Why so Negative?
Belief Formation and Risk Taking in Boom and Bust Markets[*]

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Abstract

What determines investors' risk-taking across macroeconomic cycles? Researchers have proposed rational expectations models that introduce countercyclical risk aversion to generate the empirically observed time variation in risk-taking. In this study, we test whether systematic deviations from rational expectations can cause the same observed investment pattern without assuming unstable preferences. We let subjects form beliefs in two different market environments which resemble key characteristics of boom and bust markets, followed by an independent investment task. Those subjects who learned in the negative domain form overly pessimistic beliefs and invest significantly less in an unrelated ambiguous investment option. However, similar investment patterns cannot be observed for an unrelated risky investment option, where expectations are fixed. The proposed mechanism presents an alternative explanation for time-varying risk-taking and provides new implications for both theory and policy makers.

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Introduction

How do individuals form expectations about future stock returns? The answer to this question is crucial to understand differences in risk-taking over time and in particular across market cycles. A key assumption in models that generate time-variation in risk-taking is that investors have rational expectations, which are immediately updated according to Bayes' rule when new information arrives (Barberis et al., 2001; Campbell & Cochrane, 1999; Grossman & Shiller, 1981). Implicitly these models assume that agents know the objective probability distribution in equilibrium and are as such fully aware of the counter-cyclical nature of the equity risk premium (Nagel & Xu, 2019). Yet, a number of recent surveys of investors' expectations show that this is not the case, and that investors – if anything – have rather pro-cyclical expectations: they are more optimistic in boom markets and less optimistic in recessions (Amromin & Sharpe, 2013; Giglio et al., 2019; Greenwood & Shleifer 2014).

In the light of this inconsistency, it is imperative to obtain a deeper understanding of how investors incorporate new information when they form expectations and whether this could ultimately explain differences in risk-taking across macroeconomic cycles. Prior research has shown that investors put too much probability weight on new information, if the information looks representative of previously observed data (Kahneman and Tversky, 1972). Gennaioli and Shleifer (2010) as well as Gennaioli, Shleifer, and Vishny (2012, 2015) show that representativeness can generate and amplify boom/bust financial crises based entirely on investors' beliefs. Besides the representativeness of the outcome history, Kuhnen (2015) shows that agents learn differently from outcomes in the negative domain than from the same outcome history in the positive domain. Both findings together and individually can lead to systematic distortions in how investors learn from outcomes and how they incorporate beliefs in their decision-process.

In this study, we investigate whether distorted belief formation rules (i.e. systematic violations of Bayes' rule) can explain differences in risk-taking across recessions and boom markets. To examine this relation, we conduct an experimental study with two different learning environments that closely resemble key characteristics of financial market cycles. The first learning environment characterizes a market setting in which subjects exclusively learn either in the positive (i.e. boom) or in the negative (i.e. recession) domain. The second learning environment characterizes a potentially more realistic market setting in which subjects learn from mixed-outcome distributions with either positive expected value (i.e. boom) or negative expected value (i.e. bust). We test 1) how different learning environments affect the learning rules agents employ when forming return expectations, 2) how systematic differences in beliefs resulting from different learning rules translate to risk-taking, and 3) whether different learning environments not only affect subjects' beliefs but also their risk preferences.

