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ESSAYS ON RISK AND UNCERTAINTY

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by

Sameh Habib

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Abstract

Essays on Risk and Uncertainty

by

Sameh Habib

Economic models require a formal treatment for individual preferences and expectations. Preferences are often assumed to be stable (and measurable) while expectations of the future are perfectly rational. Empirically, however, there is little evidence for stability of preferences or perfect rationality of expectations. This dissertation assesses the causes and consequences of these phenomena. The first two chapters identify novel channels leading to instability of revealed preferences in laboratory and field experiments, and the third chapter assesses the consequences of expectation bias on the outcome of policy in a general equilibrium model. Motivated by the extreme events of the financial crisis, the first chapter explores conditions under which preferences may become unstable, or more specifically, are revealed to be more or less risk-averse in response to extreme events. The results support existing literature showing that extreme events can have an economically and statistically significant effect on revealed risk aversion. The chapter 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, suggesting that agents' performance relative to a benchmark is what matters in shaping expectations. The second chapter, co-authored with Brian Giera and Biruk Tekele, focuses on risk-taking decisions of Micro-enterprises in developing countries, whose small businesses are known to exhibit high marginal rates of return to investment, but then owners fail to reinvest earned income back into their business to capture these unexploited profits. Recent studies have focused on behavioral biases as an explanation for this behavior, with an attention on mental accounting and loss aversion which could be dampening shop owners ability to grow as their aversion to loss and narrow temporal bracketing lead to under-investment in risky products. Using data from a lab-in-the-field experiment with micro-entrepreneurs in Ethiopia, we first replicate Gneezy & Potters (1997) and find that our sample does not display any myopic loss averse tendencies when bracketing temporally. We extend their experiment by allowing subjects to invest in a cross-sectionally framed set of assets with equivalent payoff and risk structure as the original temporally framed experiment. In our cross-sectional treatments we find a 46% increase in the amount allocated to the risky asset, suggesting that attitudes towards risk allocations could be affected by adjusting the perceived investment frame. Finally, the third chapter assesses the importance of expectation bias in quantifying the effects of macroeconomic policy outcomes. First, I explore the relationship between expectation bias and monetary policy shocks and find that during the post financial crisis period, monetary surprises have a significant effect on expectation bias, which I construct structurally and estimate using option prices on the S&P 500 Index. I then explore the effect of this induced change in expectation bias on the outcome of monetary policy in a general equilibrium theoretical model. The model results show that the effect of monetary policy on aggregate outcomes is highly sensitive to the policy's induced effect on expectations. If monetary tightening causes a decrease in optimism then monetary authorities can do more with less, i.e. achieve a greater effect from a one-percentage point increase in the interest rate relative to the rational expectations equilibrium. The opposite is true if tightening causes an increase in optimism.

To my family,

for their never-ending love and support.

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Chapter 1

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

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.*

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

(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

[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 follow-up 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.

1.1 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.

1.1.1 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' responses 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 procedure 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 follow-up risk preference score.

1.1.2 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 volatility of a stock. Malmendier & Nagel (2009) is perhaps the most influential 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.* (2014a) 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.* (2014a) 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.

1.2 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 1.1: (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 follow-up (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 1.1 and 1.2 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

		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 1.2: (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 $U(x) = \frac{x^{1-r}}{1-r}$.

portfolio allocation segment; portfolio returns for each round are independent and are not cumulative. The experiment, therefore, is a portfolio 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.

Subjects 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 possible groups.

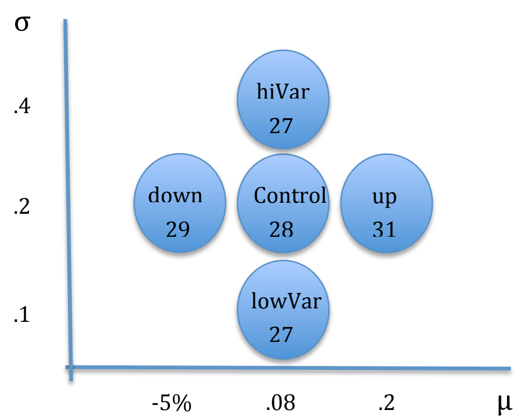


Figure 1.1: Treatment groups

Figure 1.1 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 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 (1.1) according to the specified μ and σ indicated on the figure.

$$\frac{dS}{S} = \mu dt + \sigma dz \tag{1.1}$$

The portfolio allocation segment is demonstrated in figure 1.5. 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, subjects 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.

1.3 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 1.3 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 subjects 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 indicate that the treatments were in fact experienced.

1.3.1 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 $\hat{r}$.

1.3.1.1 Mean Difference Tests

Figures 1.2 and 1.3 provide a visual perspective of the H&L results summarized in table 1.3. 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 1.3 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 1.2

Given the fact that a subject's risk preference is measured pre and post the treatment, paired mean difference tests are possible. Table 1.4 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 1.5 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 are again statistically significant with an even smaller standard error.

Comparing post *rnDiff* scores across groups provide a clear comparison across treatments. Table 1.6 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 follow-up 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 $\Delta rnDiff$ and $\Delta\hat{r}$, where $\Delta = post - pre$. There is no significance for $\Delta rnDiff$ 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.

1.3.1.2 OLS Regressions

Column (1) of tables 1.3.3 and 1.3.3 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 1.3.3, and .2 closer to risk neutrality in table 1.3.3. Column (3) of table 1.3.3 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 1.3.3.

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 1.3.3 and 1.3.3 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 1.3.3.

Although there appears to be a large effect coming from the baseline MPL, quantitatively the results change very little. In table 1.3.3 the coefficients change from -0.9 to about -0.7 for the mean treatments, whereas the results for $\hat{r}$ in table 1.3.3 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.

1.3.2 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

$$y_{it} = \beta x_{it}(v) + u_{it}, \text{ for } v = \lambda, \gamma \tag{1.2}$$

$$x_{it}(\lambda) = \sum_{k=1}^{age_{it}-1} w_{it}(k,\lambda) R_{t-k}, \text{ where } w_{it} = \frac{(age_{it}-k)^{\lambda}}{\sum_{k=1}^{age_{it}-1}(age_{it}-k)^{\lambda}} \tag{1.3}$$

$$x_{it}(\gamma) = \frac{R_{t-1} + \sum_{k=1}^{age_{it}-2} \gamma^k R_{t-1-k}}{1 + \sum_{k=1}^{age_{it}-2} \gamma^k} \tag{1.4}$$

where y_{it} is the log difference of allocation to stocks in round/age t and x_{it} is either

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

the differenced experienced past returns, *expM*, at each round/age t, or the subject's *Foregone Return*, each calculated according to equations 1.3 or 1.4.

The weighting functions in equations 1.3 and 1.4 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 1.3 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 1.4 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 1.4 is in the summation and the value of the additional term from and additional observation, unlike in 1.3 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 1.2 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 1.9 and 1.10. The dependent variable in table 1.9 is simply the first difference of the simulated treatment series, whereas in table 1.10 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 1.9 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 1.9 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 1.10, where the estimates of β represent the marginal effect of deviations from the market benchmark.

The estimates of $\hat{\beta}$ in table 1.9 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 these 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

$$g(\boldsymbol{x_i}) = \sum_{j=1}^{m} \omega_j \phi_j(\boldsymbol{x_i}) \tag{1.5}$$

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 1.11. 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 1.4 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 1.11 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 1.11, which helps explain the large $\hat{\beta}$ estimates we get in the hiVar and down groups in table 1.3.3.

The estimates of β are also consistent across both weighting functions (top and bottom panels of table 1.9). There is a small marginal effect in the up treatment, which is supported by the small $\hat{\omega}$ estimates table 1.11 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 1.9 we can see that the estimates are over all much more noisy when using (1.3) than when using (1.4). In addition, the implied weighting function by the estimates does 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 (1.3) imply functions in which subjects weigh past observations more heavily, whereas, when using (1.4) the estimates are statistically significant and imply a weighting function that weighs recent observations more heavily. The opposite is the case for the lowVar group where the estimates for (1.3) imply larger weights on recent observations whereas the estimates for (1.4) imply larger weights on past observations; neither, however, is statistically significant. The estimates for (1.3) and (1.4) 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 1.10 point to a statistically significant effect of subjects' foregone returns on their subsequent asset allocation, however, the results only hold when estimating weighting function 1.3 in the top panel. The significance of foregone returns holds up only for the lowVar group when considering weighting function 1.4 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 1.9 and 1.10 indicate the subjects are more affected by their relative performance to a benchmark rather than by the market state.

1.3.3 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.

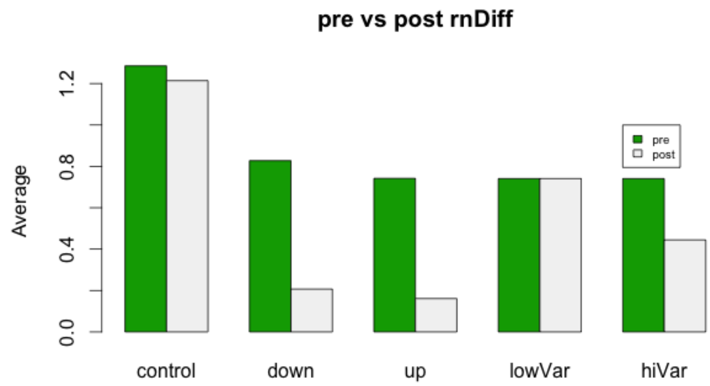


Figure 1.2: Average distance (in terms of number of lines in the MPL) away from risk-neutrality across treatment groups

	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 1.3: 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*.

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

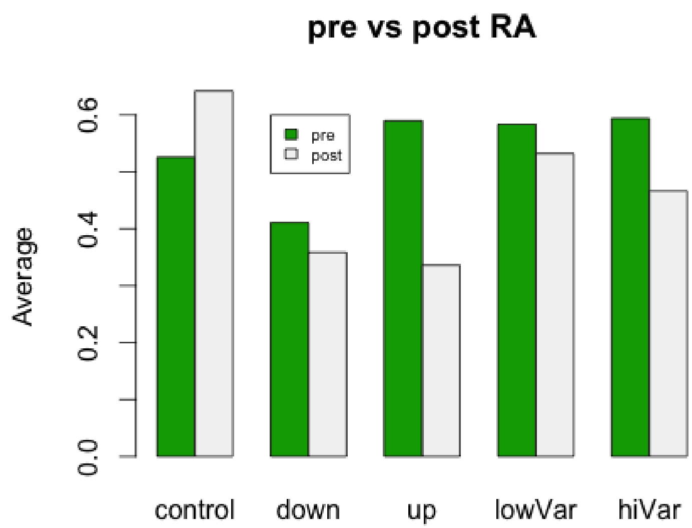


Figure 1.3: Average distance (in terms of estimates risk aversion) away from risk-neutrality across treatment groups

	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 1.5: 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 1.6: 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

	$\hat{r}$		$\Delta\hat{r}$	
	(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 1.7: OLS estimates of the treatment effects (relative to the control group) on estimated risk aversion

	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		

Table 1.8: OLS estimates of the treatment effects (relative to the control group) on distance away from risk neutrality

	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 1.9: Nonlinear least squares estimates of experienced market returns on change in allocation to risky asset. Standard errors in parentheses 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 1.10: Nonlinear least squares estimates of experienced foregone returns on change in allocation to risky asset. Standard errors in parentheses 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 1.11: 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

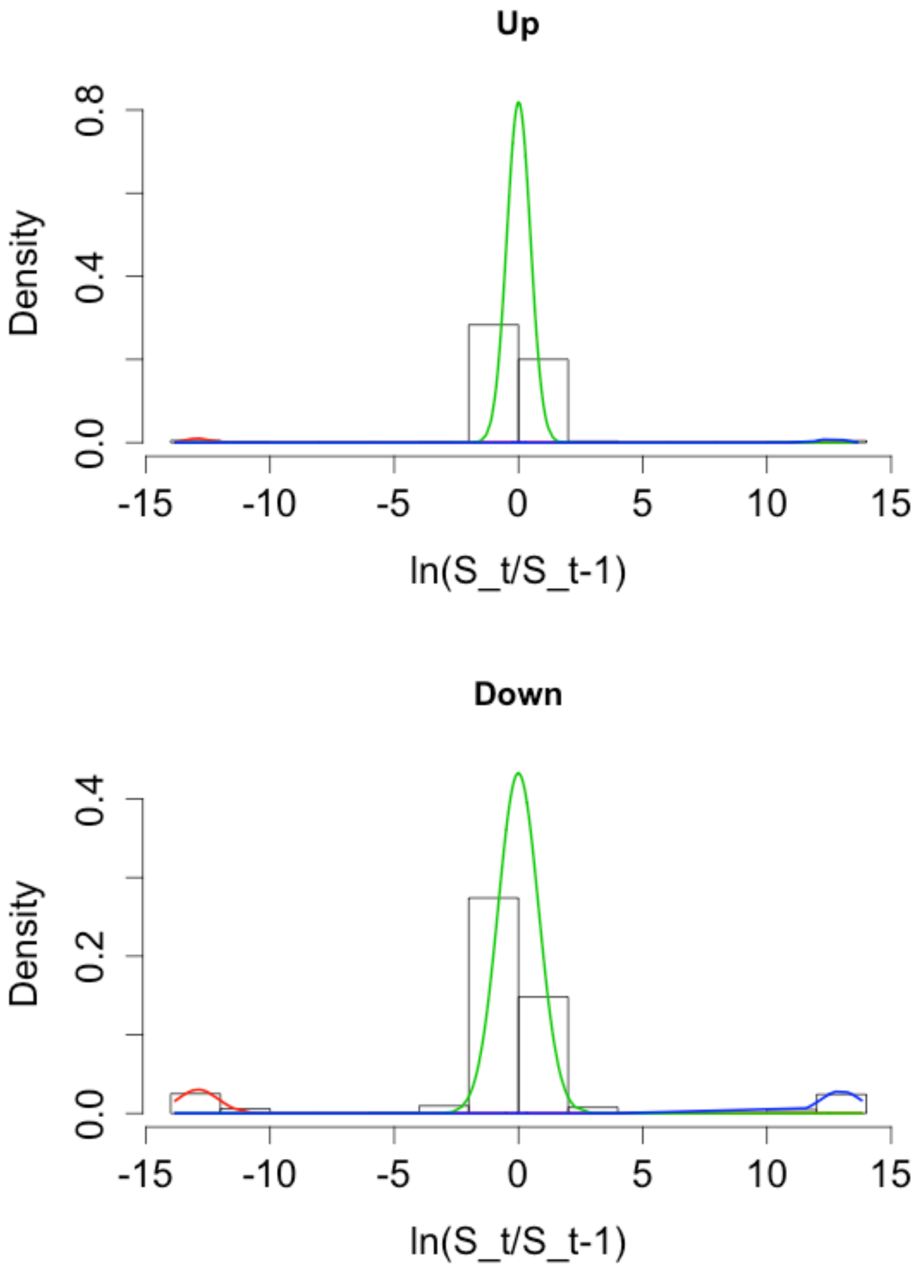


Figure 1.4: Mixture distribution estimates.

Figure 1.5: Portfolio Allocation Task

Chapter 2

Myopic Loss Aversion Across Time and Space: Evidence from an Experiment with Micro-Entrepreneurs in Ethiopia.

co-authored with Brian Giera and Biruk Tekele.

