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Malleable Risk Preferences and Learning from Experience in an Asset Allocation Game

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March 7, 2017

Abstract

Does experience modulate elicited risk preferences? How does experience shape expectations? This paper provides evidence that investors' own experiences play a key role in shaping revealed risk preferences and the weighting of past observations when forming expectations. The results suggest that experiencing severe negative or positive returns leads subjects' revealed preferences to become closer to risk neutrality, while subsequent asset allocation is affected primarily by subjects' own returns relative to the market and not by the market experience itself, indicating that agents' performance relative to a benchmark is what matters in shaping expectations.

Keywords Risk Aversion, Experiment, Experience, Asset Allocation

JEL Classification C91, G02, G11, D81

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1 Introduction and Motivation

Risk aversion and expectations are a corner stone of applied economics[1]. Economic theory usually starts by assuming a stable preference structure with a known risk attitude for economic agents who are also fully rational, as in they know the model structure and the data generating processes for all relevant variables. However, theoretical predictions are more often than not accompanied with real world and experimental data that are in contrast to theoretical predictions, leading to a questioning of the robustness of the proposed theories. For example, the instability and lack of predictability of risk preferences is a well known fact within the experimental community. Friedman *et al.* (2014) provide a comprehensive review of the state of the literature and the remarkable instability of estimated risk parameters. Similarly, full rationality has been criticized by numerous researchers with supporting evidence in Malmendier & Nagel (2009) indicating that economic agents in fact do not use the full history of data available to them found. Unfortunately, there is scarce evidence of causal relationships between states of the world and risk attitudes[2]. To address this issue, this paper provides a unique perspective into the causal determinants of the instability in risk preferences as well as the relationship between market state, asset allocation and expectation formation.

Generally, the failure to match real world and experimental data has motivated much of the recent theoretical and applied research in experimental and behavioral economics, as well as recent asset pricing and macro-finance models. The assumption of perfect rationality is increasingly replaced with agents who are learning the data generating processes and consumer preferences are becoming more driven by behaviorally inspired functional forms. These advancements, although help fit the data, are still made in isolation. In other words, the link between the stability of preferences, belief formation and the state of the world has not been addressed, which is precisely where this paper makes a contribution. The paper provides experimental evidence of the link between the stability of preferences, belief formation and the state of the world.

Recently, macroeconomic conditions have been stuck in a "new normal" state that has not been experienced by investors before. This new state is characterized by zero short-term/risk-free rate and negative real rates, ineffectiveness of monetary policy to pull the

[1] See Stigler & Becker (1977) for an excellent discussion and attempt at addressing stability of preferences

[2] Some related developing literature on this topic is discussed in section 2

economy to pre-crisis levels of growth and employment, and massive deleveraging by households and firms (at least at the onset of the great recession). This dramatic change in the macroeconomic state of the economy can have profound effects on how individuals bear and price risks. How do we expect agents to react and adjust their optimal decisions under this new environment? And, if there is a change, does it stem from a change in risk aversion and/or beliefs? The results support recent findings that preferences are affected by severe experiences, leading to the conclusion that experiencing something like the great recession can have a lasting effect on decision making through shifts in risk preferences. In addition, the results suggest that belief formation and asset allocation is driven by the type of state through which agents' are learning, with good states and bad states leading to drastically different weights placed on past experience.

In our experiment subjects face two types of uncertainty; in the baseline and followup risk preference elicitations subjects face known risk with clearly stated probabilities and outcomes, whereas in the main asset allocation task subjects face a Knightian type of uncertainty, where they know nothing about outcome probabilities and are forced to learn about the data generating process through experiencing random draws from the underlying distribution. This approach is in line with Mengel *et al.* (2015), who have a similar motivation to this paper but take a different approach in their design. This paper differs from Mengel *et al.* (2015) on a number of dimensions. Firstly, rather than focusing on the effect of imperfect knowledge, we are more interested in the effect of making repeated decisions and accumulating experience in uncertain market environments, so all our subjects start in the equivalent of their Unawareness treatment and slowly, through experience of the data generating process, become more aware of the underlying distribution. Secondly, our asset allocation segment is focused on varying the type of experience (high vs low returns) subjects faced, which corresponds to their Unawareness-POS treatment, although with a much larger variation in the shift of the underlying distribution of outcomes faced by subjects. Finally, our risk preference results are not obtained from decisions made in the experience task, but rather we utilize a standard risk elicitation methodology to establish a baseline before and a follow up after the asset allocation segment.

The experimental design provides a causal link between experience (or market environment/state) and stability of risk preferences while providing an added benefit of allowing us to make inference on how experiencing different states influences belief formation and asset allocation. The main question of interest is whether subjects' elicited risk preferences respond to spells of good or bad experiences when allocating assets between a risky and risk-free asset with a secondary inquiry exploring how different experiences affect subjects' weighting of past returns when making asset allocation decisions.

To our surprise, the effect of having experienced any severe variation in the mean of returns, up or down, resulted in subjects becoming more risk neutral in their follow up scores. The effect of experience on the weighting of past information is too noisy to pin down with reasonable confidence, however, subjects' own returns relative to the market play a key role in determining subsequent asset allocation.

The remainder of the paper is organized as follows: section 2 relates the paper to the current literature, section 3 provides an in depth explanation of the experimental design, section 4 discusses the results and section 5 concludes.

2 Related Literature

This paper contributes to two somewhat related strands of literature. There is a vast body of research concerned with the stability and predictability of elicited risk preferences, to which this paper makes a contribution by pointing out experimental tasks that can lead to instability in elicited preferences. In addition, researchers are increasingly concerned with the effects of severe experiences on risk taking and expectation formation, to which this paper contributes to the on going debate by providing experimental evidence that experienced returns play a key role on subsequent risk taking. Below is a brief summary of the aforementioned literature.

2.1 Elicited Risk Preferences

I will not attempt to cover this vast literature, however, I will discuss the main findings and the current state of discussion as it relates to this project. The debate is ongoing with no clear indication as to which camp has the upper hand.

It is important to note that there are numerous methods (or institutions) for eliciting risk preferences and stability results tend to vary tremendously across institutions. For example, Chuang & Schechter (2014) find that subjects' responces to survey questions are much more stable over time than experimental measures. Similarly, Berg *et al.* (2005) find statistically significant evidence that subjects' revealed risk attitudes vary from risk-loving when the value of a risky asset is induced by an English clock auction to risk averse when value is induced in a first-price auction. Crosetto & Filippin (2013) is a recent comprehensive comparison of five risk elicitation methods with the non-surprising conclusion that the estimated risk aversion parameters vary greatly across tasks.

