesis, this provides evidence that subjects allocation choices take on more risk as the treatment progresses. With regard to end-game effects, a similar relationship holds. Participants allocate a significantly higher proportion of their capital to asset A in periods 26-30 than in periods 1-25. This shows that participants take on significantly more risk in their allocation decisions towards the end of treatment 1.

In treatment 2, where option B is the dominant asset in the portfolio, I observe that participants allocate a lesser proportion of their risky asset capital to asset A in periods 11-20 than in periods 1-10; however, these allocation proportions are significantly higher than the optimal proportion of 25% of risky asset capital in option A. For end-game effects, similar to treatment 1, subjects allocate a higher proportion of their risky asset capital to option A in rounds 26-30 than in rounds 1-25. Again, these allocation proportions are significantly higher than the optimal allocation proportion to option A and suggest that participants make take on disproportionate amounts of risk in their final allocation decisions. In treatment 2, observing Z-scores under the treatment average hypothesis, I see that in rounds 1-10 and rounds 1-25, participants average proportion allocated to option A is not statistically different, but in the final choice rounds of 26-30, participants do allocate a significantly higher proportion of their experimental capital to option A.

In treatment 3, asset A is dominant, and I observe that participants allocate significantly less than the optimal proportion of 71.4% of their risky asset capital to asset A in periods 1-10 and 11-20. In periods 11-20, subjects showcase greater deviation from optimality as they allocate a lower proportion to option A than they do in periods 1-10. In periods 1-25, subjects' allocation decisions are not significantly different from the optimal as well as the treatment hypothesis, and in periods 26-30, unlike treatments 2 and 3, subjects do not take on higher risk and allocate significantly more risky-asset capital to asset A.

I observe the average allocation proportions in treatments 1 and 3 are similar across choice rounds. A possible explanation behind this result is that participants observe the simple fact that option A carries a higher marginal return characteristic than asset B. While option A still carries a higher marginal return than option B in treatment 2, the difference is not as large. Such similar proportional allocations support the fact that participants allocation choices do not resemble the mean-variance solution but may provide evidence that a driving factor in how subjects weight their portfolios is the marginal return characteristics of their available asset options.

Econometric Results:

To further analyze subject decision making, I implement robust OLS and Fixed Effects by subject and period model specifications. The dependent variable in each model is the amount allocated to option A in the current period. In both model specifications, I include as controls the total experimental dollar account, the return received on the allocation to option A in the last period, a binary variable equal to one if the return on the allocation to option A was negative in the last period, the return received on the allocation to option B in the last period, a binary variable equal to one if the return on the allocation to option B was negative in the last period, a binary variable equal to one if the subject allocated to option A in the last period, a binary variable equal to one if the subject lost money in the last period, and include period and interactions of period with treatment as additional controls. In the robust OLS model specification, I also control for the number of times a subject chose option B in the Holt-Laury (2002) questionnaire as a measure of risk preference.

Robust OLS:

$$Amount\ Allocated\ to\ A_t = \beta_0 + \beta_1 Experimental\ Dollar\ Account_t + \beta_2 Return\ A\ _{t-1} + C_3 Return\ A\ Negative_{t-1} + \beta_4 Return\ \mathrm{B}_{t-1} + C_5 Return\ B\ Negative_{t-1} + C_6 Allocate\ to\ A_{t-1} + \beta_7 Risky\ HL_t + C_8 LostMoney_{t-1} + \beta_9 Period_t + C_{10} Treatment + a_t$$

Fixed Effects:

$$Amount\ Allocated\ to\ A_{it} = \beta_0 + \beta_1 Experimental\ Dollar\ Account_{it} + \beta_2 Return\ A\ _{it-1} + C_3 Return\ A\ Negative_{it-1} + \beta_4 Return\ \mathrm{B}_{it-1} + C_5 Return\ B\ Negative_{it-1} + C_6 Allocate\ to\ A_{it-1} + C_7 Lost\ Money_{it-1} + \beta_8 Period_{it} + a_{it}$$

Table IV: Summary Statistics:

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Period	1,440	15.50	8.658	1	30
Subject	1,440	24.50	13.86	1	48
Draw on Asset A	1,440	0.107	0.0993	-0.154	0.419
Return on Asset A	1,440	2.951	3.568	-7.034	20.97
Draw on Asset B	1,440	0.0455	0.0603	-0.149	0.264
Return on Asset B	1,440	0.836	1.566	-7.129	11.75
Total Experimental Dollars	1,440	59.32	40.99	-1.850	242.1
Amount Allocated to Asset A	1,440	27.35	16.18	0	50
Amount Allocated to Asset B	1,440	14.91	13.85	0	50
(0-1) Subject Lost Money (Lag 1)	1,440	0.103	0.304	0	1
Risky Choices HL	1,440	4.250	2.195	0	10
Number of subjects	48	48	48	48	48

Table V: Coefficient estimates and their significance for each model specification:

Dependent Variable: ED Allocated to Asset A

VARIABLES	(1) Robust OLS	(2) Fixed Effects
Total Experimental Dollars	0.340***	0.0861**
	(0.0169)	(0.0328)
Return on Asset A (Lag 1)	0.412***	0.0298
	(0.134)	(0.142)
(0-1) Return on Asset A Negative (Lag 1)	3.940***	2.285
	(1.392)	(1.366)
Return on Asset B (Lag 1)	-1.551***	-0.396
	(0.284)	(0.257)
(0-1) Return on Asset B Negative (Lag 1)	-3.771***	-1.158
	(0.986)	(0.909)
(0-1) Allocated to Asset A (Lag 1)	9.309***	2.947
	(2.004)	(2.896)
Risky Choices HL	0.321**	
	(0.143)	
(0-1) Subject Lost ED (Lag 1)	0.967	-0.323
	(1.640)	(1.497)
Period	-1.100***	-0.104
	(0.0718)	(0.133)
(0-1) Treatment 2	-1.347	
	(0.845)	
(0-1) Treatment 3	-10.84***	
	(0.867)	
Constant	18.02***	21.15***
	(2.218)	(2.791)
Observations	1,439	1,439
R-squared	0.447	0.2567
Number of subject		48
Subject FE		YES
Period FE		YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Discussion of Regression Results (all treatments):

The coefficient estimate on subjects total ED account is positive and statistically significant at the 95% level in both model specifications and suggests that as participants progress through choice rounds and derive positive returns from their capital allocation, they allocate a significantly higher amount of their working capital to option A. The coefficient estimate on the return the subject received on their allocation to option A in the last period is positive and highly statistically significant in the robust OLS model, but is positive and statistically insignificant in the Fixed Effects model specification. The positive sign on this coefficient estimate suggests presence of sequential dependency. The coefficient estimate on the binary variable, equal to one if the subject received a negative return on their allocation to option A in the last period, is positive and highly statistically significant under the robust OLS model and positive and insignificant under the Fixed Effects model specification. The positive sign on this coefficient estimate suggests that subjects increase their allocation to option A after receiving a negative return on the prior period. This result suggests subjects may desire an asset with a higher return characteristic in order to counteract their loss. The coefficient estimate on the return on option B in the last period is negative and statistically significant under the robust OLS model and is negative and insignificant under the Fixed Effects specification. The sign of this estimate is in line with expectations as it is reasonable to assume that subjects would allocate less of their working capital to option A, and more to asset B, if B received a higher return in the last period. The coefficient estimate on the binary variable, equal to one if the subject received a negative return on their allocation to option B in the last period, is negative and statistically significant under the robust OLS model and negative and insignificant under the fixed effects model. I observe that the magnitude of this coefficient estimate is practically high, but is not in line with our hypothesis as I expect a negative return on option B in the last period would cause subjects to increase their allocation to option A in the current period. The coefficient estimate on the binary variable, equal to one if the subject allocated to option A last period, is positive and statistically significant in the robust OLS model and positive and insignificant under the Fixed Effects model. This aligns with our hypothesis as I expect this variable captures a subjects propensity to allocate working capital to option A. The coefficient estimate on the number of risky choices a subject made in the Holt-Laury (2002) questionnaire is positive and statistically significant in the robust OLS model. This is in line with expectations as I expect that subject who chose the riskier choice more often are more likely to allocate a greater proportion of their working capital to the more volatile asset option with prospect for higher return. Period controls in the robust OLS model specification are negative and statistically significant and are negative and statistically insignificant under the Fixed Effects specification. This showcases participants decrease the amount of working capital they allocate to option A as the treatment progresses. This result is out of line with our expectations as I observe, for treatment specific results, that participants increase the proportion of risky asset capital allocated to option A as they move on in choice rounds.

VII
Discussion of Results and Conclusion:

In the three treatments I implement in this experimental framework, the risk-reward characteristics of the asset options that I choose create clear differences in the optimal allocation proportions across treatments. In treatments 1 and 3, it is important to note that asset A has a higher expected return (11%) than its standard deviation (10%) whereas asset B has an expected return of (3.5%, 2%) and standard deviation (5%, 5%) in treatments 1 and 3, respectively. The simple fact that asset A has higher a higher expected return than standard deviation, while asset B does not, likely contributes to this disproportionate allocation.

In treatment 2 asset B now has a higher expected return than standard deviation. Asset A carries the same risk-reward characteristics, but asset B now has an expected return value of (8.5%) and standard deviation of (5%). In treatment two I see subjects allocate a nearly equal proportion of their experimental capital to each asset option; however, their choices are significantly different from the optimal allocation proportions according to the mean-variance solution. This raises the question, in the experimental environment, do subjects benefit from taking on a high amount of risk in their capital allocation? No participants experience bankruptcy in this experimental framework due to the fact that subjects have 50

ED to allocate every period and only hold the returns from their allocation. The risk reward characteristics of the risky assets are such that it is extremely unlikely that a subject would experience continual negative draws on an allocation. As a result, this may push subjects to take on risk in the experimental environment.