Hundreds of millions of people are engaged in some form of self-employed, micro-entrepreneurial activity (World Bank, 2010). Many studies find that these businesses are leaving profitable investments on the table, ranging from 5-20% per month (De Mel *et al.* , 2008; Udry & Anagol, 2006; McKenzie & Woodruff, 2008; Banerjee & Duflo, 2008; Fafchamps *et al.* , 2014; Beaman *et al.* , 2014; Kremer *et al.* , 2015). Why do these returns persist? Two common explanations are lack of credit and/or human capital, yet interventions find no consistent effect had on the growth or profitability of the business.[1]. Similar to this problem, investors in the US were shown to underinvest in risky assets leading to a previously unexplained puzzle regarding the premium paid on equities (Mehra & Prescott, 1985). People and firms were shown to display "Myopic Loss Averse" tendencies, which means they were bracketing too narrowly (short-sighted/myopic) along with being averse to a loss in that narrow bracket. This is shown to lead to an over-investment into safe assets, explaining the presence of a premium on stocks compared to bonds (Benartzi & Thaler, 1995). In development economics, recent field experiments have tried to connect loss aversion with a host of puzzles: (1) why injections of capital yield high estimated returns, why they are never spent down over time nor lead to substantial capital accumulation; (2) why many firm owners do not take advantage of microfinance despite the high unrealized returns to investment; (3) why many that do borrow do not invest in their business; (4) why weather insurance programs stimulate investment by farmers; and (5) why business training based on simple heuristics can induce firm owners to change their behavior (Kremer *et al.* , 2015; Drexler *et al.* , 2014; Beaman *et al.* , 2014; Blumberg & Kremer, 2014). Our first goal is to replicate the experimental results of Gneezy & Potters (1997) (henceforth GP(97)) but in the setting of small-shop owners in Addis Ababa, Ethiopia, allowing us to answer the question: Do we find evidence that the underinvestment by small firms in Sub-Saharan Africa can be explained by Myopic Loss Aversion? The initial problem we anticipate,

[1] See De Mel *et al.* (2008); Udry & Anagol (2006); McKenzie & Woodruff (2008); Banerjee & Duflo (2008); Fafchamps *et al.* (2014); Banerjee *et al.* (2015); Augsburg *et al.* (2015); Angelucci *et al.* (2015); Crépon *et al.* (2015) for recent studies on credit and microfinance, and McKenzie & Woodruff (2013) for a review on the effects from business training.

based off of prior research and pilot studies, is that firms are not able to diversify too far into the future. Most of the shops calculate profit on a weekly or monthly level, and rarely do they make investments that don't pay off in the immediate future; thus they are not able to spread risk across time relative to those in the developed world. Also, we found that the distributors our sample works with all offer bulk discounts *within* products, but never *across* products; meaning their distribution system is set up in a way that discourages taking risk across products, and instead discourages diversification. Thus, our second goal was to extend GP(97) to see if firms would allocate more risk to a portfolio of gambles framed cross-sectionally, compared to a portfolio of gambles framed across time. This allows us to answer the question: Can underinvestment in risky products change based on the dimension we ask the shop-owner to bracket across? To answer these two questions, we designed a lab-in-the-field experiment in urban Ethiopia in which we randomly varied the product and time dimension of the classic loss aversion investment game (GP(97)). We first manipulated the temporal dimension, where one group decided and then evaluated their decision each period for 12 periods, and the other group decided and evaluated their decision after three periods, for 12 periods. This second group was the "Low Frequency" group who had their risky allocation locked in for 3 periods. Next, we altered the cross-sectional dimension by having one group decide between the safe and risky asset, while the other group had to allocate the same endowment between 1 safe and a basket/portfolio of 3 identical and independent risky investments. These two treatments were crosscut to look for differential effects when both dimensions promoted wide bracketing. Our main outcomes of interest are

(1) amount allocated to the initial risky allocation decision; (2) amount allocated to the average risky allocation decision; and (3) amount allocated to the final risky allocation decision. We compare the three treatments (high frequency, portfolio, high*portfolio) to the control group who looked across multiple periods (low frequency) but for one product (individual). The sample is composed of 199 micro-entrepreneurs scattered across two sub cities of Addis Ababa, working exclusively in the small-scale retail sector. We use two main sources of data: each respondent conducted a baseline survey that collected household demographics, shop information, and behavioral parameters; then after the survey was complete, we played the game. The game was incentivized, with the average payout of 83 birr ($4) relative to average daily profit for our sample of 40 birr ($2). Thus, our payouts were on average, equal to two days of work. We have three main results, with the first two contained in table **??**: (1) We were not able to replicate the findings in GP(97) to support the idea that micro-entrepreneurs in SSA are myopically loss averse when looking across time. GP(97) show that looking further across time (wider temporal bracket) will lead to higher amounts of money put into the risky allocation as the chance of being in the loss domain at the time of evaluation will be lower since the probability is smoothed across the periods of time. Thus, we should expect to see the high-frequency group put more money into the safe asset, which we do not see. The difference is marginally positive and indistinguishable from zero. Further proving how the temporal channel doesn't work in our context, we see no interactive effect for the group that could diversify temporally and cross-sectionally. This tells us that the portfolio/cross-sectional channel dominated the temporal channel when the shop decides

how much risk to take on. This could be due to the fact that attention is zero-sum, and so an increase in attention along the cross-sectional margin might crowd out their ability to also focus on the temporal margin (Banerjee & Mullainathan, 2008). Second, we do find that small shop-owners would prefer to look cross-sectionally across a portfolio of products, leading to a 45% increase in the amount allocated towards the risky asset. Those that have access to the portfolio treatment, regardless of if they look across time or space, systemically put more of their endowment into the risky portfolio. We find the effect is robust to the period of the game we look at, as the effect starts in the first period and is consistent with all periods played. While we find evidence that our average firm is using the heuristic "rule of $1/n$" (DeMiguel *et al.* , 2009), we still see a normal distribution around the average, suggesting that firms are not collapsing to this rule and are instead making carefully optimized choices. Third, the owner's gender does not play a role in their allocation of capital towards risk and safe investments, suggesting that male and female owners have similar attitudes towards risk. In fact, our data tells us that men and women have similar risk preferences, reap similar levels of profit, but women have significantly lower inventories. This could mean that women are more careful about the products they pick (along the intensive margin of investment) while men are more concerned with increasing inventory (along the extensive margin of investment). This result is in line with De Mel *et al.* (2009a) who find that women were not reinvesting capital shocks into their business, suggesting that they have already hit their optimal allocation, leaving fewer "low hanging fruit" to be picked. There are a few limitations to this study that we need to address: First, we initially tried to conduct this experiment in the lab, but low turnout caused us to shift gears and conduct the games at the shop-owners location. This means we have a little more heterogeneity in administration as we had 3 enumerators conducting the surveys and games. Second, the decisions we present are not fundamentally the same: we were careful to make sure that the Sharpe ratio was consistent across two groups (High & Individual, vs., Low & Portfolio), but the other treatments have different risk-adjusted returns, which make the inference on behavior biased. Third, literacy and financial literacy are notoriously low in these settings. Therefore, given the complex risk and time questions, there is a chance that some things were not entirely understood. However, we feel this should affect all groups equally and thus any confusion would get differenced out. The fact that we have such stark results across multiple specifications tell us that something is going on here. We also have a number of concerns regarding the applicability of MLA in our context: (1) it is nearly impossible to prevent a shop owner from realizing his profit on a frequent basis in reality; (2) they are purchasing items with limited capital, which means the return (and subsequent evaluation of the investment) can only be calculated when the product is gone. So it could be that the existing capital constraints force an evaluation period that is quicker than ideal. (3) Diversification could have an impact on the investments return: in the presence of capital constraints, one might be forced to purchase smaller amounts of each product, thus falling below the threshold for bulk discounts which in turn further lowers the expected ROI. Finally, this could be over-simplifying the bracketing that occurs, and in fact, shops could have different bracket widths for different products. In conclusion, we present findings that micro-entrepreneurs in Ethiopia are not suffering from Myopic Loss Aversion when they look to diversify time. When we frame their inventory investments cross-sectionally, as a diversified portfolio of products, we find that adopting a wide cross-sectional bracket leads to 46% more capital allocated to risky investments. This suggests that interventions focused on framing could mitigate under-investment into risky assets, which could possibly help draw down the high marginal returns to investment into their shop. Finally, we see no differential effects by gender in terms of risk or profit, with men having significantly larger stocks of inventory, suggesting that women may be relatively more attentive to the marginal profit of each item stock as they reap the same profits with 20% smaller inventories.

2.1 Experimental Design

2.1.1 Background of Micro-Entrepreneurs in Addis Ababa

As of the 2012 census, Addis Ababa was the 10^{th} largest city in Africa with 3.4 million people. Ethiopia is one of the fasting growing countries on earth, with the World Bank recording 10.9% annual GDP growth from 2004-2014. But despite the high recent growth, it remains one of the poorest countries in the world with a GDP per capita of $550, putting it at 174^{th} out of 188 countries with a Human Development Index. Many of the micro-entrepreneurs in Addis Ababa are near the poverty line and face difficult market conditions, as found from a census we conducted with 1215 small business owners around the city. There is high competition is the marketplace as the average firm has 5 nearly identical shops within a 5-minute walk. They do not have hired employees with 80% of shops unable to employ anyone, and 54% not receiving any family help running the business. They do not own the physical space as 71% are renting the space where the shop is located, with 7% admitting to squatting on the land and not paying rent. Finally, they work very long hours with the average owner working 10-11 hours per day. Owners also face challenges at the shop where they are forced to make complex financial decisions on a daily basis, while possibly lacking the knowledge and training to make them. Three-quarters report a stockout in the previous month, 88% have never used a bulk discount when placing orders, 7% pick products based on highest marginal profit/expected return, and 79% base it off of what is easiest to get or has the highest expected turnover. Around one-quarter (26%) of sampled firms report ever keeping records of their business, with 8% doing it consistently. In terms of account separation, 37% have ever separated their business from household money, while always engaging in this activity (18%). People do not report seeking help with their problems: 8% actively talk with customers about products they want to buy, issues they have had in the past, or satisfaction with their purchase. Only 7% report regularly talking to other shops selling (providing) similar goods (services) about specific business practices, products, or strategies. Still, there seems to be a strong desire to learn more effective techniques as 93% feel a business training would be very beneficial, with 31% have ever attended one; among those that attended, 38% admit to not paying attention or forgetting the material covered, backing up the idea that the current method of training is not working for everyone. Besides lacking access to managerial capital, respondents are reporting that they are heavily constrained in their access to physical capital. The traditional method to accumulate working capital comes from external sources. Around one-quarter have an outstanding loan at baseline (mean loan amount of \$1300, median of \$700), with only 3 people getting finance through a bank.[2] The rest rely on microfinance institutions, family/friends, or local moneylenders. Unsurprisingly, this does not come close to the amount of money they would like to borrow. We asked them to think about how much they would use for different reasons (various business and household investments) in hopes of getting a realistic estimate: the mean amount demanded was \$6000 and the median amount was \$2300 — more than double their current level of inventory. Despite the lack of capital coming from banks, 40% of shops are able to access credit on an order placed with one of their distributors, while the remaining rely on private savings to expand their business. Even though there is a high percentage of small shops that have formal savings accounts (89%)[3] almost every business owner in our sample wants to be saving more (90%). Thus, people take-up informal savings devices to help achieve their goal. At baseline, 41% of our sample was involved in an IQUB (Ethiopian equivalent of a ROSCA), with 80% of these groups geared towards business savings. Through semi-structured interviews, we discovered a small number of people (20 firms) utilize novel savings lock boxes, called "Muday" in the main language, Amharic, to store money and

[2]This aligns with Abebe et al (2016) where 2 out of 426 micro-entrepreneurs around Addis Ababa had received a loan from a bank.

[3]Overall, access to formal banking among micro-entrepreneurs is not a large problem in Addis Ababa, specifically. The state-run Commercial Bank of Ethiopia (CBE) has 120 of its total 900 branches in the capital of Addis Ababa. There are other banks also with branches spread out around Addis: Dashen, Oromia, Awash, and NIB, just to name a few, however, there are no international banks operating in Ethiopia at this time. Besides banking, the CBE has started offering subsidized mortgages where interested parties have to open a CBE Mortgage Savings Account with the bank, out of which deposits cannot be withdrawn. This has led to a large increase in participation with formal banking among people in Addis.

overcome issues of self-control.[4] At the end of the day, a majority of firms (76%) take their working capital home, where the external pressure to share and internal pressure to over-consume lower the amount of money available for the business the following day. Over half of our shop owners (53%) feel strong pressure to share earned income with family members living outside the household, while 32% feel pressure to share money with neighbors (not immediate family, but living nearby). Overall, 60% of our sample told us it is difficult to save profit to reinvest later, suggesting that they leave for work the following day with less than they had planned.

2.1.2 Game #1: Temporal

The individual is confronted with a sequence of 3 independent but identical lotteries, with the following payoffs:

$$\begin{cases} Pr(Lose\ \ \$1) = 2/3 \\ \\ Pr(Win\ \ \$2.50) = 1/3 \end{cases} \tag{2.1}$$

Subjects were confronted with a sequence of twelve identical but independent rounds of this lottery. In each of the first 9 rounds (part 1), the subjects were endowed with 13 birr.[5] They then decide which part of this endowment (X_t) they wanted to bet in the lottery ($0 \leq X_t \leq 13, \quad t = 1, ..., 9$). With 2/3 probability, they will lose the

[4]This is similar to the SEED program in Ashraf *et al.* (2006), and to Dupas & Robinson (2013b) where they randomly provide informal savings boxes, "lockboxes", to encourage earmarked savings for health.

[5]At the time of the experiment, March 2016, the exchange rate was \$1 = 21 Ethiopian birr. Thus, we endowed them with \$0.65 per round.

amount invested ($-X_t$), and with 1/3 probability, they win $2.5 * X_t$. In part 2 (rounds 10, 11, and 12) the subjects were no longer endowed with any additional money from the experimenters. Instead, they had to make bets from the money earned in part 1. Subjects earnings in the 9 rounds of part 1 were first totaled and divided by 3, giving us S_i ($0 \leq X_t \leq S_i, \quad t = 10, 11, 12$). We first have two different treatments: high (H1) and low (L1): First, high frequency (H1). Subjects randomized into this group played the rounds one by one. At the beginning of round 1, they decide X_t and then are informed of the lottery realization. Thus, those in group H1 make 9 decisions in part 1 and 3 decisions in part 2. Second, low frequency (L1). Subjects randomized into this group played the rounds in blocks of 3. So at the beginning of round 1, they decide X_t which will then we locked in for the first three periods ($X_1 = X_2 = X_3$, where $0 \leq X_t \leq 13$). They are informed of the combined realizations for rounds 1, 2, and 3, which means they cannot assign a gain or loss to any particular round and only knew the aggregate result. Thus, those in group L1 make 3 decisions in part 1 and 1 decision in part 2. What should happen? Well, we want to manipulate the evaluation period. Those in L1, with a lower frequency of both decisions but realizations, should evaluate the financial consequences of betting in a more aggregate way. If subjects are characterized by tendencies of myopic loss aversion, this should make them more likely to invest money into the lottery. We should find that those in L have higher X_t's compared to those in group H1. Subjects are fully informed about the objective probability of winning and losing, and about the corresponding size of gains and losses. Importantly, we did not allow them to bet any accumulated earnings from previous rounds.

2.1.3 Game #2: Cross-Sectional

Everything in the second component of this experiment is set up the same way as in Game #1 above. The only difference is that the risky asset is not one asset, and instead, the risky "asset" is a composition of three individual assets. Each of these individual components of the portfolio has the same probability and payoff as seen in 2.1, and are entirely independent of one another. The first group, high-portfolio (H3), makes the decision whether and how much to risk, as well as evaluates the decision, each and every period. At each period of time, the decision involves allocating a fraction of their endowment to the risky portfolio, which is then spread evenly across the three independent but identical investments. The outcome is then aggregated and realized so as to avoid the respondent attaching a win or loss to a specific product. The second group, low-portfolio (L3), makes their investment decisions every three periods, similar to L1. The difference between L3 and L1 is that the amount allocated to the risky asset will be equally split between each of the three independent but identical investments. When realized, the information is aggregated and presented as an overall return from the initial decision. Comparing these two groups, L3 and H3, to their individual counterpart, L1 and H1, those making a decision over the portfolio of choices will have the same expected value and lower variance, which should induce higher risk taking. Thus, we expect to find that

2.1.4 Procedure

First, we laid out a map of Addis Ababa and the 10 sub cities. We planned on working at the Addis Ababa University (AAU) School of Commerce, so we picked the two nearby sub cities to conduct our censoring. We found the main market centers in these two sub cities, which are also close to the main market of Addis, Merkato. These areas are also known to have a large number of small retail shops called "Goraghe Suuks" which are the intended respondent for this experiment. We conducted a short listing with 200 shop owners, 100 in each of the purposely selected sub cities, found using a random walk approach from the respective market center. After compiling our census, we randomized our sample into one of four groups (HH, HL, LH, LL). We initially wanted to have this done at a centralized location to avoid confusion of the game as well as take advantage of scale economies when it comes to more qualified instruction. So we invited them to one of the 4-day slots held at AAU with 4 2-hour slots each day. After the first two days of the experiment being held at AAU, we only had 40/100 people show up.[6] With such low turnout, we instead had a team of enumerators head to each of the sampled shops to conduct the experiment with them in person. We ended up with 199 micro-entrepreneurs in our sample. The survey and experiment were administered using tablets and Survey CTO software. For those who played the game in the classroom and in their shop, both were assisted by our trained enumerators to help use the tablets, if need be. Before starting the survey and the game, respondents were informed that it would take about

[6] Abebe *et al.* (2015) conduct an experiment at AAU with small shop owners and find a very similar rate of attendance.

1 hour. For those that participated in phase 1, which required them to close down their shop and travel to the classroom, we paid them 50 birr ($2.50) upon arrival. They were also informed of the chances that they would win, with the possible payouts ranging from 0-300 birr (max of $12). In practice, nobody walked out with less than 50 birr. Before officially starting the game, they were administered an electronic survey which had the various modules: basic demographics, shop performance and characteristics, risk and loss aversion, and cognitive function (through an IQ test). We then had an introduction to the game, including two trial games that would not be paid out and were intended to prepare them for the real periods. To further assist in the understanding, a laminated sheet was laid down with the respective gamble for that person. We placed the 13 birr in front of them, in 1 birr increments, and told them to decide how much of that endowment they want to put into the gamble.

2.2 Theoretical Prediction

We first start by looking at just the temporal case, with a utility function posed by TB95 that takes the form

$$U(x) = \begin{cases} x, \text{for } x \geq 0 \\ \\ \lambda x, \text{for } x < 0 \end{cases} \tag{2.2}$$

where x is the change in wealth and λ is the parameter measuring the degree of loss aversion. The expected utility for a person in high and low-frequency groups are:

- $EU_{H1}^{LA} = \frac{2}{3}\lambda(-1) + \frac{1}{3}2.5$, which is equal to zero for $\lambda_h = 1.25$.

- $EU_{L1}^{LA} = \frac{1}{27}7.5 + \frac{6}{27}4 + \frac{12}{27}0.5 + \frac{8}{27}\lambda(-3)$, which is equal to zero for $\lambda_{L1} = 1.56$.

Therefore, combining the lotteries makes the decision more attractive for an individual with a baseline $\lambda_{H1} = 1.25$, thereby inducing more risk taking in the low-frequency group. If, instead we assume the subject has CRRA preferences s.t.

$$U(x) = \frac{x^{1-\gamma}}{1-\gamma} \tag{2.3}$$

where x is wealth plus gross return from investing in the lottery, and γ is the coefficient of relative risk aversion, then, similar to Iturbe-Ormaetxe Kortajarene *et al.* (2015)

- $EU_{H1}^{CRRA} = \frac{2}{3}U(x_1) + \frac{1}{3}U(x_2)$

- $EU_{L1}^{CRRA} = \frac{1}{27}U(x_1) + \frac{6}{27}U(x_2) + \frac{12}{27}U(x_3) + \frac{8}{27}U(x_4)$.