Deck *et al.* (2013) try to explain variation in risk taking across tasks by attributing such changes to subject's domain specific risk attitudes, however, they fail to find support for their hypothesis. A skeptical reconsideration of the entire experimental risk elicitation field can be found in Friedman *et al.* (2014), where the authors seek and fail to find an explanation for the observed inconsistencies in risk preferences across institutions. Generally there are no accepted explanations as to why we observe such dramatic changes in subjects' revealed risk preferences across institutions.

In an attempt to narrow the comparison among elicitation methods, Dave *et al.* (2010) focus on the tradeoff between elicitation methods; simple and coarse (Eckel & Grossman (2008)) vs complex and fine (Holt & Laury (2002)). They find that while the advantage of the more complex measure is an overall superior predictive accuracy, the simpler task generates less noise and similar predictive accuracy for subjects with low mathematical ability. This simple comparison reveals that there are indeed differences between methods and that these differences could be linked to observed characteristics of the subjects.

It will suffice to say that no risk elicitation procedure is without some potential flaw and that no single procedure is superior to all. To that end, potentially any procedure is as good as any for the purposes of this study. To be more exact, we seek an elicitation proceudre that is least controversial and relatively easy to interpret and implement. The most fitting procedure for the purposes of this experiment was the Holt & Laury (2002) multiple price list, from which I formulate two simple variations to serve as the baseline and followup risk preference score.

2.2 Experience and risk attitudes

Another strand of literature has been focused on the role that different experiences play in shaping risk preferences. Guiso *et al.* (2013) set off with a similar motivation to this study;

using a survey of clients of an Italian bank to measure their risk aversion after the 2007 crisis they find evidence that quantitative and qualitative measures of risk aversion increase substantially after the crisis. They conduct a lab experiment in which subjects watch a scary video (to simulate the same psychological state of mind as a crisis) and find that treated subjects had a certainty equivalent that is 27% lower than the control group, indicating that treated subjects become more risk averse. Similarly, using only market level and mutual fund data, Straehl (2012) and Smith & Whitelaw (2010) find confirming results of time varying risk aversion.

When making sequential decisions, experienced gains or losses can lead to either more or less risk taking. Weber & Zuchel (2005) were able to disentangle changes in risk taking following losses and gains through the framing of the decision in which the gains and losses are realized. It's important to note that the experimental design in this study differs considerably from Weber & Zuchel (2005) because in our experiment subjects did no realize gains or losses during the game, so the house money effect induced through the experimental design in Weber & Zuchel (2005) is not triggered. Nevertheless, their findings reveal that prior experiences influence subsequent risk taking. On a similar note, Nosic & Weber (2010) analyze the determinants of risk taking behavior and conclude that subjective risk attitudes are much better predictors of risk taking behavior than objective measures such as historical return and volatilitie of a stock.

Malmendier & Nagel (2009) is perhaps the most influencial paper on this topic. They find consistent evidence that experienced returns shape subsequent asset allocation. Using the survey of consumer finances they find that individuals who have experienced low stock returns are less likely to take financial risk, are less likely to participate in the stock market and are relatively more pessimistic about future returns.

Experience, however, is not exclusive to financial outcomes, but perhaps more important consideration should be given to outcomes affecting individuals' direct livelihood and safety. Although such traumatic events are frequently observed across the globe, there is rarely the data available to test the hypothesis of interest. Fortunately, Callen *et al.* (2014) and Hanaoka *et al.* (2014) are two cases where data exists and generally supports the claim that traumatic life experience has a significant role in shaping risk preferences. Hanaoka *et al.* (2014) use survey panel data to study the effect of the 2011 earth quake in Japan on risk preferences and find that individuals who experienced larger intensity of the quake become more risk tolerant (move closer to risk neutrality). Alternatively, Callen *et al.* (2014) document through a field experiment in Afghanistan the importance of exposure (and recollection of) violence on shaping risk preferences.

This paper contributes to this growing strand of literature by documenting experimental evidence of the importance of experience in a portfolio allocation task on subjects' revealed risk preferences.

3 Experimental Design

		Lottery A		Lottery B		Calculated	
Row	prob1	A-prize1	A-prize2	B-prize1	B-prize2	EV[A]-EV[B]	$\hat{r}$
1	0.1	4.00	0.25	2.15	1.75	-1.16	-1.05
2	0.2	4.00	0.25	2.15	1.75	-0.83	-0.54
3	0.3	4.00	0.25	2.15	1.75	-0.49	-0.16
4	0.4	4.00	0.25	2.15	1.75	-0.16	0.16
5	0.5	4.00	0.25	2.15	1.75	0.17	0.47
6	0.6	4.00	0.25	2.15	1.75	0.51	0.79
7	0.7	4.00	0.25	2.15	1.75	0.84	1.16
8	0.8	4.00	0.25	2.15	1.75	1.18	1.66
9	0.9	4.00	0.25	2.15	1.75	1.51	-
10	1	4.00	0.25	2.15	1.75	1.85	-

Table 1: (MPLa) Holt & Laury Multiple Price List parameters modified by switching the columns and adding \$0.15 to original H&L prizes. EV[L] denotes the expected value of lottery L. The last column shows the approximate solution $\hat{r}$ to the equation EU[A] = EU[B] at that line, where $U(x) = \frac{x^{1-r}}{1-r}$.