While recent survey data on expectations is helpful to establish a link between subjective beliefs and investment decisions, it does not allow inference about how investors depart from rational expectations without imposing strong assumptions. In an experiment however, we can establish a setting in which we have direct control over objective (rational) expectations and can compare them to participants' subjective beliefs. This allows us to document systematic errors in the belief formation process, which we can then relate to subjects' investment choice. In our experiment, we combine an abstract Bayesian updating task (partly adopted from Kuhnen, 2015) with an unrelated incentive-compatible investment task in a financial environment. In the Bayesian updating task subjects have to incorporate a sequence of information into their beliefs to estimate the likelihood that an asset pays dividends drawn from one of two distributions. The information subjects receive is – depending on the learning environment – either exclusively positive (boom treatment) or negative (bust treatment) in Experiment 1, or both positive and negative but drawn from distributions with either positive (boom treatment) or negative expected value (bust treatment) in Experiment 2. The underlying probability distribution, however, from which the information is drawn, is completely identical in both learning environments. In other words, a Bayesian agent in our setting should make identical forecasts irrespective of whether he learns in the positive or negative environment. After subjects completed the forecasting task, they make an unrelated investment decision in either a risky or an ambiguous lottery, which serves as a between-subject measure of belief- and preference-based risk taking. In the ambiguous lottery, we purposefully give participants room to form subjective beliefs about the underlying true probability distribution. In the risky lottery, we have perfect control over subjects' return and risk expectations since both probabilities and outcomes are known. As such, investments in the ambiguous lottery are affected by both subjects' risk preferences and their beliefs about the underlying probability distribution, while investments in the risky lottery serve as a measurement tool for risk aversion. The between-subject comparison finally allows us to isolate the effect of belief-induced risk taking caused by outcome-dependent learning rules.

First, we find that subjects who forecast the probability distribution of an asset in a negative learning environment (bust treatment) are significantly more pessimistic in their average probability estimate than those subjects who forecast the identical probability distribution in a positive learning environment (boom treatment). Consistent with the results of Kuhnen (2015), this asymmetry in belief formation resembles a pessimism bias as subjects' beliefs in the bust treatment show larger deviations from Bayesian beliefs compared to subjects' beliefs in the boom treatment. However, so far Kuhnen (2015) documents the pessimism bias only for domain-specific learning environments (similar to the environment in our first experiment), while our findings are independent of whether subjects learn exclusively from negative outcome lotteries or from mixed-outcome lotteries with negative expected value. In other words, our results suggest that the pessimism bias does not critically depend on domain-specific outcomes, which makes it even more general than previously thought.

Second, we find that systematically downward-biased beliefs resulting from asymmetric learning in adverse environments translate to lower risk-taking. Subjects in the bust treatment invest on average 47% less in the ambiguous lottery compared to subjects in the boom treatment. Additionally, they are substantially more pessimistic about the success probability of the ambiguous lottery (by about 19 percentage points). This finding is consistent with the notion that when individuals form expectations in adverse learning environments (as is frequently the case in recessions), they take significantly less risk in uncertain environments. In the risky lottery, when expectations are fixed, we test the effect of asymmetric learning rules on subjects' risk aversion. However, we do not find any significant difference between treatments on subjects' investment, indicating that preferences remained stable and were unaltered by the way subjects form expectations.

Third, we seek to better understand the link of how forecasting in different learning environments affects risk-taking and for whom the effect is most pronounced. We find that those subjects who show above-median forecasting ability in the learning task of the experiment critically drive the results. In particular, these subjects show a stronger link between the pessimism induced by the initial adverse learning environment and the subsequent (lower) risk-taking. However, and importantly, even these subjects still exhibit a pronounced pessimism bias in their probability assessment, which subsequently translates to more pessimistic beliefs about the success probability of the ambiguous asset. To rationalize why the risk-taking of the seemingly smarter agents is more affected by the learning environment, we test whether they share particular socio-demographic characteristics or whether they are more involved in the experimental task. Our analyses support the latter argument, which suggests that the here reported effect might be even stronger in the real economy, where stakes and involvement are presumably higher.

Finally, we provide evidence that the pessimism induced by adverse learning environments within our experimental setup even affects subjects' return expectations in the real economy. When asked to provide a return forecast of the Dow Jones Industrial Average, subjects in the bust treatment are significantly more pessimistic about the future performance of the index than their peers in the boom treatment. In addition to the more pessimistic expectations, we find that subjects who learn in adverse financial conditions even provide negative return estimates, while those learning in rather favorable financial conditions provide positive return estimates. Given that we are able to systematically manipulate return expectations for real world market indices even in short-living learning environment as in our experiment, we believe that the here reported effect is even more generalizable in the real economy.