Limitations to the study I present include the small number of subjects that participated in this series of portfolio choice treatments. Of 48 total subjects, 16 subjects participated in one of the three experimental treatments. Certainly, increasing the number of participants would improve the robustness of the results I present. Further, it is important to note that the 48 participants are 18-22-year-old Gettysburg College students. While I control for the risk preferences of subjects through the Holt-Laury (2002) questionnaire, it is likely the risk preferences of 18-22-year-old college students do not resemble that of, for instance, those who are closer to retirement age, which may decrease the external validity of the results I present. Finally, in the future it would be beneficial to test for the presence of an 'A-effect' in the treatment I present. It is plausible that as subject observe the risky assets in the treatments are named assets A and B, they may believe asset A is inherently better. This could easily be examined by switching the asset return characteristics of the two risky assets over the three treatments and observing whether subjects exhibit similar behavior in each case.

I emphasize the benefit of the laboratory environment in that it provides a controlled setting to observe choice behavior. Further study of human decision-making behavior is crucial in order to understand the factors which cause humans to exhibit behavioral biases. Better understanding of where humans are prone to behavioral bias is relevant when considering the actions of investors in capital markets as well as individuals' ability to properly structure their assets to achieve greater financial stability. Moreover, the breadth of evidence that suggests humans do not allocate their asset optimally advocates for better solutions to diversification, or, better access to diversification in order to solve the investors problem. The dominant asset framework in this study provides additional insight as to why there is higher volatility at the aggregate market level that results from the disproportionate amount of risk investors take on in their investment decisions.

Appendix

Experiment On-Screen Instructions:

Outline of Experimental Framework: “This is an experiment in decision making. Your payoff will depend partly on your choices and partly on chance. Please pay careful attention to these instructions. The experiment should be completed in approximately an hour and a half. During the decision-making portion of the experiment, you will be working with 'experimental dollars' (ED) that will be converted to U.S. dollars upon completion of the experiment at a ratio of 4ED = 1$ US. At the end of the experiment, you will be paid privately and in cash your earnings plus a $7-dollar participation fee.”

Payoff Instructions:

“The experiment will consist of thirty decision making rounds. In each round you will choose how to allocate 50ED between three asset options. Two of the asset options will have different risk reward characteristics. The other risk-free asset option will allow you to gain a 1% return on the capital allocated to this asset and exposes you to no risk of losing experimental dollars. In each choice period, you will see three boxes labeled A, B, and C. In each choice round, you must allocate all of your 50ED among these asset options.”

Choice Round Instructions:

“To choose an option, use the mouse to click on the box corresponding to each portfolio or cash option. Then, type in the experimental dollar amount you would like to allocate to each option. You must allocate all of your 50 ED in each period. In other words, the sum of the amount you place in each option must be equal to 50ED. An onscreen message will appear if your allocation amounts do not sum to 50 ED.

Your payoff in each round is determined by your allocation of experimental dollars to each option. The three options have the following risk reward characteristics:

Option	Average Return	Standard Deviation of Return
A	11%	10%
B	8.5%	5%
C	1%	0%

At the end of the choice round, the computer will draw, from the random-normal distribution specific to each option, a return value for your allocation. Any returns, positive or negative, will be added to your total experimental dollars, and then you will move on to the next decision round. In the next decision round, you will have access to the same 50 experimental dollars that you had at the start of the treatment, and the resulting gain or loss from your allocation decision will be added to your total experimental dollars. This process will be repeated for a total of thirty decision rounds. At the end of the thirty rounds, you are asked to complete a brief questionnaire, and then you will be called out individually and paid in private. Your payment will be the $7 participation fee plus your total experimental dollars converted into real dollars at a rate of: 4ED = 1USD."

Example Decision Round:

"Here is an example of a decision round: 'You begin the experiment with 3$ in experimental dollars and allocate one experimental dollar to each option. For option A, the computer would draw a return from a distribution with an expected return value of eleven percent and standard deviation of ten percent. This return would be applied to the 1$, and the return amount would be allocated to your total experimental dollar account. For option B, the computer would draw a return from a distribution with an expected return value of eight and a half percent and standard deviation of five percent. This return value would again be applied to the $1, and the return amount would be allocated to your total experimental dollar account. The dollar allocated to option C would receive the guaranteed return of one percent and this capital would be allocated to your total experimental dollar account. In the next choice round, you would have access to the same $3 in experimental dollars to allocate among the available asset options. '

You will notice that the asset options have different expected returns. Note also that the asset options with higher expected returns have higher standard deviations-this means they also have an increased chance of negative returns or outsized positive returns.

In the following screens, you will observe a series of 'draws' that display the return on a $1ED allocation to each asset option, as in the above example."

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