As mentioned above, the goal of the experiment is to test the effect of severe market environments on agents' elicited risk aversion. I establish a baseline (pre) and followup (post) level of risk aversion for participants in the first and third segment of the experiment, respectively, utilizing two variations of the well known Holt & Laury (2002) (H&L) multiple price list (MPL) elicitation procedure. Tables 1 and 2 show the modified H&L MPLs utilized in the first and third segments of the experiment. In the second segment, subjects make a sequence of myopic portfolio allocations between a risky asset, with an unknown return, and a risk-free asset with a known return. Subjects are endowed with a new endowment at the beginning of each of the 20 rounds in the portfolio allocation segment; portfolio returns for each round are independent and are not cumulative. The experiment, therefore, is a portfolio

		Lottery A		Lottery B		Calculated	
Row	prob1	A-prize1	A-prize2	B-prize1	B-prize2	EV[A]-EV[B]	$\hat{r}$
1	1	1.95	1.55	3.80	0.05	-1.85	1.23
2	0.9	1.95	1.55	3.80	0.05	-1.51	0.88
3	0.8	1.95	1.55	3.80	0.05	-1.18	0.62
4	0.7	1.95	1.55	3.80	0.05	-0.845	0.38
5	0.6	1.95	1.55	3.80	0.05	-0.51	0.13
6	0.5	1.95	1.55	3.80	0.05	-0.17	-0.13
7	0.4	1.95	1.55	3.80	0.05	0.16	-0.46
8	0.3	1.95	1.55	3.80	0.05	0.49	-0.91
9	0.2	1.95	1.55	3.80	0.05	0.83	-1.65
10	0.1	1.95	1.55	3.80	0.05	1.16	-

Table 2: (MPLb) Holt & Laury Multiple Price List parameters modified by reversing the rows and subtracting $0.05 from original H&L prizes. EV[L] denotes the expected value of lottery L. The last column shows the approximate solution $\hat{r}$ to the equation EU[A] = EU[B] at that line, where $U(x) = \frac{x^{1-r}}{1-r}$.

allocation segment in between two different H&L MPLs.

I employ two different MPLs for a couple reasons. First, I need to establish a baseline level of risk aversion prior to treatment assignment in the portfolio allocation segment. Second, an additional variation serves the purpose of driving subjects away from simply recalling their decisions in the baseline elicitation. Therefore, any results found by comparing across two groups randomized across two different elicitation methods would overcome any MPL specific bias.

Subject are randomly assigned into groups defined by a sequence MPLi – treatment – MPLj. For each treatment in the portfolio allocation segment we have two possible arrangements for the pre and post H&L MPL, leaving us with two groups per portfolio allocation treatment. For example, in the control portfolio allocation treatment, subjects can be either in a group defined by the sequence MPLa – control – MPLb, or in a group defined by the sequence MPLb – control – MPLa. The experiment features a full factorial design in which subjects are randomly assigned into all of the possbible groups.

Figure 1 summarizes the five treatments in the portfolio allocation segment. Within each circle is the name I use to reference the group as well as the number of subjects in the

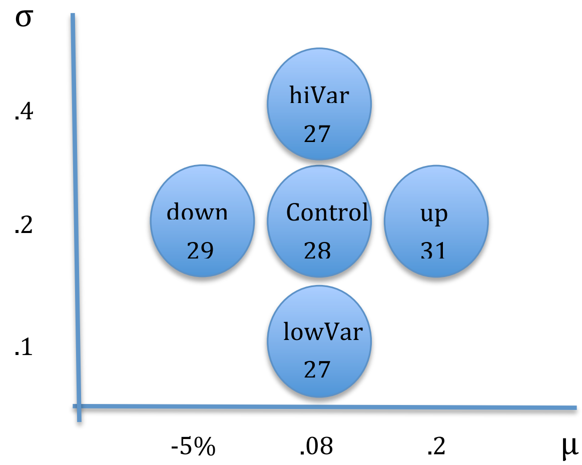

Figure 1: Treatment groups

group. As the figure demonstrates, treatments differ in the mean, μ, and variance, σ, of the simulated returns. For each treatment I simulate a sequence of 25 daily realizations from the stochastic process in equation (1) according to the specified μ and σ indicated on the figure.

$$\frac{dS}{S} = \mu dt + \sigma dz \tag{1}$$

The portfolio allocation segment is demonstrated in figure 5. The segment starts with the chart containing a sample of five realizations from the treatment process in order to provide the subjects with a historical reference of the process for the risky asset. Subjects use the slider on the bottom of the chart to allocate their endowment for the period and once all subjects click confirm allocation the realization of the stochastic process for the round is drawn on the chart in blue, along with the subject's portfolio value for the round drawn in green. Each round is calibrated to represent a year of returns with each tick representing a day. At the end of each round of the portfolio allocation segment subjects see their gains or losses from the round and the results are stored for potential payment. Subjects start the following round with a new endowment. So, subject are faced with a repeated one-period asset allocation decision.

Subjects are paid for one randomly selected decision from the 40 decisions made in the experiment; ten in each of the H&L segments and 20 in the portfolio allocation segment. If the randomly selected decision falls in the H&L segments, then a ten-sided die is rolled to play the selected lottery, if the decision is one made in the portfolio allocation segment then subjects are paid according to the value of their portfolio at the end of the selected round at a predetermined conversion rate.

4 Results

The experimental design allows us to disentangle the effect of experienced returns on elicited risk preferences as well as the relationship between subjects' asset allocations and experienced returns. The former answers whether experiencing severe returns drives risk preferences in any particular direction, while the latter addresses whether subjects do indeed over or under allocate to a certain asset class after experiencing high or low returns.

Table 3 provides summary statistics of the main outcomes of interest in the experiment. The average of the two risk aversion scores (discussed in more detail below) in the pre and post segments across all subjects in a given group consistently show that the mean treatments have the most pronounced differences. The columns under market provide the sample moments of the simulated series that the subjects experienced in the different treatments. The response of the stock and bond allocations across subjects shows that on average the mean treatments have the largest difference between stock and bond allocations. In the up treatment subjects allocate almost 60% to stocks, which is the highest allocation to stocks across all groups, whereas in the down treatment subjects allocate over 60% to bonds, which is the highest allocation to bonds across all groups. This is promising as it indicates that subject are responsive to the treatments. In addition, subjects were not able to successfully time the market as their portfolio returns accurately reflect the simulated moments, which indicates that the treatments were in fact experienced.

4.1 Risk Preferences

The main outcome of interest is the follow-up (or post portfolio allocation) H&L score, for which I have two alternatives. Traditionally, a subject's risk aversion score (or range) is obtained by solving for the risk aversion coefficient that would make the subject indifferent between lotteries A and B on the lines around the subject's switch point. For example, if a subject chose lottery B in MPLa in lines 1-6 and then switched to lottery A for lines 7-10, then the subject's risk aversion coefficient is obtained in lines 6 and 7 by solving for the risk aversion parameter, $\hat{r}$, that would make the subject indifferent between the chosen lotteries on line 6 and on line 7. The subject's estimated risk aversion parameter is in between the estimated $\hat{r}$ from line 6 and line 7.