To get a sense of the values of x (allocation to gamble from endowment) that maximize these expression, we take the FOC for EU_{H1}^{CRRA} and EU_{L1}^{CRRA} and plot x for different levels of $\gamma > 0$ Given equation 2.2, the problem for the high and low frequency 3 product groups now becomes

- $EU_{H3}^{LA} = \frac{1}{27}2.5 + \frac{6}{27}\frac{4}{3} + \frac{12}{27}\frac{1}{6} + \frac{8}{27}\lambda(-1)$, which is equal to zero for $\lambda_{H3} = 1.56$. Note that it is exactly the same as the $L1$ group.

- $EU_{L3}^{LA} = \sum_{g=i}^{7} p_i x_i + \sum_{l=j}^{3} \lambda p_j x_j$, which is equal to zero for $\lambda_{L3} = 2.11$. In this case we have 10 possible states (with many more possible outcomes) 3 of which are losses.

Figure 2.1: x on vertical axis and γ on horizontal axis

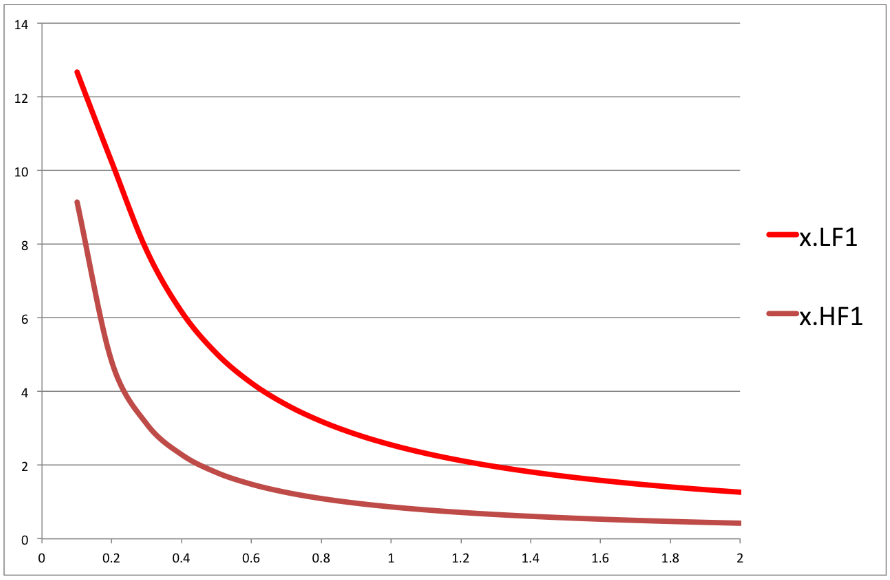


Figure 2.2: Outcome Spaces for Each Treatment Group. Bars in red represent losses.

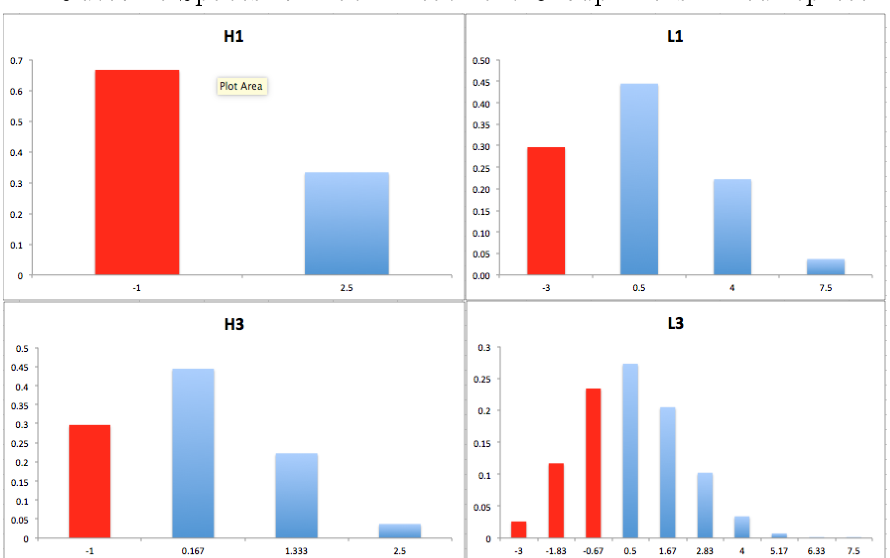
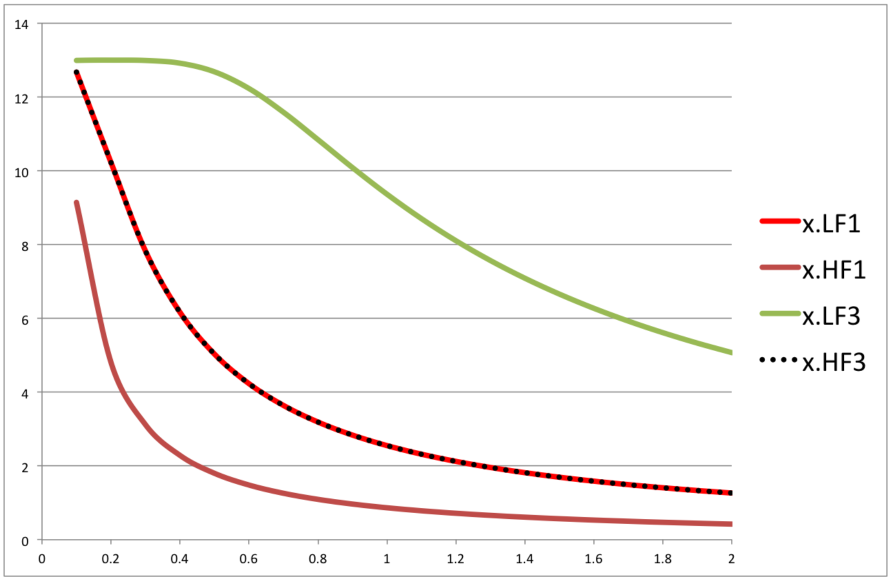


Figure 2.3: x (change in wealth) on vertical axis and γ (coefficient of relative risk aversion) on horizontal axis



Again the theoretical prediction here is that we should observe higher allocation to the risky asset in the $L3$ group relative to the $H3$ (and $L1$) group. Given equation 2.3, we have

- $EU^{CRRA}_{H3} = \frac{1}{27}U(x_1) + \frac{6}{27}U(x_2) + \frac{12}{27}U(x_3) + \frac{8}{27}U(x_4)$, and

- $EU^{CRRA}_{L3} = \sum_{s=i}^{10} p_i U(x_i)$.

Again we take the FOC for EU^{CRRA}_{H3} and EU^{CRRA}_{L3} and plot x for different levels of $\gamma > 0$

treatment	S_{LF}	S_{HF}	λ_{LF}	λ_{HF}
1 product	0.17	0.10	1.56	1.25
3 products	0.30	0.17	2.11	1.56

Table 2.1: Sharp ratios $S = \frac{EV_i}{\sigma_i}$, and loss aversion parameters λ for each treatment group. Note that the values are exactly the same for the H3 and L1 groups

2.3 Results

Our first main specification of interest just compares those in our sample to the results found in GP(97). The results from our replicated experiment can be found in Table 2.3. Column (1) compares two groups: those allowed to invest each round (high frequency) and those that invest across three periods (low frequency). According to GP(97), we should find a negative and significant coefficient. However, we find that our estimate is not only insignificantly different from zero, it actually has a positive point estimate. Therefore we do not find evidence that our sample of micro-entrepreneurs displays tendencies of myopic loss aversion, at least under the traditional definition involving temporal allocations. Column (2) adds a host of controls to the regression. Despite the theoretical implication from randomization that we do not need to control for any observable characteristics, we had a few baseline variables out of balance and would like to improve the precision of our estimates. Adding in the controls only increases the point estimate, slightly. Columns (3) and (4) take advantage of the experiments outcome of interest, which takes on a value from 0 to 1. This allows us to estimate a fractional response model and report the marginal effects. Here we see that the more basic OLS gives us very similar estimates, both in the bivariate and multivariate specification, to the fractional response model. To further assist in the understanding of what happened in the first part of the experiment, we look at the PDF and CDF's drawn in Figure 2.4. The left figure shows the PDF, while the right side shows the CDF plots of their final risk allocation. As we can see, there are no stark differences between these two distributions.

Table 2.2: Non-parametric Tests for Distributional Equality

Wilcoxon Signed-Rank Test	Variable	Kolmogorov - Smirnov Test			
		Low Frequency & Individual	High Frequency & Individual	Low Frequency & Portfolio	High Frequency & Portfolio
	Low Frequency & Individual	-	0.6750	0.0000	0.0000
	High Frequency & Individual	0.4810	-	0.0002	0.0009
	Low Frequency & Portfolio	0.0000	0.0000	-	0.8420
	High Frequency & Portfolio	0.0000	0.0001	0.5320	-

Table 2.2 performs two non-parametric tests for the equality of two distributions: The Kolmogorov-Smirnov test, and the Wilcoxon Signed-Rank test. We want to focus on the first column, second row, or the second column, first row, where both show us that the two distributions are not statistically different from one another.

Next, we look at the extension component of the project. Here we will look at the effect had on small business owner investment decisions when giving them the chance to diversify their investments across a portfolio of investments. Column (1) of Table 2.5 shows that given the chance to diversify risk across a portfolio of three independent but identical investments led to 45% (or 17.5pp) higher allocation to the riskier asset. Our estimate is also highly significant at even conservative significance levels. Controlling for a host of controls in column (2) once again slightly alters the point estimate (dropping from 17.5pp to 16pp, or from 45% down to 42%) but doesn't affect the statistical or economic significance. Column (3) shows the combined regression, provid-

Table 2.3: Treatment Effects on Risky Allocations – Temporally

	OLS		Fractional Response	
VARIABLES	(1) Allocation	(2) Allocation	(3) Allocation (ME)	(4) Allocation (ME)
High Frequency	0.0239	0.0281	0.0239	0.0277
	(0.0276)	(0.0288)	(0.0274)	(0.0274)
Constant	0.466***	0.377**		
	(0.0189)	(0.146)		
Observations	199	199	199	199
Controls	No	Yes	No	Yes

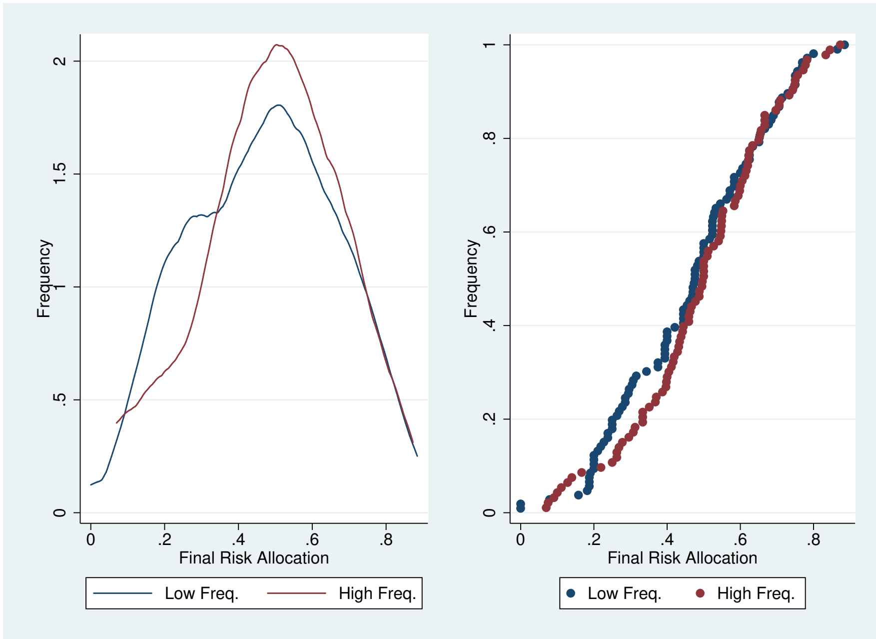
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4: *

Notes: The first and third columns look at the individual bivariate treatment effects, with the second and fourth column are including controls for age, education, gender, experience, log(profit), number of household members, and whether or not they have a bank account.

ing a dummy for those given the portfolio, those given the more frequent activity, and then the combined effect for those given both. Our point estimate of the effect of being able to diversify across products jumps back to 45%, with the more frequent information and evaluation still has no impact. Jointly being provided with higher frequency information and decisions, along with a portfolio of products, meaning this group has the most overall decisions/allocations to make, slightly brings down the amount allocated towards the riskier investment. However, this effect is not significant which tells us that the dimension that mattered when deciding what kind of investments to make was purely cross-sectional. The dimension of time and temporal diversification was not present in our sample of small Ethiopian business owners. Columns (4) - (6) perform the same specification under a different model. Here we use the fractional response model with our coefficients representing the marginal effect of being able to spread the endow-

Figure 2.4: Results - Temporal MLA



ment over a portfolio of investments. The coefficients are very stable across the different models, both with and without controls. Thus we feel comfortable with the robustness of our results across various estimation techniques. Figure 2.5 corroborates our findings, showing a clear difference between these two distributions of allocations. When given the chance to diversify a portfolio, our respondents monotonically increased the amount invested into the risky gamble. This effect is present across the entire distribution.[7]

[7] One other thing to note is that the distributions resemble a normal distribution. A common criticism of these experiments involves respondents choosing the corner solution: risk everything or risk nothing. Our sample had a small fraction of the population at the extremes: 2 people wanted everything now, and nobody invested everything into the risky gamble.

Figure 2.5: Results - Cross-Sectional MLA

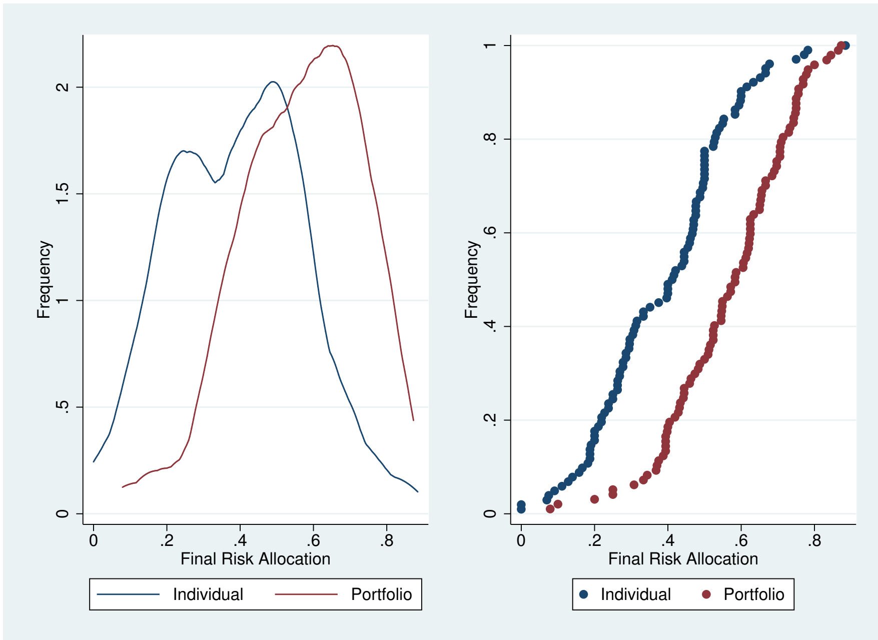


Figure 2.6: Results - Combined MLA

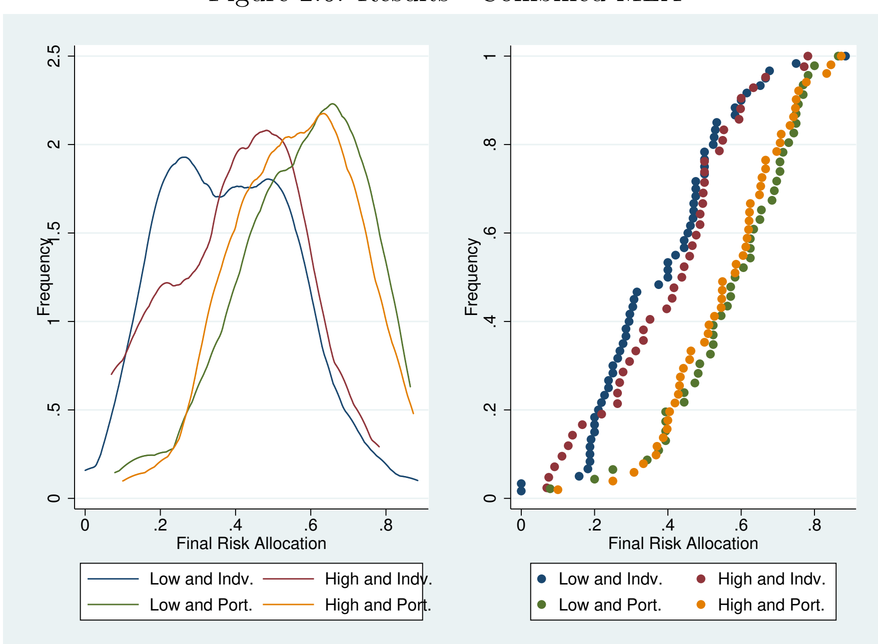


Figure 2.7: Results - Distributional Effects

Figure 2.8: Sub-Group Analysis - Business Performance by Gender

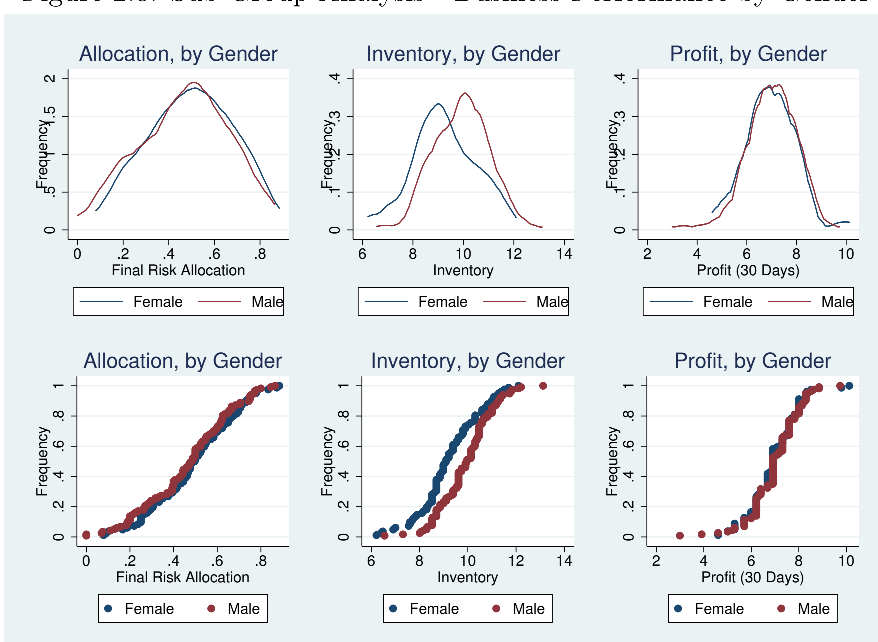


Table 2.5: Treatment Effects on Risky Allocations – Cross Sectionally

	OLS			Fractional Response		
VARIABLES	(1) Allocation	(2) Allocation	(3) Allocation	(4) Allocation (ME)	(5) Allocation (ME)	(6) Allocation (ME)
Portfolio	0.175***	0.160***	0.175***	0.172***	0.157***	0.172***
	(0.0246)	(0.0269)	(0.0366)	(0.0233)	(0.0255)	(0.0349)
High			0.0266			0.0268
			(0.0384)			(0.0389)
High*Portfolio			-0.0348			-0.0351
			(0.0529)			(0.0514)
Observations	199	199	199	199	199	199
R-squared	0.205	0.251	0.253			
Controls	No	Yes	Yes	No	Yes	Yes
Control Mean	.383	.383	.383	.383	.383	.383
Control SD	.179	.179	.179	.179	.179	.179

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: *

Notes: Columns (1)-(5) have the dependent variable as their final risk allocation, while columns (6)-(10) are the average risk allocations across all the decisions they made. The first three columns look at the individual bivariate treatment effects, with the fourth column adding in all the treatments, and the fifth column including controls for age, education, gender, experience, log(profit), number of household members, and whether or not they have a bank account.