Our findings contribute to several strands of literature. Most importantly, our results provide a direct and causal link of how systematic distortions in investors' expectations can affect their willingness to take financial risks. The most prominent rational expectations models that generate high volatility of asset prices and the countercyclical equity risk premium introduce modifications into the representative agent's utility function, which effectively generates countercyclical risk aversion (Campbell and Cochrane, 1999; Barberis et al., 2001). This implies that during bust markets investors become more risk averse and consequently demand a higher risk premium, and they become less risk averse during boom markets, thus demanding a lower risk premium. Recently, Cohn et al. (2015) present experimental evidence supporting this notion, while Guiso et al. (2018) present survey evidence in line with this argument.[1] However, in our experimental design, we can confidently rule out that a change in preferences can explain our findings. Instead, we show that expectations and how they are formed can generate similar feedback loops as implied by countercyclical risk aversion, without having to assume unstable preferences. If bust markets systematically induce pessimistic expectations about future returns for a substantial subset of investors, this may reduce the aggregate share invested in risky assets of an economy, which in turn generates downward pressure on prices due to excess supply. In line with our results, Amromin and Sharpe (2014) find that households' lower willingness to take risks during recessions is rather driven by their

[1] There are also recent papers who challenge the notion of countercyclical risk aversion as tested in Cohn et al. (2015), such as Alempaki et al. (2019) and König-Kersting & Trautman (2018).

more pessimistic subjective expectations than by countercyclical risk aversion. Similarly, Weber et al. (2013) show that the self-reported risk attitudes of UK online-broker customers remained relatively stable over the recent financial crisis.

Our study also relates to the findings reported in recent surveys of investor return expectations (Amromin & Sharpe, 2014; Giglio et al., 2018; Greenwood & Shleifer, 2014). A common finding is that survey expectations of stock returns are pro-cyclical (i.e. investors are more optimistic during boom markets and more pessimistic during recessions), and as such inconsistent with rational expectation models. A first attempt to reconcile this puzzling finding was made by Adam et al. (2018), who test whether alternative expectation hypotheses proposed in the asset pricing literature are in line with the survey evidence. However, they reject all of them. In our study, we also find that investors' expectations are pro-cyclical, as they are more optimistic when learning in favorable environments then when learning in adverse environments. As such, the belief formation mechanism tested in our study may provide an interesting starting point for alternative theories of belief updating featuring pro-cyclical expectations.

Our finding also relates to the literature on investors' experience (Graham & Narasimhan, 2004; Malmendier & Nagel, 2011, 2015; Malmendier & Tate, 2005; Malmendier et al., 2011). The literature posits that events experienced over the course of an investor's life have persistent and long-lasting effects. In the spirit of this literature, learning rules more frequently applied throughout investors' lives may exert a greater influence on the way they form beliefs and ultimately on their willingness to take risks. For example, investors who experienced the Great Depression in their early career were more frequently exposed to negative stock returns, which might have affected the way they form beliefs about future economic events. As a result, these investors are more pessimistic in their assessment of future stock returns and less willing to take financial risks compared to those who experienced the post-war boom until the 1960s in their early life.

The here reported mechanism and its effect on risk-taking may also have important policy implications. For example, if investors are overly pessimistic in recessions, they may expect lower returns and reduce their equity share. As a consequence, the pro-cyclical nature of beliefs resulting from partly distorted belief formation rules reported in our study may amplify the intensity and the length of market phases.

The remainder of the paper is organized as follows. Section I outlines the experimental design, and briefly discusses the most important design aspects. Section II contains our hypotheses, while Section III describes summary statistics of our sample and randomization checks. Section IV presents our findings, and Section V concludes.