The problem with this approach is that it limits the interpretation of risk aversion to the specific CRRA utility functional form, which is not well defined in the case when subjects switch columns more than once or when in the case of no column switch. Therefore, any analysis utilizing $\hat{r}$ excludes subjects with more than one column switch.

Alternatively, *rnDiff* is the number of safe choices (from the column with prizes close together, e.g., 1.75 or 2.15 in MPLa) less the number of rows where the safe choice has the larger expected value (or the point where a risk neutral person, who is an expected value maximizer, would switch columns). The analysis on *rnDiff* and $\hat{r}$ tell the same story although the effect appears to be stronger and more significant when considering $\hat{r}$.

4.1.1 Mean Difference Tests

Figures 2 and 3 provide a visual perspective of the H&L results summarized in table 3. As is evident from the plots, the average *rnDiff* score in the H&L segments pre and post the portfolio allocation segment are nearly identical in the control and lowVar groups, whereas the difference in the hiVar group seems to be marginally significant. The mean treatments, or the up and down groups, appear to have the largest difference. Figure 3 tells a similar story for the mean treatments for $\hat{r}$, however, there is a bit more variation in the other groups relative to *rnDiff* in figure 2

Given the fact that a subject's risk preference is measured pre and post the treatment, paired mean difference tests are possible. Table 4 reports the results from paired t-tests and Wilcoxon signed rank tests on the difference between a subject's pre and post *rnDiff* score. The data is a bit too noisy for the test to be statistically significant for the up or down treatments individually, however, when the data is combined into the mean treatment group we see that subjects on average are half a line closer to risk neutrality after experiencing severe high or low returns. The Wilcoxon signed rank test supports the findings in the t-test but indicates that the difference in the down treatment maybe a bit noisier when calculated using the distribution-free Wilcoxon signed rank test. Table 5 reports the results of the same tests repeated for the estimated subject $\hat{r}$ scores. The differences for the up group and combined mean treatment is again statistically significant with an even smaller standard error.

Comparing post *rnDiff* scores across groups provides a clear comparison across treatments. Table 6 compares the mean of *rnDiff* in the post H&L segment across groups. T-tests and Wilcox rank sum tests of the difference of the mean of the groups along the column less the control group are reported. The effect is largest when comparing the control group with the mean treatments, when considered individually or when combined. The evidence suggest that subjects in the mean treatments chose on average one less risky option than the control group in the followup H&L segment. The results for $\hat{r}$ tell the same story with a shift in $\hat{r}$ of about 0.3 towards risk neutrality in the mean treatment groups.

A more stringent test of the effect of the treatments is a comparison of the change in the H&L score pre and post the portfolio allocation segment within a treatment group between the treatments and the control group. Columns 5-8 in tables **??** report mean difference tests for Δ*rnDiff* and $\Delta\hat{r}$, where $\Delta = post - pre$. There is no significance for Δ*rnDiff* but we can see that the standard errors on the mean treatments is by far the smallest, unfortunately the effect is not large enough to be significant. However, the results for $\Delta\hat{r}$ confirm the findings obtained thus far for the mean treatment.

4.1.2 OLS Regressions

Column (1) of tables 7 and 8 report simple OLS estimates that confirm the results obtained in the mean comparison tests. Each variable is a dummy for the subjects in the respective treatments. Again we see that subjects in the mean treatments are on average one line closer to risk neutrality in table 8, and .2 closer to risk neutrality in table 7. Column (3) of table 7 again confirms that the difference between pre and post is also significant for the mean groups when considering $\hat{r}$, while the effect is too small with a relatively large standard error when considering *rnDiff* in column (4) of table 8.

Recall that subjects saw either MPLa or MPLb in the baseline H&L segment with the condition that subjects who saw MPLa (MPLb) in the baseline segment were assigned to MPLb (MPLa) in the follow-up segment. With proper randomization the treatment effect due to the mean treatments should not be affected by this sequence, as the group contains as many subjects who saw MPLa in the baseline (and follow-up) as subjects who saw MPLb. However, for the sake of completeness and to rule out any effect due to the specific MPLs, I augment the specification in column (2) and (4) of tables 7 8 to include a dummy for MPLa in the baseline H&L segment. In addition, I add a dummy for subjects who multi-cross in the pre or post H&L segment separately in table 8.

Although there appears to be a large effect coming from the baseline MPL, quantitatively the results change very little. In table 8 the coefficients change from -0.9 to about -0.7 for the mean treatments, whereas the results for $\hat{r}$ in table 7 remain unchanged after including the baseline MPL dummies. The results indicate that even when accounting for the different MPL sequences and for multi-crossing subjects, experiencing severe high or low returns tends to push elicited risk preferences towards risk neutrality.

4.2 Asset Allocation

Using subjects' allocations in the asset allocation segment we can test for the effect of experienced returns on subsequent asset allocation utilizing a similar specification as in Malmendier & Nagel (2009). Naturally my data lacks the rich controls obtained with survey data, but it triumphs in that it's purely experimental with random treatment assignment, which implies that the treatment effect is not confounded due to omitted variables. In addition, due to the structure of the experiment, all subjects in my sample are the same age[3], so subjects in a treatment group lack cross-sectional variation in experienced market returns, *expM*, however, there is considerable variation between subjects when experience is determined by subjects' *foregone returns*, or the difference between their realized portfolio return and the market return in a given period.

The goal is to estimate the relationship between allocation to stocks and past experienced returns, which takes the general nonlinear form

$$y_{it} = \beta x_{it}(v) + u_{it}, \text{ for } v = \lambda, \gamma \tag{2}$$

[3]Here age refers to rounds within the portfolio allocation segment

$$x_{it}(\lambda) = \sum_{k=1}^{age_{it}-1} w_{it}(k,\lambda)R_{t-k}, \text{ where } w_{it} = \frac{(age_{it}-k)^{\lambda}}{\sum_{k=1}^{age_{it}-1}(age_{it}-k)^{\lambda}} \tag{3}$$

$$x_{it}(\gamma) = \frac{R_{t-1} + \sum_{k=1}^{age_{it}-2}\gamma^{k}R_{t-1-k}}{1+\sum_{k=1}^{age_{it}-2}\gamma^{k}} \tag{4}$$

where y_{it} is the log difference of allocation to stocks in round/age t and x_{it} is either the differenced experienced past returns, *expM*, at each round/age t, or the subject's *Foregone Return*, each calculated according to equations 3 or 4.