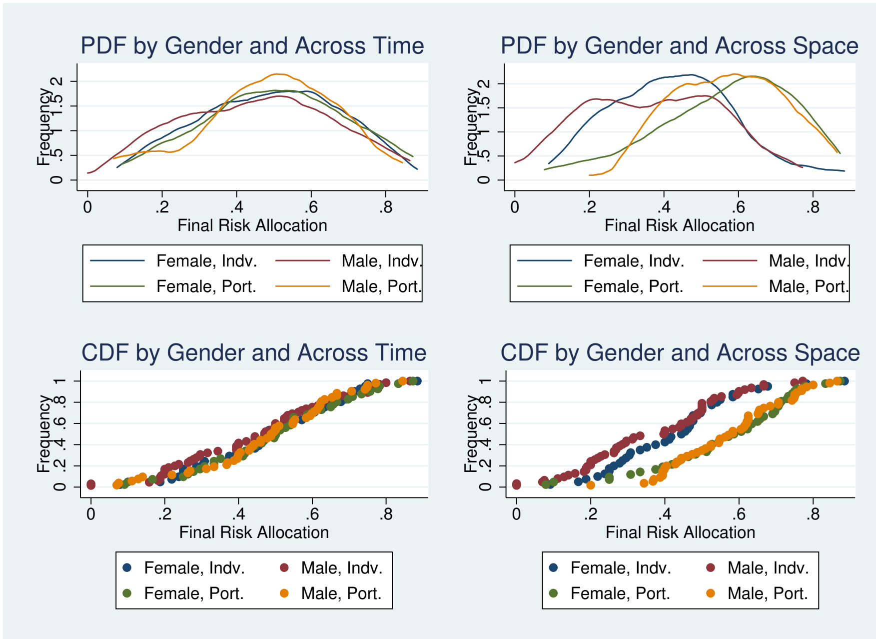
	OLS			Fractional Response			OLS - γ
VARIABLES	(1) Average	(2) Last	(3) Last	(4) Last (ME)	(5) Last (ME)	(6) Last (ME)	(7) Risk Aversion
High Frequency			-0.0135			-0.0135	-0.309***
			(0.0339)			(0.0338)	(0.0493)
Portfolio	0.173***	0.178***		0.174***	0.170***		0.852***
	(0.0352)	(0.0325)		(0.0306)	(0.0332)		(0.0970)
High*Portfolio							-0.730***
							(0.108)
Constant	0.364***	0.383***	0.574***				0.566***
	(0.0269)	(0.0232)	(0.0251)				(0.0374)
Observations	111	111	97	111	111	97	198

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

2.4 Conclusion

Small businesses around the developing world have been shown to leave high return investments unrealized. This typically gets addressed through either physical or hu-

Figure 2.9: Sub-Group Analysis - Treatment Effects by Gender



man constraints, which are alleviated by providing capital injections into the business or some sort of management training course that teaches these business owners how to improve their situation. The problem is that, overall, these types of interventions have not been all that effective at either improving the business or helping draw down these high returns. In the developed world, a behavioral finance concept known as Myopic Loss Aversion has been used to explain why high-risk stocks carry such a premium compared to low-risk bonds. Research has found that investors have a narrow bracket (short term time horizon) while being sensitive to losses within that narrow frame, which causes an underinvestment into riskier investments (Benartzi & Thaler, 1995). We replicate the famous Gneezy & Potters (1997) experiment, but with a sample of 199 micro-entrepreneurs around Addis Ababa, Ethiopia, compared to students or professional fund managers. This game entails manipulating the evaluation and realization frequencies to see if those with more frequent financial choices take on systematically lower levels of risk compared to those with longer frames and thus who are able to spread the loss over more periods. We then extend this game to look along a different dimension than is normally done in the MLA literature: we give a random sample of respondents the ability to face gambles with the same statistical properties, except now they are diversifying across a portfolio/basket of goods. Given anecdotal evidence from surveys with small shop owners, along with recent theoretical work by Blumberg & Kremer (2014), we conjecture that those in the portfolio group will be allocating relatively more to their risky asset than the group who just invests in one product. We have three main results, with the first two contained in table 2.5: (1) We were not able to replicate the findings in GP(97) to support the idea that micro-entrepreneurs in SSA are myopically loss averse when looking across time. GP(97) show that looking further across time (wider temporal bracket) will lead to higher amounts of money put into the risky allocation as the chance of being in the loss domain at the time of evaluation will be lower since the probability is smoothed across the periods of time. Thus, we should expect to see the high-frequency group put more money into the safe asset, which we do not see. The difference is marginally positive and indistinguishable from zero. Further proving how the temporal channel doesn't work in our context, we see no interactive effect for the group that could diversify temporally and cross-sectionally. This tells us that the portfolio/cross-sectional channel dominated the temporal channel when the shop decides how much risk to take on. This could be due to the fact that attention is zero-sum, and so an increase in attention along the cross-sectional margin might crowd out their ability to also focus on the temporal margin (Banerjee & Mullainathan, 2008).

Chapter 3

Sentiment, Learning and the Transmission of Monetary Policy

3.1 Introduction

Expectations are often a (if not *the*) central component in determining equilibrium outcomes in economic models. The standard "rational expectations" (RE) approach to dealing with expectations assumes that economic agents have correct beliefs on average and know the structure of the economy and its parameters as well as exogenous shocks. These unreasonable requirements on agent beliefs have lead to a number of methods relaxing the assumptions imposed by rational expectations. In this paper, I relax the RE assumption in a general equilibrium model by following the learning approach of Evans & Honkapohja (2012), where agents are as smart as econometricians who use limited information to make forecasts. I do so in order to study the implications of capital return expectation shocks when sentiment[1] and monetary policy shocks are correlated. Section 3.3 documents the relationship between changes in sentiment and unexpected monetary policy shocks which will serve as a motivation for assuming correlated expectation shocks in the learning model. I embed expectation shocks in a New-Keynesian model featuring wage and price rigidities with limited participation in the capital market. This framework allows me to assess whether the presence of segmentation influences the effects of expectation shocks (or changes in sentiment). The baseline RE solution of the model features little dependence for market participation on the outcome of monetary policy. Given the sensitivity of the expectation shocks studied in this paper to capital returns, I re-examine the near irrelevance of market segmentation to monetary shocks and shed new light on the effectiveness of monetary policy in a limited participation model. I find that the degree of market participation acts as an amplifier to the effect coming from expectation shocks, indicating that the degree of market participation is in fact relevant for monetary policy. Wage stickiness for both capital owners and hand-to-mouth consumers, as in Ocampo Díaz (2013) and Ascari *et al.* (2017), is necessary to preserve the desired (negative) relationship between interest rates and aggregate demand, which is shown by Bilbiie (2008) to be reversed in a limited participation model without wage stickiness. I follow the same parameterization of the model as in Ocampo Díaz (2013) in order to preserve comparability. Under adaptive learning[2], expectations are replaced

[1]Sentiment, expectation shocks and optimism refer to the same thing; optimism is upward biased (positive) sentiment whereas pessimism is downward biased (negative) sentiment. Expectation shock is the realization of sentiment in some form, positive or negative

[2]Different methods to relaxing rational expectations are usually motivated by the underlying modeling goal of the research project. For example, in Malmendier & Nagel (2011) point to a specific type of bias in expectations arising from life-time experience. This motivated Collin-Dufresne *et al.* (2017) and Nakov & Nuño (2015) to model asset prices with heterogeneity in expectations arising from age

by forecasts generated by a learning algorithm. Agents observe relevant states and use them to form expectations of future variables. These forecasts enter the dynamics of the model and generate a time varying actual law-of-motion (ALM) of the model that is consistent with forecasts and a conjectured solution form for the model. Learning in New-Keynesian (NK) type models is either centered on the theoretical properties and expectational-stability conditions (E-stability) of a certain model such as Evans & Mitra (2013), or on estimation of dynamic stochastic general equilibrium (DSGE) models embedded with learning such as Slobodyan & Wouters (2012) who find that learning models fit the data better than their RE counterpart. I depart from this tradition slightly by focusing on the dynamics of the learning equilibrium when expectation shocks are correlated with monetary surprises in a model built for policy analysis. By construction, there is no systematic error in learning model forecasts as the idiosyncratic component drops out after taking expectations of the forecasting equation. In this paper I drop this assumption and include persistent sentiment, or expectation shocks, in the agent forecasting equations that is meant to capture bias in beliefs. These shocks cause forecasts to be above or below what is implied by the learning model itself. Expectation shocks serve as a simple way of capturing the consequences of heterogeneity in beliefs, risk preferences or psychological factors, such as overweighting of tail events, which can have dramatic consequences for asset prices and the aggregate economy. This approach

(equivalently experience) and the learning mechanisms. The models produced waves of pessimism and optimism (sentiment) that greatly enriched the dynamics of asset prices, which helped the model implied return moments to match real data much better relative to RE predictions. Another approach developed by Sims (2003) builds around the fact that information is costly to acquire and process and that humans have limited capacity to processing all available information. This leads agents to optimize choice over attention to certain variables and judge the benefit of the observed variable through its effect on the entropy of the predictive model.

is used by Milani (2011) and Milani (2017) to explore the implications of expectation shocks on the business cycle in a reduced form DSGE model, Evans & Honkapohja (2003) to study monetary policy design, and Elias (2016) to study asset prices and estimate expectation shocks and learning process parameters. Sentiment is generally defined as the aggregated errors in investor beliefs. This can be the result of any number of unobservable factors such as; i) heterogeneity in beliefs and/or preferences, or ii) behavioral biases such as the tendency to overweight tail probabilities. Theoretically, these factors contribute to pricing deviations from rational expectation due to bouts of optimism (pessimism) that push asset prices above (below) what they ought to be with expectations taken with respect to the true probability measure driving returns. Sentiment can be defined structurally within an economic framework and estimated with the help of observed market data. This is exactly what Barone-Adesi *et al.* (2016) do with the founding theory fully developed in Shefrin (2008), and to some extent Polkovnichenko & Zhao (2013) and Stork *et al.* (2017) who consider pricing under Kahneman & Tversky (1979) Prospect Theory. Both structural approaches utilize index option data to estimate a measure for sentiment implied by the theoretical model. Further discussion of the underlying theory and estimation approaches undertaken to estimate sentiment is in section 3.2.3. The paper features a few key empirical and theoretical contributions. First, I estimate the response of sentiment to monetary policy shocks, which provides a clear link between the source and correlation of the expectation shock in the model. My empirical findings suggest that in the 2004-2014 period sentiment responds to monetary surprises with a positive correlation. That is, optimism is increased in the face of a monetary tightening or higher interest rates. Second, I study the impact of expectation shocks on the transmission of monetary policy. I find that the effect of a monetary shock is sensitive to sentiment, learning, and the degree of market segmentation. Expectation shocks aside, learning generally enhances and prolongs the effects of interest rate shocks. However, when monetary shocks induce a response in sentiment, the resulting outcomes depend on how sentiment responds to interest rates. With constant gain and positive correlation the decline in consumption and investment is only half of the RE response at impact, but remains at a level below steady state for some periods before overshooting the steady state and converging from above. Overshooting also happens when gain is decreasing but much faster. With full capital market participation and in response to a policy shock, a negatively correlated expectation shock keeps investment below steady state for many periods past the shock. This effect is mitigated by decreasing capital participation to 70% (baseline parameterization), where both positively and negatively correlated shocks converge towards steady state under all gain parameter values. The model seems to be stable and close to RE under decreasing gain and less stable with some evidence of cyclical behavior at gain = 0.05. My findings are in line with recent results in Alessi & Kerssenfischer (2016) who find that estimating a structural factor model augmented with a large dataset accounting for missing information in VARs results in monetary surprises having a larger and longer lasting effect on asset prices. These findings echo my empirical results while my theoretical results corroborate the concerns discussed by Alessi & Kerssenfischer (2016) in response to their findings.

The rest of the paper proceeds as follows. Section 3.2 defines structural sentiment and explains the procedure for estimating it. An event study of the effect of unanticipated monetary policy shocks on sentiment follows in section 3.3. Section 3.4 describes the structure of the theoretical model, learning mechanism and expectation shocks while section 3.5 discusses simulation and equilibrium results. Finally, section 3.6 concludes.

3.2 Structural Sentiment

The first task in assessing the effects of sentiment on the economy's responses to monetary policy shocks is to obtain an estimate of sentiment. There are no definitive or uncontroversial measures of sentiment nor is it observable, posing a serious challenge for researchers. This section outlines two different approaches, model-free or structural, taken in the literature to measure sentiment.

3.2.1 Model-free Sentiment Measures

In this approach, sentiment is usually proxied using survey data, market trading data and firm level valuation errors. Some examples are Baker & Wurgler (2006) who defines sentiment by combining six different proxies into an index that captures their common component. The index (BW henceforth) is shown to be correlated with the cross section of stock returns with differentiated effect on small, young and volatile stocks relative to larger more stable ones. BW demonstrate the importance of sentiment in the determination of subsequent equity returns. However, the highest frequency of the BW index is monthly, which limits its ability to capture the day to day changes in sentiment needed to estimate the effect of monetary policy events. Han (2008) uses three proxies for sentiment ranging from market trading data and index mis-valuation measures to show that they correlate strongly with index option risk-neutral skewness, which is synonymous to the implied volatility smile. Han (2008) inspired numerous follow-up studies that link investor sentiment, as well as other firm observables, to pricing anomalies in the options market. For example, Friesen *et al.* (2012) show that belief heterogeneity explains cross-sectional variation in risk-neutral skewness better than firm risk-based factors for a cross-section of U.S. firms while Coakley *et al.* (2014) shows that the relationship between sentiment and risk-neutral skewness depends on the underlying firm style with a positive (negative) relationship between sentiment and growth (value) index options.

3.2.2 Structural Sentiment

Shefrin (2008) develops a behavioral pricing theory with fully heterogeneous agents, while Barone-Adesi *et al.* (2016) develop an estimation procedure, based on the model in Shefrin (2008), that produces a series of model-implied sentiment functions resulting from the aggregation of heterogeneous market participants. Sentiment is defined as the function mapping the transformation of objective/true beliefs into (biased) market beliefs. The model demonstrates how the pricing kernel can be decomposed into two components; a neoclassical one corresponding to marginal utility and a behavioral one corresponding to sentiment. This interpretation of the pricing kernel, which embodies the sentiment function, allows for rich explanations for the shape of the pricing kernel. Humps and irregularities that are often observed in the pricing kernel embody optimism and overconfidence while changes in the shape of the pricing kernel over time reflects changes in investors' preferences and sentiment. That being said, the estimates provided can not distinguish between changes that are the result of heterogeneous beliefs or preferences; the sentiment function embodies the aggregation of *all* investor heterogeneity. As a result, sentiment is not just a function of beliefs, but also of changes in risk preferences. This is what I refer to as structural sentiment and is the type of sentiment used in the event study below. Pricing anomalies in options prices, which are linked to sentiment factors, represent different market participants. Jackwerth & Rubinstein (1996) and Bates (1991) show that since the 1987 market crash institutional investors have been paying 10-100 times the price implied by log-normality for tail event payoff claims[3]. In this case, the 1987 crash was an extreme negative event, for which put options are the protective instrument. Figure 3.3 demonstrate this well known empirical fact showing how the prices of option contracts with payoff claims in the tails of the gross return distribution imply much higher volatility in the true underlying return distribution than what is observable or known to be true by some measure or another. On the other hand, single stock options, especially out-of-the-money (OTM) calls, are largely traded by speculating individual investors who, in the words of Félix *et al.* (2016), treat these options more as lottery tickets with a potential of high levered payoff. This is precisely the point addressed in Stork *et al.* (2017), who build a structural sentiment measure based on implied volatility skew in index and single stock options markets. They assume

[3]The fact that investors are still overpaying for these claims is further supportive evidence for the argument made in Malmendier & Nagel (2011) and is supported by my own experimental results in "Malleable Risk Preferences and Learning from Experience in an Asset Allocation Game" that individual risk preference and learning behavior is affected by extreme events.

a pricing kernel emerging from a prospect theory identification of utility and estimate model implied probability weighting function with single stocks and the index options in order to account for investor types in the market. They define sentiment as the difference in implied volatility skew between index and single stock options markets. Identifying sentiment according to an equilibrium behavioral pricing model provides a clear foundation for the sources of bias and mis-pricing observed in the empirical pricing kernel. Given the fact that there exists no clear empirical measure for the notion of market sentiment, relying on an equilibrium model to identify sentiment provides a less controversial framework for identifying and measuring sentiment, provided that the behavioral pricing model is accepted. Another advantage of structural sentiment is that it is horizon dependent. We can obtain a sentiment measure for returns at any future horizon for which we have an estimated distribution. Figures 3.1 and 3.2 plot the sentiment function at the two and six month return horizon with the corresponding alteration in market beliefs reflected in the difference between the p_R and p measures. Figure 3.4 plots optimism, difference in expected value between p and p_R, as defined per Shefrin (2008) at the two, four, six and twelve months horizons estimated following the methodology in Barone-Adesi *et al.* (2016). It is evident that sentiment is highly variable depending on the horizon, an advantage of structural sentiment that is lacking in the BW index. In addition, the BW index and structural sentiment seem to be more correlated prior to the financial crisis than during or after the crisis. The change in sentiment around the time of the crisis also seems to be horizon dependent. At short horizons, two and four months, sentiment seems to have collapsed around the 2008-2009 period, whereas longer run, 6 and 12 months, sentiment seems to show beliefs consistent with trend reversal, i.e. sentiment for 6 and 12 months returns at the trough of the recession are very optimistic. This, however, doesn't seem to be the case for the shorter run horizons where immediate fear and uncertainty are the main drivers of return beliefs at short horizons.