The weighting functions in equations 3 and 4 allow for weights that could be constant, increasing or decreasing in age while adding only one additional parameter to be estimated, λ or γ. For each subject i, I treat each round in the portfolio allocation segment as year t and calculate x_{it} given a value for the respective weight parameter.

The weighting function in equation 3 is the same as the one employed in Malmendier & Nagel (2009) and is much more closely tied to the subject's age in its formulation. Given an age, the function places larger weights on recent observations for $\lambda > 0$, and a larger weight for past observations for $\lambda < 0$. On the other hand, the function in 4 is borrowed from Cheung & Friedman (1997), which was initially designed to test individual learning behavior in repeated normal form games within a laboratory experiment. It was mainly designed to test whether subjects place any value on past observations versus the most recent observations. The only connection with age in 4 is in the summation and the value of the additional term from and additional observation, unlike in 3 where the change in age affects each term given a value for λ. If $0 < \gamma < 1$ then weights are larger for more recent observations while $\gamma > 1$ means weights are larger for past observations.

Given the random treatment assignment of experienced market returns, we can be confident that the strict exogeneity assumption, $E[\mathbf{u_{it}}|\mathbf{x_{it}}, \alpha_{\mathbf{i}}] = \mathbf{0}$, $t = 1, .., T$, is satisfied. The only potential identification issue with equation 2 is with regards to the variance structure. The estimates of β and λ will be consistent only if $E[\mathbf{u_{it}}\mathbf{u_{it}}'|\mathbf{x_{it}}, \alpha_{\mathbf{i}}] = \mathbf{0}$. To address this issue I report results obtained from first-differenced (FD) regressions (combating potential serial correlation in the errors) with robust standard errors clustered at the subject level (combating potential heteroskedasticity in the cross section) for the full sample as well as for each treatment group and report the results in tables 9 and 10. The dependent variable in table 9 is simply the first difference of the simulated treatment series, whereas in table 10 the dependent variable is foregone returns, or the difference between the subject's realized portfolio return and the market return in that period.

Based on the findings in Malmendier & Nagel (2009), we expect the β estimates on experience to be significant for all groups. However, as mentioned previously, the coefficient estimates in table 9 are not directly comparable to the results in Malmendier & Nagel (2009) or Cheung & Friedman (1997) since there is considerable variation in experienced returns in the Malmendier & Nagel (2009) sample, which is not the case for my treatment groups, and there is no strategic interaction in my sample, which is the case in Cheung & Friedman (1997). We can only interpret the coefficients in table 9 as the marginal effect of experienced returns on stock allocation *within* the specific treatment group. The benefit, however, is that we can distinguish the magnitude of the effect of experience for distinctly different market environments. Alternatively, there is considerable variation in subjects' *foregone returns* in table 10, where the estimates of β represent the marginal effect of deviations from the market benchmark.

The estimates of $\hat{\beta}$ in table 9 are too noisy and none of the estimates are statistically significant, the standard errors would likely be much smaller with a larger sample size and with a greater degree of variation between the subjects. The effect, although not statistically significant, of a one percentage point increase in experienced returns in the down and hiVar (or bad states) groups is much larger than in the up and lowVar (or good states) groups regardless of which weighting function is used on experienced returns. Two possible factors may lead to this results. First, subjects may be more aggressive in their subsequent allocations to stocks in the down group given that they on average under allocate to stocks relative to the up group. Second, subjects in the down group may be relatively more enticed to allocate to stocks when they receive a favorable signal about stocks than subjects in the up group. We can test the former claim formally by estimating a mixture model on the log difference of stock allocations for both groups. A mixture model is a natural way to model heterogeneity in a number of latent classes, in this case the latent class is groupings of $\ln(\frac{S_t}{S_{t-1}})$. It models the statistical distribution of $\boldsymbol{x_i}$ as a mixture, or weighted sum, of other distributions and takes the general form

$$g(\boldsymbol{x_i}) = \sum_{j=1}^{m} \omega_j \phi_j(\boldsymbol{x_i}) \tag{5}$$

where $\boldsymbol{\theta} = (\boldsymbol{\omega}, \boldsymbol{\phi})$ is the parameter vector to be estimated. The ω_j weights must sum to unity and the components of the $\boldsymbol{\phi}$ vector includes all distribution specific parameters. Given the latent nature of the model, I estimate $\hat{\boldsymbol{\theta}}$ with $j = 3$ normal distributions using the Expectation Maximization algorithm and report the results in table 11. The choice of 3 underlying groupings for $\ln(\frac{S_{it}}{S_{it-1}})$ is informed by simple observation of the sample histogram, which indicates that there are three main clusters for the data, in the center and at the who tails.

We can see in figure 4 that the estimation with $j = 3$ sub-distributions fits the data well for both the up and down groups. The three means for up and down treatments in table 11 are fairly close and centered at the middle and two tails of the distribution as expected. However, the biggest difference between up and down is the variance of the estimated distributions. As we hypothesized, there is evidence that the down group had a greater number of larger large changes in S_t, as is evident by the larger share, $\hat{\omega}$, of the tail distributions, and larger variance estimates, $\hat{\sigma}$, for each of the three distributions for the down group. A similar yet weaker structure is found when comparing the hiVar and lowVar groups as is indicated in the lower panels of table 11, which helps explain the large $\hat{\beta}$ estimates we get in the hiVar and down groups in table 7.

The estimates of β are also consistent across both weighting functions (top and bottom panels of table 9). There is a small marginal effect in the up treatment, which is supported by the small $\hat{\omega}$ estimates table 11 for the up group in the tail distributions. A possible explanation can be that subjects who were more likely to allocate to stocks as they had better experiences were already allocating to stocks as the experience was building, hence the marginal effect of an increase in experienced returns is small. It is hard to find an explanation for the negative estimates in the lowVar treatment.

Comparing the results for the two weighting function parameters in table 9 we can see that the estimates are over all much more noisy when using (3) than when using (4). In addition, the implied weighting function by the estimates do not always tell the same story. The weighting parameter estimates in the down, lowVar and full sample groups imply different weighting structures. For example, in the down group and in the full sample, the estimates when using (3) imply functions in which subjects weigh past observations more heavily, whereas, when using (4) the estimates are statistically significant and imply a weighting function that weighs recent observations more heavily. The opposite is the case for the low-Var group where the estimates for (3) imply larger weights on recent observations whereas the estimates for (4) imply larger weights on past observations; neither, however, is statistically significant. The estimates for (3) and (4) for the remaining groups imply weighting functions with similar shapes. The significance of the estimates for the full sample and down groups is likely mostly driven by the effect arising from experiencing the down states.

The estimates of $\hat{\beta}$ in table 10 point to a statistically significant effect of subjects' foregone returns on their subsequent asset allocation, however, the results only hold when estimating weighting function 3 in the top panel. The significance of foregone returns holds up only for the lowVar group when considering weighting function 4 in the lower panel. In general, none of the weighting function parameters are estimated with precision. The results indicate that subjects on average allocated more to the risky asset whenever they were able to outperform the benchmark (market return). The results are more evident in the down and lowVar group where the marginal effect is an increase of about 2% in allocation to the risky asset for a 1% increase in foregone returns. Comparing the results in tables 9 and 10 indicate the subjects are more affected by their relative performance to a benchmark rather than by the market state.

4.3 Conclusion and Discussion

This paper provides experimental evidence of the effect of experience in a financial setting on risk preferences. The experimental treatments assign subjects into five different market environments with the goal of isolating the effects of specific features of the market environment on subjects' risk taking behavior. We elicited subjects' risk aversion based on the Holt & Laury (2002) multiple price list before and after a portfolio allocation task in which subjects made a sequence of myopic (one-period) asset allocation decisions between a risk-free and a risky asset. Subjects were randomly assigned into one of five treatments characterized by a pair (μ, σ) defining the risky asset stochastic process in the portfolio allocation segment.

The results reveal a striking relationship between experience in the asset allocation segment and risk taking behavior. We study three measures of risk taking behavior, two arising from the H&L elicitation scheme and one from the portfolio allocation segment. We find that the effect of experience can be attributed primarily to extreme variation in the mean. The results show that subjects' risk preferences tend towards risk neutrality after experiencing extreme variation in the mean. In addition, the marginal effect of past experienced returns on asset allocation is driven by subjects' foregone returns rather than by the aggregate state of the market.

The implications of these findings are considerable and can be of extreme value for market participants and policy makers. It can also help explain why we experience spells of low returns and high volatility following negative shocks. The negative estimates for λ in the hiVar and down treatments indicates that agents are highly influenced by recent events in those states, so it's reasonable to expect that following an exogenous shock that drives returns lower, the subsequent behavior of agents will be much more influenced by the shock. In other words, this provides an explanation as to why large negative shocks lead to more persistent bouts of volatility and negative returns relative to positive shocks.

A promising direction for future research is to explore the degree of persistence in λ and γ. The results discussed above point to a large variation in the weighting function depending on the experienced states, and since real world experiences alternate between good and bad, it is reasonable to expect a distribution for λ and γ depending on the demographic structure and past experiences of the cross section of market participants.

Additionally, knowing the marginal propensity to allocate into risky assets conditional on the current market state can be of value for policy makers involved in the sale or purchase of any market security. For example, central banks operating in the foreign exchange, fixed income or equities market. However, it's reasonable to expect varying degrees of sensitivities in allocation depending on the specific market, which is an additional avenue for future research.

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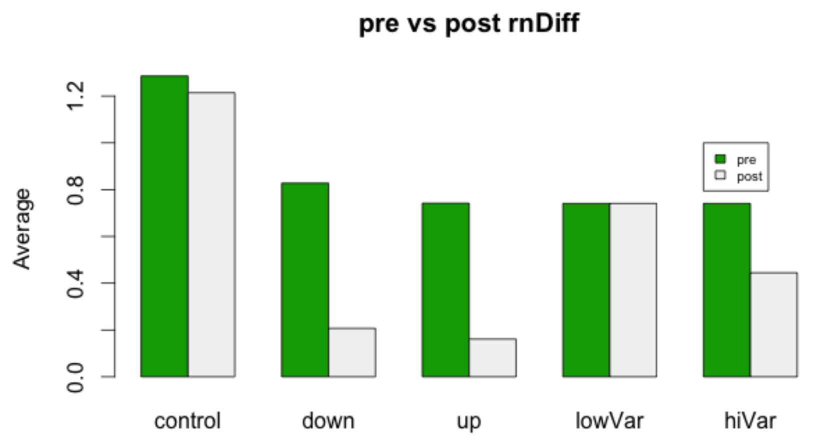


Figure 2

	rnDiff		$\hat{r}$		Market		Allocations		Portfolio Return	
Treatments	Pre	Post	Pre	Post	μ	σ	Stocks	Bonds	μ	σ
Control	1.28	1.21	0.525	0.641	0.03	0.03	44.5	55.4	0.02	0.01
Up	0.74	0.16	0.410	0.358	0.18	0.06	59.6	40.3	0.12	0.035
Down	0.82	0.20	0.589	0.335	-0.07	0.04	39.3	60.6	-0.02	0.013
lowVar	0.74	0.74	0.583	0.532	0.06	0.01	45.5	54.4	0.04	0.004
hiVar	0.74	0.44	0.593	0.466	0.03	0.19	52.5	47.4	0.03	0.086

Table 3: Summary statistics of all variables (averaged over all subject) in a given treatment. H&L pre and post correspond to the difference between the number of safe choices made from an expected value maxmizer, *rnDiff*.