The main dataset used in this paper is composed of options on the S&P 500 index, so the results to follow represent more the bias of institutional investors than that of small individual investors. In that sense, this is perhaps the first limitation of the analysis to follow, as it focuses only on a subset of market participants, granted they are a large proportion. However, in the limited asset market participation (LAMP) model this serves as a benefit since the expectation shock is only affecting market participants or capital owners, for which institutional investors are a good representative sample.

3.2.3 Sentiment and Behavioral SDF

The model developed in Shefrin (2008) lays out an aggregation theorem and proof showing that a representative investor composed of many heterogeneous investors exists but is not unique. Regardless of the uniqueness of the observed aggregate investor, the theorem proves that the aggregated error, or sentiment function, is a function of the difference between objective beliefs and aggregated (biased) expectations and the difference between aggregate risk aversion and its counterpart had all investors had correct beliefs. The resulting observed SDF will then be the sum of two components, marginal utility of the aggregate investor and the resulting sentiment error. Given CRRA preferences, the SDF is defined as

$$M_{t,T}(\beta,\gamma) = \beta(S_T/S_t)^{-\gamma} \tag{3.1}$$

where β and γ are the aggregate coefficients of time and risk preferences and (S_T/S_t) is the gross return on the market portfolio serving as a proxy for the growth rate of consumption. Taking the log of (3.1) yields

$$log(M_{t,T}(\beta,\gamma)) = log(\beta) - \gamma log(S_T/S_t) \tag{3.2}$$

The corresponding expression of the log of the behavioral SDF developed in Shefrin (2008) is given by

$$log(M_{t,T}) = \Lambda_{t,T} + log(\beta_t) - \gamma_t log(S_T/S_t) \tag{3.3}$$

where $\Lambda_{t,T}$ is the time varying sentiment function. Chapter 14 in Shefrin (2008) demonstrates the dependence of $\Lambda_{t,T}$ and γ_t on (S_T/S_t), where the full derivation of (3.3) is provided. The sentiment function, $\Lambda_{t,T}$, is a log-change of measure transforming the objective measure p to the aggregated representative investor measure p_R

$$p_R = pe^{\Lambda_{t,T}}\beta_{t,p}/\beta_t \tag{3.4}$$

where $\beta_{t,p}$ rescales β_t to ensure that p_R is a proper measure, i.e. integrates to one. The sentiment function can be interpreted as deviation from market efficiency, or equivalently market mis-pricing, due to investor heterogeneity. Recall that the pricing kernel is defined over gross return states and that sentiment is the residual component of the empirical pricing kernel after the neoclassical component is explained away. This means that positive (negative) regions of the sentiment function are indications of state prices that are too high (low). With p and p_R in hand, we can calculate optimism, which is defined as the expected market return under the representative investor and objective measures

$$sentiment \equiv (E_t^{p_R}[S_T/S_t] - E_t^{p}[S_T/S_t]) \times 100 \tag{3.5}$$

where these expectations are with respect to date t information set and are computed by numerically integrating the respective measures over gross returns states. Similarly, we can define overconfidence as the difference in expected volatility between the two measures

$$confidence \equiv \left(\sqrt{Var_t^{p_R}[S_T/S_t]} - \sqrt{Var_t^{p}[S_T/S_t]}\right) \times 100 \tag{3.6}$$

3.2.4 Estimation Procedure

The recovery of the empirical pricing kernel follows closely the method developed in Barone-Adesi *et al.* (2008). First, the objective distribution on a given day is obtained by estimating a GJR-GARCH model on ten years of historical S&P500 returns ending on that specific day.

$$\begin{aligned} ln(S_t/S_{t-1}) &= \mu_t + \epsilon_t \\ \sigma_t^2 &= \omega + \beta\sigma_{t-1}^2 + \alpha_0\epsilon_{t-1} + \alpha_1 I_t \epsilon_{t-1} \end{aligned} \tag{3.7}$$

where $\epsilon_t = \sigma z_t$ and z_t is the standardized innovation. I_t is an indicator function equal to one if $\epsilon_{t-1} < 0$ which allows the model to features a leverage effect that captures the higher volatility when bad news ($\epsilon_{t-1} < 0$) is realized relative to good news ($\epsilon_{t-1} > 0$). On a given day the objective distribution is obtained by using the estimated parameters, $\theta = \mu, \omega, \beta, \alpha_0, \alpha_1$, to simulate returns using the filtered historical simulation (FHS) method outlined in Barone-Adesi *et al.* (2008). The objective return distribution $p(S_T/S_t)$ for $\tau = T - t$ period return is obtained by kernel smoothing the distribution of paths at step τ. On every day in the sample, the risk-neutral distribution, $q(S_T/S_t)$, is obtained through the calibration of the GARCH model (3.7) to the cross-section of out of the money options. Given a set of parameters θ^* samples paths are simulated using the FHS method. The GARCH call option prices with maturity τ and strike price K are obtained by

$$C = e^{-r\tau} \sum_{l=1}^{L} max(S_{t+\tau}^{l} - K, 0)/L \tag{3.8}$$

where L is the number of simulated paths and $S_{t+\tau}^{l}$ is the l^{th} simulated price at time $t+\tau$. The risk-neutral GARCH parameters are obtained by minimizing the squared error of the difference between the GARCH implied price and the observed market price for all option traded on a given day. With the objective and risk-neutral GARCH parameters in hand two sets of 50,000 paths are simulated; one using the $p-measure$ parameters θ, and the other using the $q-measure$ parameters θ^*. The empirical pricing kernel, $M_{t,T}$, is obtained by taking the discounted ratio of the smoothed distributions at $T = t + \tau$.

$$M_{t,T} = e^{-r(T-t)} \frac{q(S_T/S_t)}{p(S_T/S_t)} \tag{3.9}$$

the next step is to decompose the empirical log SDF into the neoclassical and behavioral components. On every day in the sample a grid of 100 points, $i = 1, ..., 100$, of gross returns, $(S_T^{(i)}/S_t)$, spanning the support of the empirical SDF is used as a regressor to explain the empirical log SDF, $log(M_{t,T}^{(i)})$. Estimated intercepts and coefficients serve as estimates for $log(\beta_t)$ and γ_t, respectively. With the estimates in hand, we can obtain a fitted value for $\log(M_{t,T}^{(i)}(\beta, \gamma))$ for each value of the gross return on the grid. The estimate of the sentiment function, $\Lambda_{t,T}$, is calculated as the difference between the empirical and neoclassical SDF on each point in the grid

$$d_{t,T}^{(i)} = log(M_{t,T}^{(i)}) - \log(M_{t,T}^{(i)}(\beta, \gamma)) \tag{3.10}$$

3.3 Empirical Investigation of Sentiment

Given the structural sentiment estimates, I proceed with two empirical exercises. The first is an event study looking at how the behavioral component of the pricing kernel (i.e. sentiment or optimism) is affected by information shocks through changes in fed fund futures or announcements and speeches by FOMC members. The second exercise focuses on the return predictability of optimism where we'd expect that periods of above average to optimism precede/predict subsequent returns.

3.3.1 Event Study

I identify monetary policy shocks according changes in fed funds futures around policy announcement for the period 2004-2008. In order to identify monetary policy shock during the ZLB period, I classified FOMC announcements, speeches and press releases in the period 2008-2014 into three categories; loosening, tightening, and non-notable. Regardless of the type of communication or shock identification, the estimation procedure outlined above is carried out on the days around the event. In particular, for each variable (optimism or confidence) I take the average on the five days prior and five days following (including) the day of the event. The event study is finally carried out on the difference between the outcome variable after and before the event. Given this difference I estimate the following cross-sectional regression on all the events in the 2008-2014 sample.

$$X_e = \alpha + \beta_1 tight_e + \beta_2 loose_e + \varepsilon \tag{3.11}$$

where X_e is the change in sentiment or confidence on event e. Tight and loose are dummy variables that are equal to one if the observation/event is a tightening event or a loosening event relative to non-notable events where no new information is revealed (omitted dummy). And the following regression for the period 2004-2008

$$X_e = \alpha + \beta_1 FFF_k + \varepsilon \tag{3.12}$$

where FFF_k is the change in fed fund futures in a narrow window around the announcement and $k = tw, ww$ defines the size of the window; tight window $(-10min, +20min)$, tw, or wide window $(-15min, +45min)$, ww. Comparing outcome variables on the five days prior to the announcement to the five days after (including) the announcement may seem at odds with standard event study analysis, however, this is a common approach to comparing market beliefs (for example see Mandler (2012)) around notable announcements. Tables 3.1 and 3.2 summarize the results from the regressions 3.11 and 3.12, respectively. The coefficient estimates are not quite comparable as the shock is identified in terms of basis points for the 2004-2008 sample, and in terms of a dummy variable for the 2008-2014 period. However, it is immediately apparent that the direction of correlation is not stable and that when the estimated coefficients are statistically significant the correlation is reversed across the two sample periods. That is, in the 2004-2008 period it seems that tightening shocks may lead to less optimism, whereas in the 2008-2014 period, tightening announcements produce an increase in optimism. In the 2008-2014 sample the events covered the first exit from QE1, tapering of QE3 and the final exit and end of QE programs. The direction of correlation is not surprising as it indicates that markets took the tightening news as an indication that the macroeconomic conditions have improved enough to warrant a reversal in the unconventional measures undertaken during and after the crisis. This signaled to market participants that the macroeconomic state, at least as it's judged by FOMC members, is re-normalizing. The effect on confidence is in line with the optimism story, where a negative coefficient here indicates that the tightening announcements during the ZLB period lead to an increase in confidence (overconfidence). The 2004-2008 sample is quite small and I would take the results with a bit of caution. Optimism and confidence don't seem to have a statistically significant relationship, however, the direction of the relationship does seem to be reversed for some of the coefficients. It is not surprising to find no significant coefficients in this period as the majority of events were not really shocks, but were rather anticipated moves along an established direction of increasing interest rates up until the financial crisis. In fact if I end the sample in the fall of 2007 (right after the first reversal in policy, true shock, within the sample) I find a huge significant effect on optimism and confidence at the six-month horizon. In short, this sample suffers from a weak identification of monetary shock because most of the events are either anticipated or there is no change in fed-funds futures.

3.3.2 Sentiment and Return Predictability

The next step is to test the predictive power of sentiment on subsequent returns. A significant relationship provides evidence that belief bias does indeed drive returns and that a change in sentiment induced by monetary shocks can lead to actual changes in returns, i.e. returns are not only affected at the moment of policy announcement, but are pushed further as time passes through change in sentiment. The literature on return predictability is extensive and hence there is little doubt regarding what variables ought to be included in a return prediction regression. I chose a subset of variables most notably known to be able to predict returns and run regressions of the form

$$r_{t,t+h} = \alpha_0 + \alpha_1 sentiment_{t,t+h} + \alpha_2 vix_t + \alpha_3 EP_t + \alpha_4 ts_t + \varepsilon_t \tag{3.13}$$

where $sentiment_{t,t+h}$ is sentiment at time t for horizon h, $r_{t,t+h} = \frac{S_{t+h}}{S_t}$ is the gross h period subsequent return, vix_t is the change in the first-difference of VIX at time t, EP_t is the most recent S&P500 earnings divided by the index price/level at time t, and finally ts_t is the term spread at time t. The variables included in this regression are only a subset of the full set of return predictors, however, they are the most relevant and most used in the literature. The regressions are run on daily data for the period 2004-2014 with all variables (except sentiment, which is already stationary) differenced. Table 3.3 summarize the results from the above regression. We see that at very short horizons sentiment doesn't seem to be driving short-term returns while the remaining variables have the expected signs. At the four and six month horizon we begin to see a significant positive relationship between subsequent returns and sentiment with the biggest effect showing up at the 4 month horizon.

3.4 Learning in a LAMP Model

The model presented here follows closely the set-up in Ocampo Díaz (2013). The main goal is to quantify how the economy responds to interest rate shocks when capital return expectation shocks are correlated with interest rate shocks, as was shown to be the case in section 3.3. The transmission of monetary policy in this model works directly through the wage channel as the response of non-Ricardian (hand-to-mouth) wage directly affects aggregate demand through its effect on consumption of the non-Ricardian household. And also through the real rate channel through its effect on ex-ante real rate, which directly affects the consumption smoothing Ricardian household Euler equation (EE). The main addition to the model presented here is the incorporation of an adaptive learning mechanism augmented with expectation shocks. The results presented below are obtained with the standard least squares (LS) learning recursion with constant gain. Alternative specifications for the learning mechanism are explored as a robustness check in section **??**. The economy is composed of two types of agents. A fraction Γ is type "a", the non-Ricardian or rule-of-thumb consumers. These consumers do not have access to any consumption smoothing mechanism. The remaining fraction $(1 - \Gamma)$ is type "b", the Ricardian or capital owners, who have access to capital accumulation and a risk-free bond to smooth consumption. I assume perfect risk sharing within type, so aggregate quantities for each type can be expressed as averages of the specific types. The rest of the economy consists of labor agencies, intermediate good producers, final good aggregator, and a monetary policy authority that sets the nominal interest rate. Nominal wage rigidities for both household types are required in order to prevent the inversion of the slope of the IS curve[4]. Ocampo Díaz (2013) points out that wage rigidities for rule-of-thumb consumers act as an "automatic stabilizer" in response to sudden inflation shocks.

[4] In Bilbiie (2008), limited asset market participation has a non-linear effect on most predictions of the standard full-participation model as the elasticity of aggregate demand to interest rates depends non-linearly on the degree of asset market participation. As interest rates change, real wages (and marginal cost) change, which lead to a change in asset holders dividend income. The invertability issue occurs when the share of asset holder is small or if elasticity of labor supply is low; in those case the potential variation in profits accruing to asset holders offsets the interest rate effect on demand of asset holders.

Wage stickiness prevents wages from fully adjusting in response to inflationary pressures, which lowers the average real wage of rule-of-thumb agents relative to the flexible wage case. Ricardian households rent capital to intermediate goods producers in a competitive market, while Ricardian and non-Ricardian wages are set by households and are each sold to the respective labor agency in a monopolistically competitive market. After labor is aggregated by the two labor agencies it is sold to an aggregate labor agency that combines Ricardian and non-Ricardian labor indexes into a single labor index sold to intermediate goods producers in a competitive market. Intermediate goods firms use labor and capital to produce differentiated goods, which are sold in a monopolistic competition market to the final goods aggregator, which then sells the final good to households in a competitive market. The final good is used by households for consumption and investment in capital. Intermediate good firms are assumed to face rigidities in prices as in Calvo (1983). Below I present the general set-up of the problem, for a detailed derivation of the log-linear system see Ocampo Díaz (2013).

3.4.1 Households

The economy is composed of a unit measure of households with a fraction Γ of no-Ricardians and remaining fraction $(1-\Gamma)$ Ricardian agents. The problem for either type of agent is to maximize

$$E_t \sum_{i=0}^{\infty} \beta^i \left(\frac{c_{j,t+i}^{1-\sigma}}{1-\sigma} - \chi \frac{h_{j,t+i}^{1+v}}{1+v} \right) \tag{3.14}$$

where$j \in (0,1)$ is an agent index, $c_{j,t}$ and $h_{j,t}$ are consumption and labor hours, respectively, $\beta \in (0,1)$ is the time discount factor, $v > 0$ is the labor supply elasticity, and σ is the coefficient of relative risk aversion. In order to facilitate aggregation and focus on aggregate outcomes without worrying about wealth distribution I assume that both agents have access to a complete set of Arrow-Debreau (AD) securities that are only traded within type, $a_{j,t}$, which allows agents within each type to completely ensure income.