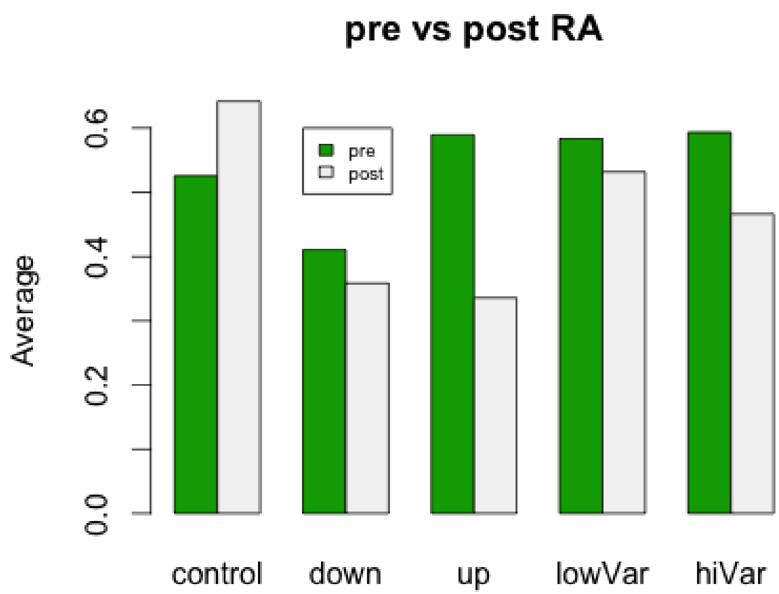


Figure 3

	t-test			Wilcoxon rank sum test	
Treatments	mean of diff.	df	p-value	W	p-value
Control	0.07	27	.85	192	.95
Up	0.58	30	.16	275*	.09
Down	0.62	28	.16	249	.28
lowVar	0	26	1	190.5	.98
hiVar	0.29	26	.57	169.5	.57
mean	0.6**	59	.04	1035**	.04
variance	.14	53	.66	703	.70

Table 4: Paired t-test and Wilcoxon signed rank test. Difference between *rnDiff* pre and post the portfolio allocation segment.

	t-test			Wilcoxon rank sum test	
Treatments	mean of diff.	df	p-value	W	p-value
Control	-0.13	23	.22	113	.30
Up	0.21***	18	.01	151**	.02
Down	0.06	20	.29	136	.48
lowVar	0.05	23	.47	178	.43
hiVar	0.003	17	.99	90	.86
mean	0.13***	39	.00	569**	.03
variance	.02	41	.56	510	.46

Table 5: Paired t-test and Wilcoxon signed rank test. Difference between *raMean* pre and post the portfolio allocation segment.

	rnDiff		$\hat{r}$		ΔrnDiff		$\Delta\hat{r}$	
	t-test	Wilcox	t-test	Wilcox	t-test	Wilcox	t-test	Wilcox
Up	-1.05***	609***	-0.31**	396**	-0.51	509	-0.34***	332***
	(0.00)	(0.00)	(0.03)	(0.05)	(0.36)	(0.25)	(0.01)	(0.01)
Down	-1.01**	543**	-0.29**	405**	-.55	452	-0.19	311
	(0.01)	(0.02)	(0.03)	(0.03)	(0.34)	(0.45)	(0.11)	(0.18)
lowVar	-0.47	452	-0.11	375	0.07	375	-0.18	357
	(0.20)	(0.20)	(0.29)	(0.22)	(0.94)	(0.97)	(0.15)	(0.15)
hiVar	-0.77	474*	-0.18	388	-0.22	389	-0.13	253
	(0.11)	(0.10)	(0.21)	(0.16)	(0.72)	(0.85)	(0.31)	(0.35)
mean	-1.03***	1152***	-.30***	801**	-0.53	961	-0.26**	643**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.28)	(0.27)	(0.02)	(0.02)
variance	-0.62*	926*	-0.14	713	-0.07	746	-0.15	610
	(0.08)	(0.08)	(0.16)	(0.12)	(0.88)	(0.93)	(0.17)	(0.15)

Table 6: Two sample t-test and Wilcoxon rank sum test on subjects' risk scores in the treatment groups minus the control group. p-values reported in parentheses

Table 7

	Dependent variable: $ln(S_t/S_{t-1})$			
	$\hat{r}$		$\Delta\hat{r}$	
	(1)	(2)	(3)	(4)
pre	0.524^{***}	0.540^{***}		
	(0.070)	(0.071)		
down	-0.228^{**}	-0.222^{**}	-0.204^{*}	-0.193^{*}
	(0.094)	(0.094)	(0.114)	(0.112)
up	-0.277^{***}	-0.277^{***}	-0.348^{***}	-0.344^{***}
	(0.098)	(0.097)	(0.117)	(0.115)
lowVar	-0.159^{*}	-0.156^{*}	-0.186^{*}	-0.179
	(0.091)	(0.091)	(0.110)	(0.108)
hiVar	-0.107	-0.108	-0.135	-0.135
	(0.099)	(0.098)	(0.119)	(0.117)
MPLaPre		0.077		0.150^{**}
		(0.062)		(0.073)
Constant	0.385^{***}	0.338^{***}	0.134^{*}	0.059
	(0.074)	(0.083)	(0.078)	(0.085)
Observations	106	106	106	106
R^2	0.392	0.402	0.085	0.122
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 8

	Dependent variable:ln(S_t/S_{t-1})					
	rnDiff			Δ rnDiff		
	(1)	(2)	(3)	(4)	(5)	(6)
pre	0.102	0.455***	0.440***			
	(0.072)	(0.071)	(0.072)			
down	−0.961**	−0.760**	−0.772**	−0.549	−0.490	−0.583
	(0.425)	(0.345)	(0.333)	(0.620)	(0.409)	(0.400)
up	−0.997**	−0.695**	−0.579*	−0.509	−0.342	−0.365
	(0.419)	(0.341)	(0.333)	(0.610)	(0.403)	(0.399)
lowVar	−0.418	−0.183	−0.225	0.071	0.136	0.083
	(0.433)	(0.352)	(0.339)	(0.631)	(0.417)	(0.405)
hiVar	−0.714	−0.480	−0.399	−0.225	−0.161	−0.190
	(0.433)	(0.352)	(0.341)	(0.631)	(0.417)	(0.409)
MPLaPre		2.277***	2.216***		3.465***	3.441***
		(0.268)	(0.262)		(0.260)	(0.252)
multicrossPre			−1.217***			−0.969**
			(0.341)			(0.408)
multicrossPost			0.932**			1.404***
			(0.368)			(0.437)
Constant	1.083***	−0.509	−0.396	−0.071	−1.804***	−1.788***
	(0.316)	(0.317)	(0.315)	(0.442)	(0.320)	(0.312)
Observations	142	142	142	142	142	142
R^2	0.072	0.395	0.449	0.012	0.572	0.603
Note:						*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:ln(S_t/S_{t-1})				
$\Delta expM$	full	down	up	lowVar	hiVar
$\hat{\beta}$	4.28	13.75	0.28	−1.39	18.33
	(5.06)	(19.59)	(0.37)	(1.64)	(21.42)
$\hat{\lambda}$	−0.16	−0.028	31.21	11.13	−1.88*
	(1.55)	(2.32)	(119.97)	(19.44)	(1.1)
$\hat{\beta}$	2.56	9.56	0.34	−5.98	21.40
	(1.82)	(5.21)	(0.63)	(6.51)	(17.39)
$\hat{\gamma}$	0.83***	0.85***	0.17	1.08*	3.77
	(0.18)	(0.21)	(1.11)	(0.64)	(2.96)
Obs	2525	491	558	486	486
Note:			*p<0.1; **p<0.05; ***p<0.01		

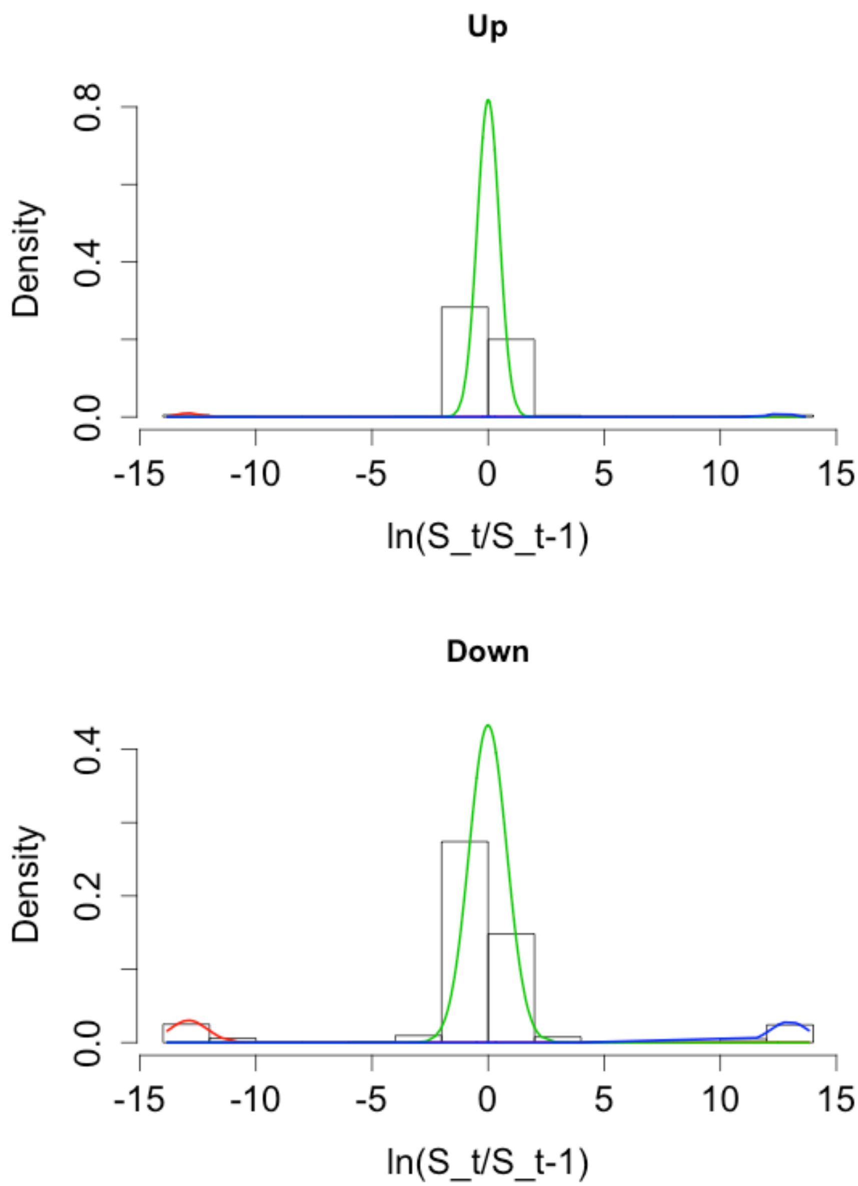
Table 9: Nonlinear least squares estimates of experienced market returns on change in allocation to risky asset. Standard errors in parenthese are clustered at subject level.

	Dependent variable:ln(S_t/S_{t-1})				
Foregone Return	full	down	up	lowVar	hiVar
$\hat{\beta}$	1.28***	2.47*	-0.15	2.32***	1.43
	(0.5)	(1.29)	(0.19)	(0.77)	(0.84)
$\hat{\lambda}$	65.4	33.31	-1.79	13.28	12.74
	(352)	(82.75)	(25.09)	(22.30)	(18.4)
$\hat{\beta}$	-0.36	-0.60	-0.52	2.99***	1.20
	(0.30)	(0.488)	(0.54)	(1.11)	(0.71)
$\hat{\gamma}$	1.79	1.64	1.60	0.30	0.12
	(4.07)	(12.85)	(2.33)	(0.43)	(0.60)
Obs	2525	491	558	486	486
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 10: Nonlinear least squares estimates of experienced foregone returns on change in allocation to risky asset. Standard errors in parenthese are clustered at subject level.

Parameter		$\hat{\omega}$	$\hat{\mu}$	$\hat{\sigma}$
	(1)	0.01	-12.66	0.67
up	(2)	0.97	0.01	0.67
	(3)	0.01	12.14	0.67
	(1)	0.02	-12.51	0.72
down	(2)	0.95	0.01	0.72
	(3)	0.02	12.5	0.72
	(1)	0.01	-12.66	0.67
lowVar	(2)	0.97	0.01	0.67
	(3)	0.01	12.14	0.67
	(1)	0.02	-12.51	0.72
hiVar	(2)	0.95	0.01	0.72
	(3)	0.02	12.5	0.72

Table 11: Estimates from a mixture of normals model for $\ln(\frac{S_t}{S_{t-1}})$ with $j = 1, 2, 3$ sub-groups. $\hat{\omega}$ is the fraction of the sample in group j, $hat\mu$ and $\hat{\sigma}$ are the mean and variance of group j



Up
Density
0.0
0.4
0.8
-15
-10
-5
0
5
10
15
ln(S_t/S_t-1)
Down
Density
0.0
0.2
0.4
-15
-10
-5
0
5
10
15
ln(S_t/S_t-1)

Figure 4

Figure 5: Portfolio Allocation Task