3.4.1.1 Non-Ricardian agents

Rule-of-thumb agents maximize (3.14) by choosing $c_{j,t}$, $w_{j,t}$ and a portfolio of AD securities, $a_{j,t}$, one for each event in the state space ζ, purchased or sold at price $q_{j,t}$ only to households of the same type. The budget constraint is given by

$$w_{j,t}h^s_{j,t} + a^*_{j,t} = c_{j,t} + \int q_{j,t+1}a^{(\zeta)}_{j,t+1}d\zeta_{t+1,t} \tag{3.15}$$

In addition to (3.15), agents face a labor demand constraint obtained from the problem of the non-Ricardian labor agency problem and is used by the agent in choosing the optimal wage. All agents face nominal wage rigidities and can optimally set wages with probability $1 - \xi_a$. The non-Ricardian problem can be characterized by the aggregated budget constraints and wage inflation, π_{wa}, Philips curve for the non-Ricardian households.

3.4.1.2 Ricardian agents

The wage setting problem for Ricardian agents is identical to the non-Ricardian households. Ricardian agents, however, have access to consumption smoothing through capital accumulation and a risk-free bond in zero net supply. The objective function is still the same form as (3.14) but optimization is subject to

$$
\begin{aligned}
r_t^k k_{j,t} + w_{j,t} h_{j,t}^s + b_{j,t-1}\frac{i_{t-1}}{\pi_t} + \frac{Pr_t}{1-\Gamma} + a_{j,t}^* &= c_{j,t} + x_{j,t} + b_{j,t} + \int q_{j,t+1} a_{j,t+1}^{(\zeta)} && (3.16)\\
k_{j,t+1} &= \phi(\tfrac{x_{j,t}}{k_{j,t}}) k_{j,t} + (1-\delta) k_{j,t} && (3.17)
\end{aligned}
$$

where i_t is the gross nominal interest rate, π_t is the gross inflation rate for the price of final goods, and $\phi(\frac{x_{j,t}}{k_{j,t}})$ represent capital adjustment costs. The solution is characterized by the Euler equation, budget constraint and capital accumulation in (3.16) along with Ricardian wage inflation, π_{wb}, Phillips curve and the definition for Tobin's Q, which is the relative price of capital for Ricardian agents.

3.4.2 Labor agencies

There are three labor agencies in the model; one for each type of household and a final labor index aggregator. The problems for each household agency is identical; a labor agency takes the wage set by the households as given and determine demand for each labor type by maximizing profits.

3.4.2.1 Aggregate labor agency

Aggregate labor agency buys type a and b labor index and combines to produce an aggregate labor index defined by $h_t = h_{a,t}^{\Gamma} h_{b,t}^{1-\Gamma}$. The problem is to max

$$\max_{h_{a,t},h_{b,t}} w_t h_t - w_{a,t} h_{a,t} - w_{b,t} h_{b,t} \tag{3.18}$$

subject to the labor aggregation technology. Here w_a, h_a, w_b, and h_b are aggregate wage and labor hours of types a and b, respectively. The first order conditions are given by

$$h_{a,t} = \Gamma \frac{w_t}{wa,t} h_t \tag{3.19}$$

$$h_{b,t} = (1-\Gamma) \frac{w_t}{wb,t} h_t \tag{3.20}$$

$$h_t = h_{a,t}^{\Gamma} h_{b,t}^{1-\Gamma} \tag{3.21}$$

3.4.2.2 Ricardian and non-Ricardian labor agencies

Households sell their labor to a labor aggregator at wage $w_{j,t}$. The problem of the type specific labor agency is to chose labor supply given a labor aggregator technology and wages set by the households. Type $k \in (a,b)$ labor agency maximizes

$$\max_{\forall j \in (0,1)} w_t^k h_{k,t}^s - \int_0^1 w_{j,t} h_{j,t} dj \tag{3.22}$$

subject to labor aggregation technology $h_{k,t}^s = \left[\int_0^1 h_{j,t}^{\frac{\eta-1}{\eta}} dj\right]^{\frac{\eta}{1-\eta}}$. The optimality conditions associated with labor agency k and labor type j for $k \in (a,b)$ and $j \in (0,1)$

are

$$h_{j,t} \quad = \left(\frac{w_{j,t}}{w_{k,t}}\right)^{-\eta} h^s_{k,t} \tag{3.23}$$

$$\tag{3.24}$$

Plugging into aggregation technology for each agency we get an expression for type k wage index

$$w_{k,t} = \left(w_{j,t}^{1-\eta} dj\right)^{\frac{1}{1-\eta}} \tag{3.25}$$

3.4.3 Household wage setting problem

Each household $j \in (0, 1)$, regardless of its type, supplies differentiated labor variety $h_{j,t}$. Each household maximizes lifetime utility subject to the budget constraint and the demand for its labor variety by the labor agency. Similar to price setting firms, households face wage rigidities in the sense that the household can only adjust its wage to the optimal wage with probability $1-\xi$, if the household can not adjust its wage then it remains unchanged at the previous period value. The problem is defined by the same lifetime objective utility, but now the relevant constraints are

$$P_{t+i}c_{t+i} \qquad = w_{j,t}h_{j,t+i} \tag{3.26}$$

$$h_{j.t+i} \quad = \left(\frac{w_{j,t}}{w_{t+i}}\right)^{-\eta} h_{t+i} \tag{3.27}$$

which leads to the following wage setting optimality condition

$$\sum_{i=o}^{\infty}(\beta\xi)^i h_{j,t+i}U_c\left(c_{j,t+i},h_{j,t+i}\left[\frac{w_t^*}{P_{t+i}}-\frac{\eta}{\eta-1}MRSj,t+i\right]\right) \qquad (3.28)$$

where $MRS_{j,t+i} = -\frac{U_h(j,t+i)}{U_c(j,t+i)}$ is the marginal rate of substitution between labor and consumption.

3.4.4 Firms

The firm side of the model is standard. The final good is produced by a representative firm aggregating intermediate goods through a CES aggregator with elasticity of substitution ϵ so that the final good is given by $Y_t = \left(\int_0^1 Y_t(j)^{\frac{\epsilon-1}{\epsilon}}dj\right)^{\frac{\epsilon}{\epsilon-1}}$. Final goods producers are competitive and max profit $P_tY_t - \int_0^1 P_t(j)Y_t(j)dj$ each period, where P_t is the aggregate price index and $P_t(j)$ is the price of intermediate good j. The demand for intermediate good j is standard and given by $Y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t$ and the price index is given by $P_t^{1-\epsilon} = \int_0^1 P_t(j)dj$. There is a continuum of monopolistically competitive intermediate goods producers who maximize profits by setting prices and choosing labor and capital. All firms have the same technology and only differ in their ability to set prices where only a fraction $1-\theta$ can reset prices optimally at any given point. Firm j technology is defined by $Y_t(j) = z_t k_{j,t}^{\alpha} h_{j,t}^{1-\alpha}$, where z_t is aggregate productivity shock and is defined as $z_t = \rho_z z_{t-1} + \varepsilon_{z,t}$, and $h_{j,t}$ is firm j demand for labor. Cost minimization implies that

$$r_t^k \quad = \alpha\varphi_t k_{j,t}^{\alpha-1} h_{j,t}^{1-\alpha} \tag{3.29}$$

$$w_t^k \quad = (1-\alpha)\varphi_t k_{j,t}^{\alpha} h_{j,t}^{-\alpha} \tag{3.30}$$

Given the Calvo price adjustment process faced by intermediate firms, the price setting problem for intermediate good producers is $\max E_t \sum_{i=0}^{\infty} (\theta\beta)^i \Lambda_{t,t+i} [P_t(j) Y_{t,t+i}(j) - \Psi_{t+i} Y_{t,t+i}(j)]$ subject to the final producer demand for firm j intermediate good, where Ψ_{t+i} is the cost of production. $\Lambda_{t,t+i}$ is the stochastic discount factor of type a households. The FOC for the price setting firm reduces to $\sum_{i=0}^{\infty} (\beta\theta)^i E_t \left[\Lambda_{t,t+i} Y_{t+i} \left(P_t^* - \Xi_p \psi_{t+i}\right)\right]$, where Ξ_p is the mark-up and ψ_{t+i} is nominal marginal cost. From here the standard form for the Phillips curve is obtained

$$\pi_t = \beta E_t \pi_{t+1} + \frac{(1-\epsilon)(1-\epsilon\beta)}{\epsilon} \tilde{\varphi}_t \tag{3.31}$$

where $\tilde{\varphi}_t$ is deviation of marginal costs from a zero inflation steady state. Expectations are obtained by least square learning as discussed below.

3.4.5 Monetary policy

The one-period interest rate is set by the monetary authority according to the rule:

$$i_t = \rho_i i_{t-1} + (1-\rho_i)(\phi_\pi \pi_t + \phi_y \tilde{y}_t) + \varepsilon_{i,t} \tag{3.32}$$

where $\tilde{y}_t$ is the deviation of output gap from its zero inflation steady state value.

3.4.6 Aggregations and Equilibrium

The model equilibrium conditions are linearized around a zero inflation steady state and aggregation is obtained relatively simply thanks to the presence of AD securities. Aggregation and linearization details are fully explained in Díaz *et al.* (2012) and will be skipped here for the sake of brevity. Equilibrium is defined by a set of prices $\{w_t, i_t, P_t, r_t\}$ that are taken as given, and a set of endogenous variables that solve the consumer, labor agency and firm problems while all market clear in every period t, such that $y_t = c_t + x_t$, $h^s_{a,t} = h_{a,t}$, $h^s_{b,t} = h_{b,t}$, and $c_t = \Gamma c_{a,t} + (1 - \Gamma)c_{b,t}$.

3.4.7 Adaptive learning

I implement an adaptive learning mechanism in the model following the techniques developed and popularized by Evans & Honkapohja (2003). The linearized model can be expressed in a reduced form as

$$AY_t = A_0 + A_1 E_t Y_{t+1} + A_2 Y_{t-1} + B1 W_t \tag{3.33}$$

$$W_t = \Gamma W_{t-1} + \Pi \epsilon_t \tag{3.34}$$

where the matrices $\{A, A_0, A1, A2, B1\}$ are functions of the model parameters, Y_t is a vector of endogenous state variables and W_t is a vector of exogenous shocks. Solutions to models of this form can be expressed in terms of the Minimum State Variable (MSV) solution

$$y_t = a + by_{t-1} + cw_t \tag{3.35}$$

where the vector y_t contains endogenous states and forward looking variables. Following the adaptive learning literature and deviating from RE, I assume that expectations are formed using a linear function of the endogenous and exogenous states driving the model

$$y_t^f = \alpha_{t-1} + \Omega_{t-1}^T Z_{t-1} \tag{3.36}$$

where Z_{t-1} is a vector of endogenous and exogenous states and y_t^f are variables appearing with a lead in the model. This is what's often referred to in the adaptive learning literature as the perceived law of motion (PLM), which when plugged into the MSV solution form produces the actual law of motion (ALM) that is consistent with the model an learning mechanism. The model outlined in section 3.4 has 6 endogenous state variables $\{k, x, w_a, w_b, i, z\}$ and two exogenous shocks $\{e_z, e_i\}$, and 6 forward looking variables $\{\pi, c_b, r, q, \pi_{wa}, \pi_{wb}\}$. Therefore, α_{t-1} is a 6×1 vector and Ω_{t-1} is a 6×8 matrix of coefficients. Every period, agents update their beliefs using a recursive least squares (RLS) algorithm

$$\phi_t = \phi_{t-1} + gR_{t-1}Z_{t-1}(y_t^f - \phi_{t-1}^T Z_{t-1})^T \tag{3.37}$$

$$R_t = R_{t-1} + g(Z_{t-1}Z_{t-1}^T - R_{t-1}) \tag{3.38}$$

where $Z_t = \left(1, (y_t^s)^T, w_t^T\right)^T$ is a vector of endogenous variables y_t^s and exogenous shocks w_t that is used to forecast forward looking variables, R_t is the estimated covariance matrix, and $\phi_t = \left(\alpha, \Omega^T\right)$ collects all the belief coefficients. At this point an assumption must be made regarding the timing of the learning process in order to avoid a simultaneity between the variables needed in the forecasting equation and the determination of the endogenous variables. Avoiding this issue requires that forecasts be made with the $t-1$ information set. Endogenous variables are determined at the end of the period, so agents enter period t knowing period $t-1$ values of the endogenous variables, which are used in the beginning of period t to update the forecasting parameters for period t. At this point values of exogenous shocks in period t are realized and agents use $t-1$ values of the endogenous states along with period t exogenous shocks and updated parameters to form expectations. At this point the ALM is updated and period t endogenous states are realized. In the results to follow I assume perfect knowledge about the constant, i.e. it's zero and agents know, therefore there is no constant in the learning algorithm. Given this form of expectation formation, the ALM determining the evolution of the endogenous state variables in the model is determined by

$$y_t = T(\phi_{t-1})y_{t-1} + V(\phi_{t-1})\varepsilon_t \tag{3.39}$$

where $T(\phi_{t-1})$ and $V(\phi_{t-1})$ are parameter matrices which are a function of the deep model parameters and the updated learning parameters. These matrices are what Evans & Honkapohja (2003) refer to as the T-map, which defines the expectational stability of the REE under learning. Given the general form of a recursive learning algorithm

$$\theta_t = \theta_{t-1} + \gamma_t Q(t, \theta_{t-1}, X_t) \tag{3.40}$$

for parameter vector θ and state vector X_t, the convergence of the system depends on the gain parameter/sequence γ_t and updating scheme $Q(t, \theta_{t-1}, X_t)$, where in recursive least squares $Q(t, \theta_{t-1}, X_t) = y_t^f - \phi_{t-1}^T Z_{t-1}$ and γ_t can be constant or decreasing and strictly positive. I will report results below for constant gains such that $\gamma_t \in [.01, .05]$ and decreasing gain such that $\gamma_t = 1/t$. As shown in Evans & Honkapohja (2003), the convergence of any such stochastic recursive learning algorithm is approximated by the ordinary differential equation (ODE)

$$\frac{d\theta}{d\tau} = h(\theta(\tau)) \tag{3.41}$$

where $h(\theta(\tau)) = \lim_{t\to\infty} EQ(t, \theta_t t - 1, \tilde{X}_t)$ for $\tilde{X}_t$ obtained by holding θ fixed at it's $t-1$ value. If the ODE has a point θ^* that is locally asymptotically stable, then the algorithm converges to θ^*. Generally, the asymptotic stability of the learning algorithm is determined by the stability of the ODE, which in turn depends on the stability of its Jacobean matrix $J(\theta^*) = D_\theta h(\theta(\tau))$.

3.4.8 Expectation shocks

Expectations are formed every period according to the most recent update of the parameter matrix ϕ and lagged endogenous and current exogenous states. A simple way of introducing bias in beliefs, which can be a byproduct of a number of factors ranging from heterogeneity to behavioral biases, I introduce a shock to the expectations formed in the learning model. This is motivated by the results uncovered in section 3.3 showing evidence that sentiment (or the bias in beliefs, corresponding to the expectation shock in this context) responds to monetary policy shocks, that is policy induces change in sentiment. The estimates in section 3.3 indicate that unexpected monetary policy tightening increases the bias in beliefs about gross capital returns by 0.16%, which provides a useful guide for the direction and size of the relationship while sentiment sample autocorrelation serves as an estimate of the expectation shock persistence. Recall from section 3.3 that the empirical SDF from which sentiment is extracted is defined over the space of gross equity return, $ln(S_T/S_t)$, where $T-t$ is the return horizon, which is quarterly in the estimation and parameterization of the model. The equivalent return in the model can be defined as

$$E_t\tilde{R}_{t+1} \equiv \beta E_t\tilde{q}_{t+1} - \tilde{q}_t + [1-\beta(1-\delta)]E_t\tilde{r}_{t+1} \tag{3.42}$$

where $\tilde{R}_{t+1}$ is the deviation of gross return from steady state. If we assume that the estimated response in sentiment to monetary surprise is a deviation from steady state, then what is required to match the estimates effect is to produce a bias in $E_t\tilde{q}_{t+1}$ and $E_t\tilde{r}_{t+1}$ that results in $E_t\tilde{R}_{t+1}$ increasing by 0.16. One can further break $E_t\tilde{R}_{t+1}$ into expected capital gains, $E_t\tilde{q}_{t+1} - \tilde{q}_t$, and expected yield $E_t\tilde{r}_{t+1}$. In order to achieve an increase in gross return, $E_t\tilde{R}_{t+1}$, we can either assume that the deviation is a result of change in expected capital gains, higher yields, or a combination of the two. Below I report results for the extreme cases, i.e. all the effect coming from either capital gains or yield, as well as a case where half of the gain is obtained from each. This rough parameterization allows a direct comparison of the sensitivity of the model to the source of expectation shock. Below I report two parameterization in response to a 10% increase in the policy rate; one for a large increase in $E_t\tilde{R}_{t+1}$, amounting to a 2% increase (decrease) in quarterly expected return, and another for a small 0.5% change.

The forecasts generating the ALM are now defined by

$$y_t^f = \phi_t Z_{t-1} + e_{e,t} \tag{3.43}$$

$$e_{e,t} = \rho_e e_{e,t-1} + \varepsilon_{e,t} \tag{3.44}$$

where $e_{e,t}$ is a 6×1 vector of expectation shocks and $\varepsilon_{e,t}$ is the vector of random innovations controlling expectation shock and is entirely made up of $\varepsilon_{i,t}$, that is, the only source of exogenous variation in sentiment stems directly from interest rate surprises and how they correlate with sentiment. The subset of $e_{e,t}$ pertaining to capital returns and correlated with interest rate surprises is given by

$$\begin{bmatrix} e_{q,t} \\ e_{r,t} \end{bmatrix} = \begin{bmatrix} \rho_q & 0 \\ 0 & \rho_r \end{bmatrix} \begin{bmatrix} e_{q,t-1} \\ e_{r,t-1} \end{bmatrix} + \begin{bmatrix} \rho_{q,i} \\ \rho_{r,i} \end{bmatrix} \varepsilon_{i,t} \tag{3.45}$$

where the vector $[e_{q,t}, e_{r,t}]'$ is the subset of $e_{e,t}$ that is contemporaneously correlated with interest rate shocks, $\varepsilon_{i,t}$, and $[\rho_{q,i}, \rho_{r,i}]'$ is the correlation between sentiment and interest rate shocks. These correlations are the parameters determining the size and direction of change in sentiment at the onset of policy shocks. They are set, as discussed above, in order to achieve a large or small change in expected gross returns on capital.

3.5 Simulations and impulse responses

For every specification of parameters I run 1000 simulation of the model for 1000 periods and take the average of the final period learning parameters and corresponding T-map and V-map to produce the impulse responses in the following figures. Tables 3.4 - 3.7 report standard deviation averaged over the 1000 simulations across different learning parameters. Two main features can be gleamed from the tables; learning parameters and initial conditions matter a lot for the dynamics of the model. Random initial conditions can be mitigated when $\gamma = 1/t$, but when γ is constant the simulations blow up as variables move far away from steady state. Table 3.5 highlights the difference between shocks to capital gains vs. rental rate. In both cases variables are amplified, but rental rate shocks seem to amplify the deviations by 2-10 times for some variables. The effect is similar for positively and negatively correlated shocks in table 3.6 with rental rate shocks creating slightly higher variation. Random initial conditions in addition to expectation shocks move variables far from steady state and tend to blow up as time goes on, that is the "stable" ϕ matrices do not force variables towards steady state. The results reported below are sensitive to the choice of gain in the learning algorithm. I start by reporting impulse responses functions (IRFs) for aggregate variables following a tightening shock. I report IRFs for the REE solution as well as the learning model after the parameter matrix ϕ_t has converged to a stable value ϕ^*, which I obtain by averaging the final period ϕ matrix across 1000 simulations. The ϕ^* matrices used in the IRFs below are stable matrices at period 1000, although the convergence happens much earlier in the simulation. Unlike Díaz *et al.* (2012), who shows that Γ doesn't play a role in the effect of monetary surprises, I find that the response in output and inflation under learning with or without expectation shocks is sensit3ive to the degree of market participation. Furthermore, limited market participation serves as a stabilizer when expectations shocks are introduced, helping bring output and inflation back to steady state much more rapidly than when all agents are Ricardian. The decreasing gain parameterization has the closest resemblance to RE while constant gains exhibit more non-monotonic responses. Figures 3.5 plots the IRFs for output and inflation under learning with expectation shocks and without for the model with only Ricardian households. Inflation responds as intended initially, however, with learning there is an overshooting that occurs irrespective of the presence of expectation shocks. This amplification, however, is accentuated upwards (downwards) with negatively (positively) correlated expectation shocks. Output overshoots in only one of the learning models initially but returns to the same direction as RE in the following periods. All learning models are generally slow to get back to steady state, but that effect is much stronger in output than inflation. The number of periods it takes to get back to steady state is highly sensitive to market participation. When all households are Ricardian, expectations shocks produce a large amplification in output that remains elevated above or below steady state for many periods depending on the direction of the correlation. When market participation is limited to 70% the learning dynamics appear to be dampened but remain qualitatively the same. Figure 3.7 plot output and inflation for this case showing that output converges back to steady state much more rapidly, although an overshooting still occurs with expectation shocks. Inflation in this case is amplified more so than when $\Gamma = 0$ and is slower to return to steady state relative. The sensitivity to market participation is accentuated once beliefs are biased. Expectation shocks are added to the rental rate and price of capital separately then simultaneously as per section 3.4.8. Shocks on the rental rate appear to generate a stronger response than shocks to capital gains. Rental rate shocks provide the incentive for Ricardian consumers to forego current consumption for longer periods, leaving consumption and output below steady state for many periods after the shock. This process is much quicker under decreasing gain than constant gain, where investment and consumption remain below steady state for a long period. The same happens under capital gains shocks but the process takes much longer to unfold. Figures 3.6 and 3.8 show the responses in investment and rental rate for the $\Gamma = 0$ and $\Gamma = .3$ cases, respectively. The response in investment has large amplifications when expectation shocks are introduced, but this effect is greatly dampened when $\Gamma = .3$. In this case, the presence of non-Ricardian agents acts as a stabilizer to expectation shocks.

3.6 Conclusion

Beliefs are a central component determining equilibrium outcomes in economic models. In this paper I study the relationship between bias in beliefs and monetary policy shocks. By augmenting an otherwise standard limited capital participation new-Keynesian model with learning and expectation shocks, I uncover an unexplored channel of transmission working through bias in beliefs. The effect of this channel is not trivial as it can cause strong amplifications that can either strengthen or dampen the effect of policy depending on the direction of bias correlation and degree of market participation. When belief bias is positively correlated with monetary tightening aggregates tend to overshoot steady state and dampen the intended effect of policy, while negative correlation strengthens the effect of policy. These results serve as a note of caution to the monetary authority as they point out a previously unexplored channel of transmission for policy. Ultimately monetary policy needs to be less or more responsive in order to achieve the same intended policy outcome. The next natural step is to examine the design of optimal monetary policy that takes into account belief bias and its effect on aggregates.

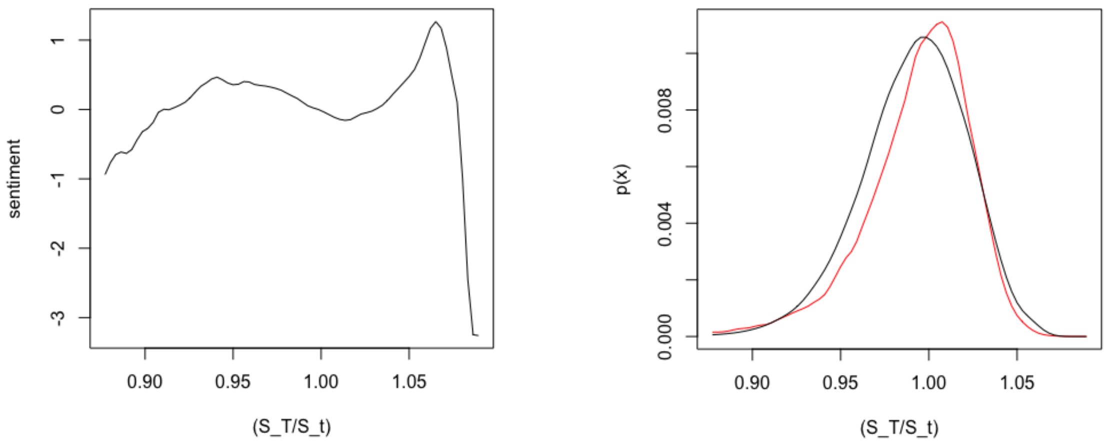


Figure 3.1: Sentiment function (left panel) with resulting biased measure, p_R (black), and true measure p (red) for two month gross return expectation, S_T/S_t, as of 2012-09-05.

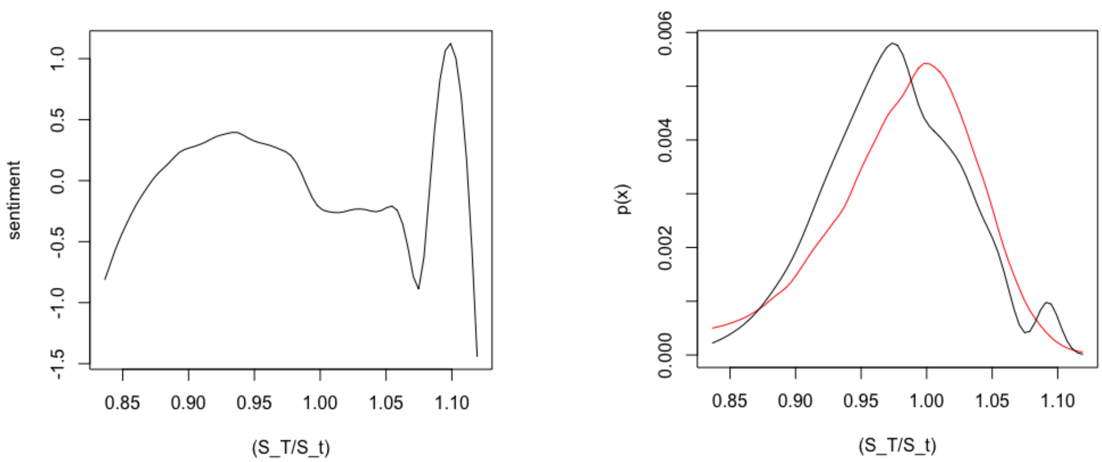


Figure 3.2: Sentiment function (left panel) with resulting biased measure, p_R (black), and true measure p (red) for six month return expectation as of 2012-09-05.

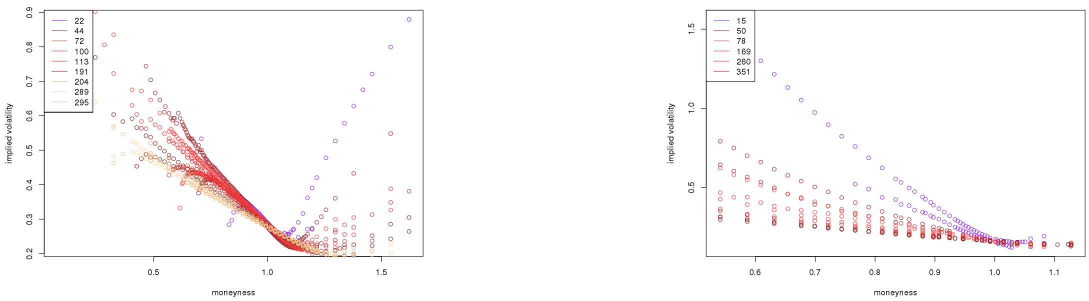


Figure 3.3: Volatility implied by the Black-Scholes pricing formula given observed option prices on December 8th 2011 (left panel) and January 2nd 2004 (right panel). Numbers in legend correspond to days to expiration of options.

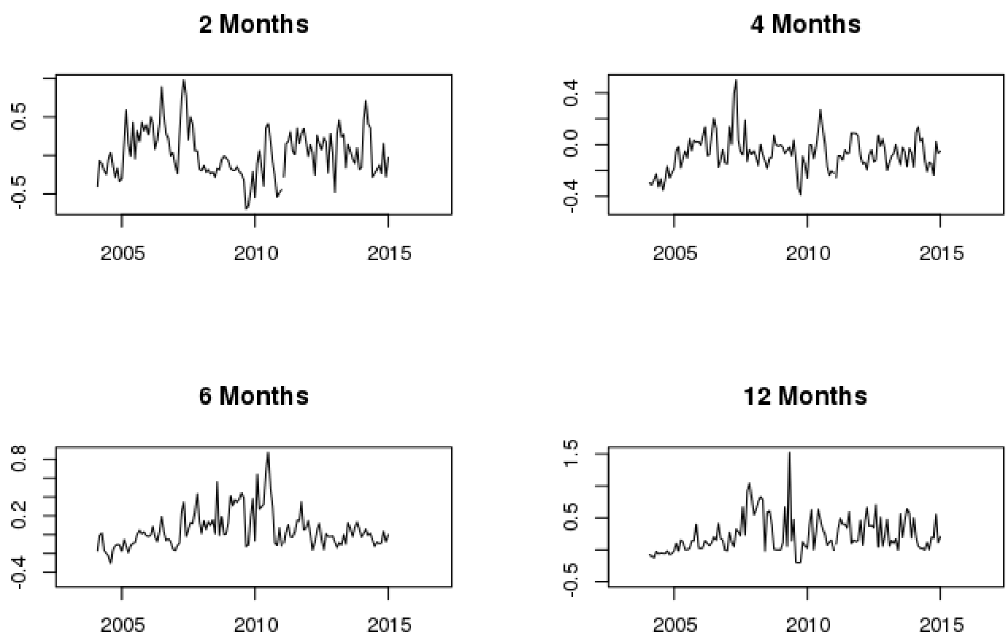


Figure 3.4: Monthly structural sentiment averaged over the month for 2, 4, 6, and 12 month returns

	Δ *optimism*			Δ *overconfidence*		
	2-months	4-months	6-months	2-months	4-months	6-months
tight	0.140*	0.162**	0.144	−4.321	−4.877**	−3.709
	(0.071)	(0.066)	(0.128)	(2.595)	(2.184)	(4.112)
loose	0.016	0.030	−0.084	−0.482	−1.154	2.378
	(0.056)	(0.052)	(0.100)	(2.031)	(1.709)	(3.218)
Constant	−0.004	−0.013	−0.022	0.039	0.418	0.691
	(0.034)	(0.031)	(0.061)	(1.231)	(1.036)	(1.951)
Observations	58	58	58	58	58	58
R^2	0.067	0.099	0.047	0.049	0.083	0.033
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 3.1: Dependent variable in left panel is the change in structural optimism as defined in equation 3.5 (after less before monetary policy events). The right panel is the change in the second moment as defined in equation 3.6.

	Δ *optimism*			Δ *overconfidence*		
	2-months	4-months	6-months	2-months	4-months	6-months
	(1)	(2)	(3)	(4)	(5)	(6)
FFF_{tw}	0.016	0.089	−0.392	−0.736	−2.979	13.748
	(0.028)	(0.424)	(0.698)	(1.050)	(14.667)	(24.744)
Constant	−0.001	0.018	0.029	0.037	−0.640	−1.178
	(0.001)	(0.016)	(0.027)	(0.041)	(0.578)	(0.975)
Observations	34	34	34	32	32	32
R^2	0.010	0.001	0.010	0.016	0.001	0.010
FFF_{ww}	0.009	−0.016	−0.348	−0.472	0.475	11.543
	(0.023)	(0.341)	(0.561)	(0.847)	(11.804)	(19.890)
Constant	−0.002	0.017	0.030	0.039	−0.623	−1.219
	(0.001)	(0.016)	(0.026)	(0.041)	(0.574)	(0.967)
Observations	34	34	34	32	32	32
R^2	0.005	0.0001	0.012	0.010	0.0001	0.011
Note:						$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3.2: Change in structural sentiment in response to monetary policy shocks identified as normalized changes in fed-funds futures (FFF) in the minutes around FOMC press release for the period 2004-2008. FFF_{tw} refers to change in tight-window range (-10 min, +20 min) while FFF_{ww} is for range (-15 min, +45 min)

	2m	4m	6m
	(1)	(2)	(3)
optimism	0.003	0.023***	0.010
	(0.003)	(0.008)	(0.006)
dClose	0.004***	0.006***	0.006***
	(0.001)	(0.001)	(0.002)
dEPnom	6.806***	5.623**	4.297
	(1.820)	(2.705)	(3.357)
termSpread	−0.001	0.002	0.010***
	(0.001)	(0.002)	(0.002)
Constant	1.018***	1.031***	1.032***
	(0.003)	(0.004)	(0.005)
Observations	2,604	2,731	2,731
R^2	0.016	0.013	0.014
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 3.3: Dependent variable is subsequent return of respective horizon.

	RE		$\gamma = 1/t$		$\gamma = 0.01$		$\gamma = 0.05$	
	transit	**stable**	**transit**	**stable**	**transit**	**stable**	**transit**	**stable**
y	0.074	0.071	0.116	0.116	0.115	0.261	0.113	12.089
c	0.076	0.074	0.116	0.116	0.116	0.368	0.113	15.068
h	0.251	0.255	0.186	0.193	0.185	0.409	0.19	18.301
w	0.039	0.04	0.027	0.009	0.026	0.071	0.037	6.982
k	0.03	0.028	0.031	0.019	0.031	0.016	0.025	0.296
x	0.068	0.064	0.115	0.114	0.114	0.069	0.111	2.19
i	0.069	0.065	0.117	0.114	0.117	0.052	0.114	1.677
π	0.018	0.019	0.009	0.013	0.009	0.083	0.019	1.044
r	0.224	0.227	0.186	0.193	0.186	0.387	0.191	14.046
q	0.068	0.064	0.116	0.116	0.116	0.069	0.112	2.194
y	0.075	0.075	193.914	125.829	311.585	2610.379	128.576	655.117
c	0.078	0.078	197.696	148.058	323.593	3246.778	130.608	801.044
h	0.248	0.257	291.126	188.698	471.597	3916.122	195.218	984.132
w	0.04	0.04	177.643	79.862	286.512	945.706	101.817	723.227
k	0.029	0.029	28.058	30.614	40.673	156.209	17.608	33.388
x	0.066	0.068	195.707	93.156	291.879	421.793	131.722	216.127
i	0.068	0.07	108.755	33.383	168.915	243.881	73.28	158.361
π	0.019	0.019	72.554	22.171	112.647	162.554	48.847	105.551
r	0.22	0.228	343.829	177.476	572.214	3408.061	238.379	894.957
q	0.067	0.069	188.937	79.12	290.923	416.228	131.917	214.266

Table 3.4: Standard deviation of change in selected endogenous variables for RE consistent initial beliefs, top panel, and random initial beliefs, lower panel, at different gain parameters, $\Gamma = 0$

	$\gamma = 1/t$		$\gamma = 0.01$		$\gamma = 0.05$	
	transit	**stable**	**transit**	**stable**	**transit**	**stable**
y	0.117	0.13	0.115	0.236	0.113	12.569
c	0.117	0.13	0.116	0.335	0.114	15.674
h	0.187	0.208	0.192	0.379	0.19	19.026
w	0.027	0.025	0.028	0.065	0.037	6.889
k	0.034	0.039	0.032	0.015	0.025	0.278
x	0.116	0.135	0.114	0.067	0.111	2.05
i	0.117	0.114	0.117	0.054	0.112	1.608
π	0.01	0.024	0.01	0.08	0.019	0.985
r	0.187	0.203	0.192	0.354	0.191	14.717
q	0.117	0.132	0.115	0.067	0.113	2.056
y	0.113	18.097	0.111	0.534	0.119	41.162
c	0.114	16.99	0.115	0.669	0.122	51.551
h	0.186	21.822	0.181	0.716	0.201	61.528
w	0.03	8.995	0.009	0.054	0.016	11.382
k	0.049	26.995	0.007	0.049	0.008	0.55
x	0.112	35.955	0.099	0.153	0.106	3.668
i	0.114	4.875	0.112	0.076	0.115	3.287
π	0.01	3.348	0.01	0.096	0.013	2.093
r	0.186	23.945	0.181	0.732	0.201	65.249
q	0.113	28.001	0.1	0.144	0.108	3.66

Table 3.5: Standard deviation of change in selected endogenous variables for RE consistent initial beliefs at different gain parameters with expectations shocks in capital gains, top panel, and rental rate, lower panel, $\Gamma = 0$.

	$\gamma = 1/t$		$\gamma = 0.01$		$\gamma = 0.05$	
	transit	**stable**	**transit**	**stable**	**transit**	**stable**
y	0.112	16.455	0.11	0.763	0.123	40.812
c	0.113	17.411	0.114	0.957	0.127	51.131
h	0.187	24.341	0.179	1.097	0.204	60.97
w	0.029	3.943	0.009	0.055	0.016	10.568
k	0.051	6.45	0.007	0.065	0.008	0.556
x	0.114	18.933	0.098	0.186	0.108	3.483
i	0.115	4.836	0.115	0.084	0.117	3.1
π	0.011	3.33	0.01	0.097	0.012	1.963
r	0.187	21.484	0.18	1.097	0.204	64.32
q	0.114	16.42	0.099	0.175	0.11	3.48
y	0.113	17.152	0.113	1.953	0.117	30.942
c	0.113	17.898	0.111	2.458	0.116	38.769
h	0.187	25.797	0.186	2.868	0.198	46.548
w	0.029	4.232	0.049	0.083	0.047	12.845
k	0.042	4.931	0.059	0.121	0.036	0.567
x	0.113	16.299	0.126	0.2	0.124	4.011
i	0.116	5.723	0.118	0.119	0.118	2.847
π	0.011	3.881	0.014	0.096	0.022	1.875
r	0.187	23.113	0.186	2.839	0.198	42.052
q	0.114	15.911	0.125	0.187	0.126	4.026

Table 3.6: Standard deviation of change in selected endogenous variables for RE consistent initial beliefs at different gain parameters with positively correlated expectations shocks in capital gains and rental rate, top panel, and negatively correlated, lower panel, $\Gamma = 0$.

	$\gamma = 1/t$		$\gamma = 0.01$		$\gamma = 0.05$	
	transit	**stable**	**transit**	**stable**	**transit**	**stable**
y	252.909	547.575	106.735	2211.997	161.152	3289.562
c	292.941	574.033	111.096	2762.155	175.261	4088.921
h	378.487	728.15	160.756	3317.676	244.277	4934.492
w	265.648	214.915	58.758	243.08	99.694	1586.457
k	20.252	462.613	10.602	80.67	24.734	70.366
x	161.676	1444.598	97.211	167.697	130.674	528.268
i	154.625	117.567	41.222	107.63	63.821	460.028
π	103.127	78.322	27.56	71.693	42.537	306.666
r	456.938	722.082	171.662	3343.271	255.598	5929.295
q	154.59	1134.264	97.204	158.584	129.454	528.89
y	214.548	313.234	2256.697	15928.979	2058.53	9765.349
c	214.29	371.282	2336.273	19867.563	2176.589	12157.208
h	323.874	448.001	3419.85	23895.429	3113.278	14648.941
w	77.455	139.355	1752.039	2873.39	592.236	4150.36
k	20.045	243.905	311.797	475.781	252.222	199.338
x	222.062	310.825	2103.196	1622.94	1706.715	1406.67
i	64.514	51.834	1159.459	931.605	817.676	1275.679
π	43.073	34.475	772.988	621.047	545.113	850.445
r	327.818	442.712	3827.411	22745.376	3210.009	17637.698
q	223.362	232.862	2098.757	1592.275	1699.113	1417.037

Table 3.7: Standard deviation of change in selected endogenous variables for Random initial beliefs at different gain parameters with positively correlated expectations shocks in capital gains and rental rate, top panel, and negatively correlated, lower panel, $\Gamma = 0$.

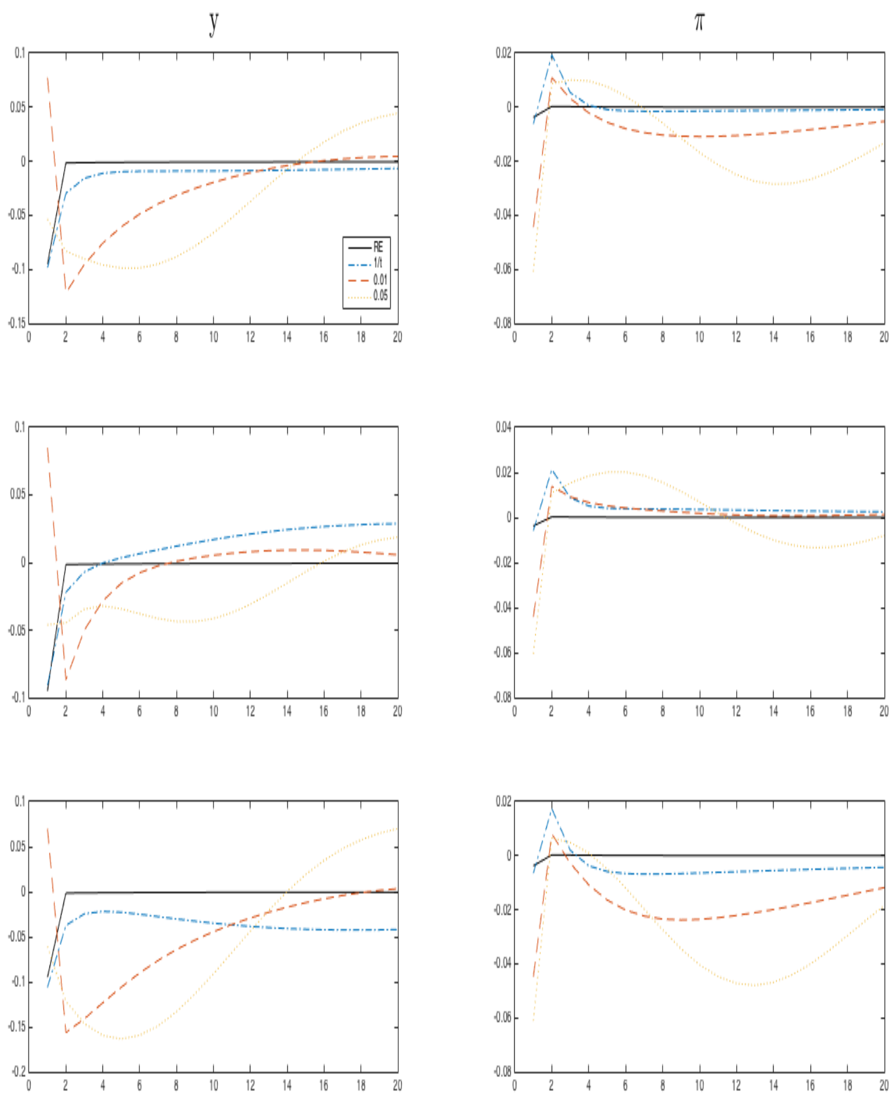


Figure 3.5: Outout and inflation IRFs to tightening shock in RE and learning models with $\Gamma = 0$. No expectation shocks in top row followed by positively and negative correlated shocks in middle and bottom rows, respectively. Shocks are calibrated to generate a 2% increase in expected gross return emanating from $E_t\tilde{r}_{t+1}$ and $E_t\tilde{q}_{t+1}$.

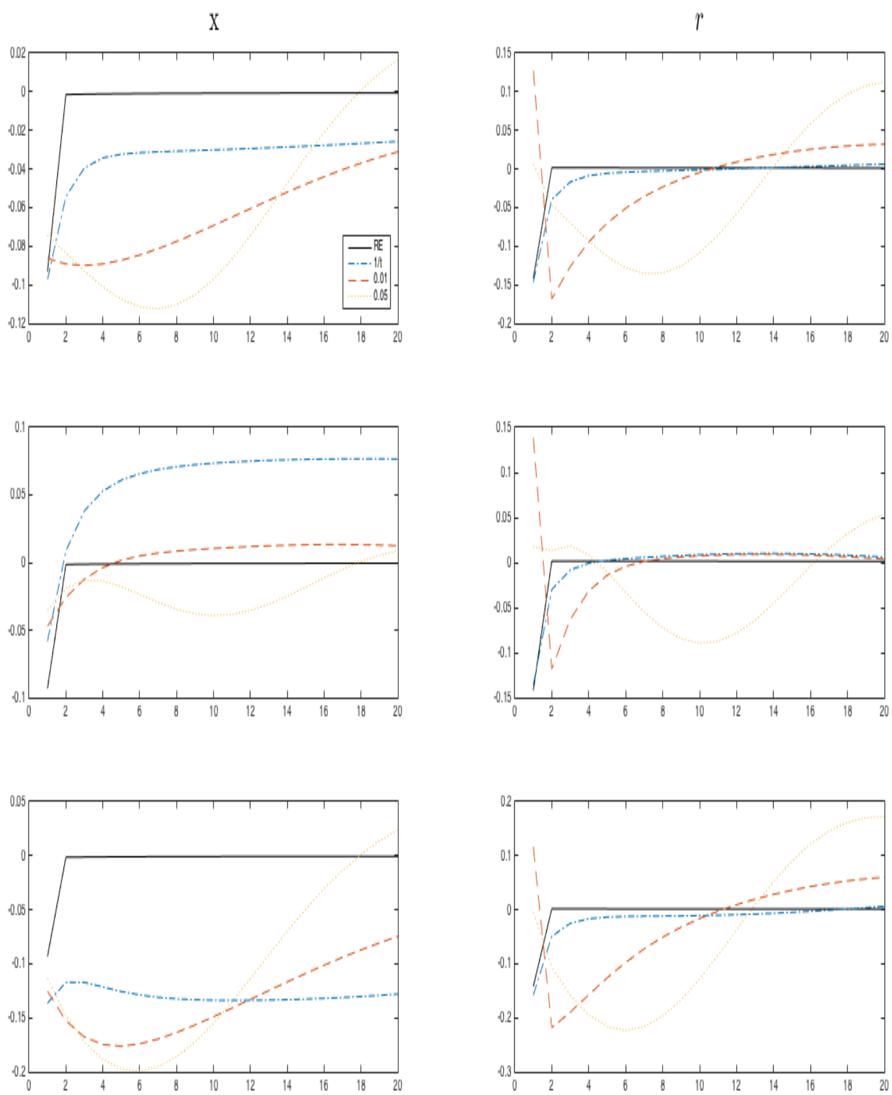


Figure 3.6: Investment and rental rate IRFs to tightening shock in RE and learning models with $\Gamma = 0$. No expectation shocks in top row followed by positively and negative correlated shocks in middle and bottom rows, respectively. Shocks are calibrated to generate a 2% increase in expected gross return emanating from $E_t\tilde{r}_{t+1}$ and $E_t\tilde{q}_{t+1}$.

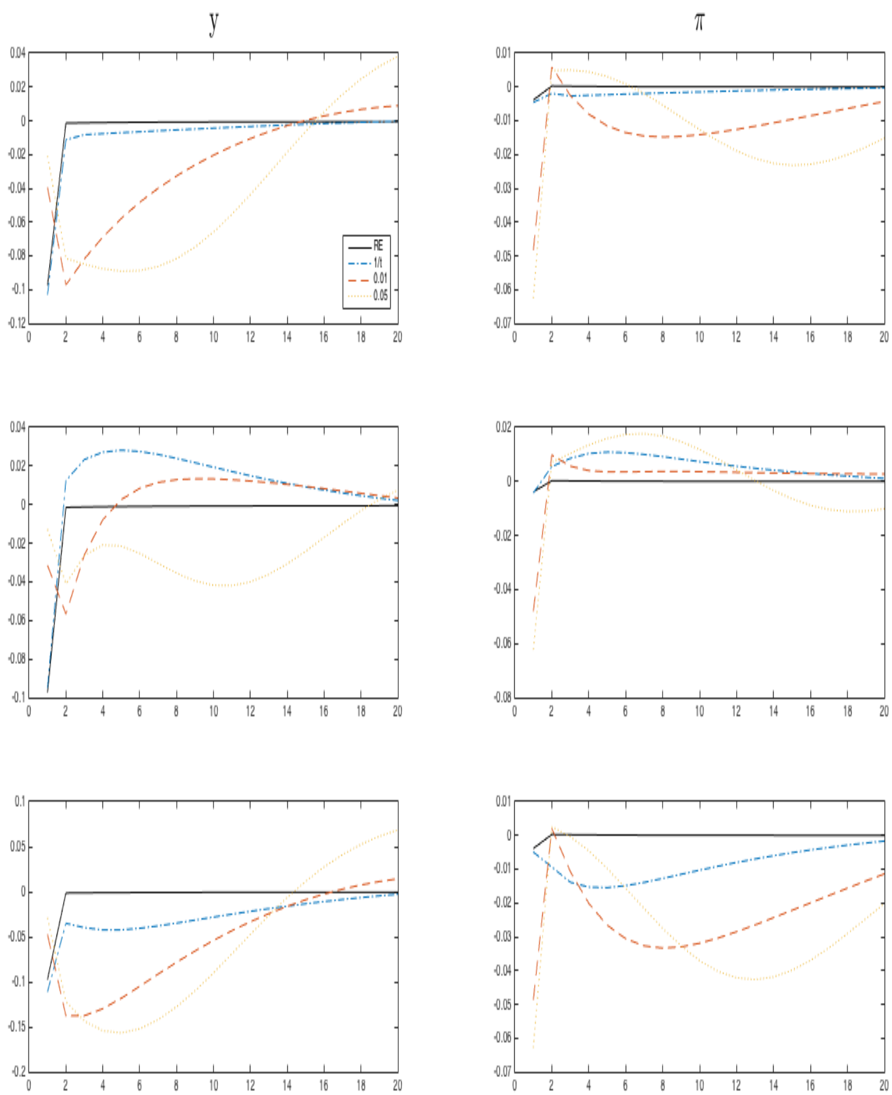


Figure 3.7: Outout and inflation IRFs to tightening shock in RE and learning models with $\Gamma = 0.3$. No expectation shocks in top row followed by positively and negative correlated shocks in middle and bottom rows, respectively. Shocks are calibrated to generate a 2% increase in expected gross return emanating from $E_t\tilde{r}_{t+1}$ and $E_t\tilde{q}_{t+1}$.

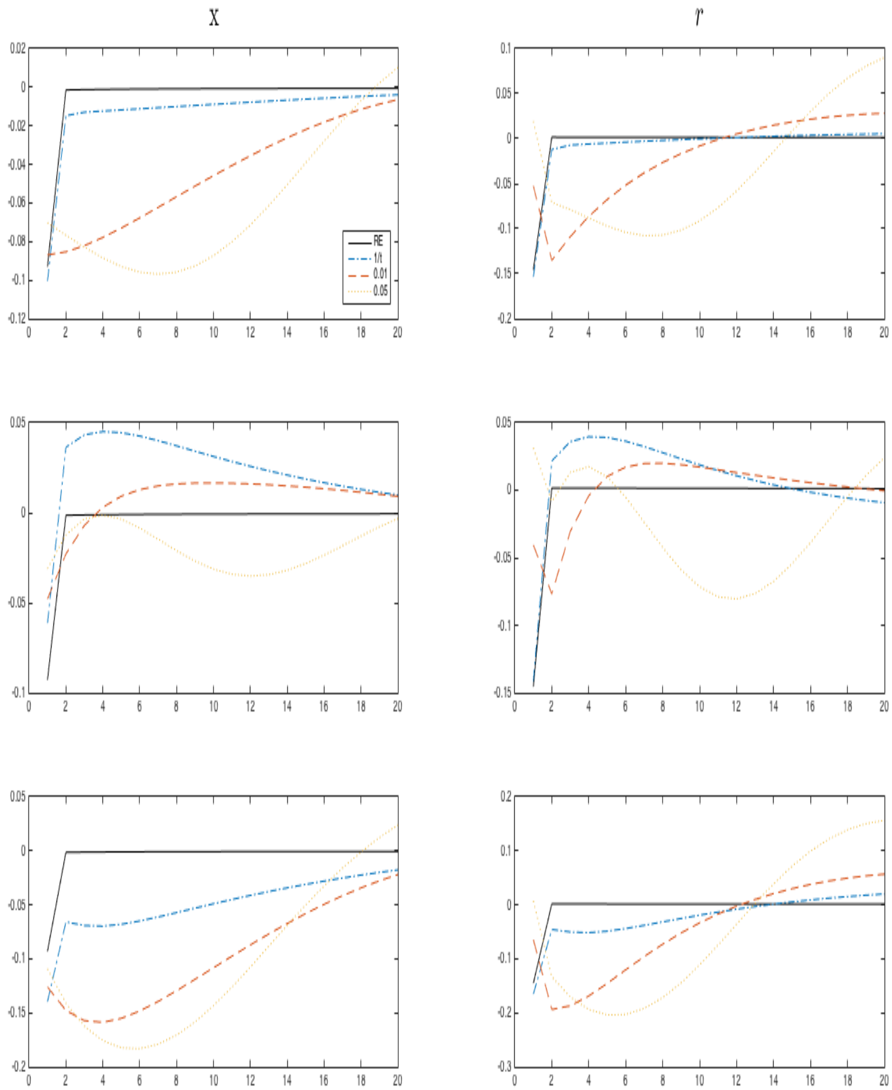


Figure 3.8: Investment and rental rate IRFs to tightening shock in RE and learning models with $\Gamma = 0.3$. No expectation shocks in top row followed by positively and negative correlated shocks in middle and bottom rows, respectively. Shocks are calibrated to generate a 2% change in expected gross return emanating from $E_t\tilde{r}_{t+1}$ and $E_t\tilde{q}_{t+1}$.

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