I. Experimental Design

A. Description of the Experiment

Seven-hundred fifty-four individuals (458 males, 296 females, mean age 34 years, 10.3 years standard deviation) were recruited from Amazon Mechanical Turk (MTurk) to participate in two online experiments. MTurk advanced to a widely used and accepted recruiting platform for economic experiments. Not only does it offer a large and diverse subject pool compared to lab studies (which frequently rely on students), but it also provides a response quality similar to that of other subject pools (Buhrmester et al., 2011; Goodman et al., 2013).

Both experiments consist of two independent parts, a forecasting task (Bayesian updating) and an investment task. The experiments differ with respect to the forecasting task, but are identical with respect to the investment task. In the forecasting task, which is partly adapted from Kuhnen (2015), we create a learning environment which resembles key characteristics of boom and bust markets. In Experiment 1 subjects learn from either exclusively positive outcome-lotteries (i.e. boom-scenario) or negative outcome-lotteries (i.e. bust-scenario). In Experiment 2 subjects learn from mixed outcome-lotteries but which have either a positive expected value (i.e. boom-scenario) or a negative expected value (i.e. bust-scenario). In detail, subjects receive information about a risky asset, whose payoffs are either drawn from a "good distribution" or from a "bad distribution". Both distributions are binary with identical high and low outcomes. In the good distribution, the higher payoff occurs with a 70 % probability while the lower payoff occurs with a 30 % probability. In the bad distribution, the probabilities are reversed, i.e. the lower payoff occurs with a 70 % probability while the higher payoff occurs with a 30 % probability. The actual payoffs depend on both the experiment and the treatment to which subjects are assigned. In both experiments, subjects are randomly assigned to either a "*boom*" treatment or a "*bust*" treatment. In the first experiment, the payoffs of the risky asset are either exclusively positive or negative, which resembles domain-specific learning. The payoffs in the boom treatment are either +15, or +2, whereas they are -2, or -15 in the bust treatment. In the second experiment, the payoffs of the risky asset are drawn from mixed-outcome lotteries, with either a positive or a negative expected value. The payoffs in the boom treatment are either +15, or -2, whereas they are +2, or -15 in the bust treatment. While the payoffs across treatments are mirrored, the underlying two distributions of the risky asset from which outcomes are drawn are identical.

In both experiments, subjects make forecasting decisions in two consecutive blocks each consisting of eight rounds. At the beginning of each block, the computer randomly determines the distribution of the risky asset (which can be good or bad). In each of the eight rounds, subjects observe a payoff of the risky asset. Afterwards, we ask them to provide a probability estimate that the risky asset draws from the good distribution and how confident they are about their estimate. As such, subjects will make a total of 16 probability estimates (8 estimates per block). To keep the focus on the forecasting task and to not test their memory performance, we display the prior outcomes in a price-line-chart next to the questions. To ensure that subjects have a sufficient understanding of the forecasting task, they had to correctly answer three comprehension questions before they could continue (see Appendix B).

In the second part of each experiment, the investment task, subjects are randomly assigned to invest in either an *ambiguous* or a *risky* Gneezy and Potters (1997) lottery with an endowment of 100 Cent. In both lotteries, the underlying distribution to win is 50 %. However, to introduce uncertainty and to provide subjects the freedom to form beliefs, the success probability remains unknown to them in the ambiguous lottery. In both lotteries, subjects can earn 2.5 times the invested amount if the lottery succeeds, whereas they lose the invested amount if the lottery fails. Subjects can keep the amount not invested in the lottery without earning any interest. In addition to the lottery investment, subjects in the ambiguous treatment are asked to provide an estimate of the success probability of the ambiguous lottery. Subjects in the risky treatment are not asked about a probability estimate as the objective success probability is known and clearly communicated.

The experiments concluded with a brief survey about subjects' socio-economic background, a 10-item inventory of the standard Life Orientation Test (Scheier, Carver, & Bridges, 1994), self-assessed statistic skills, stock trading experience and whether a participant was invested during the last financial crisis. Both parts of the experiment were incentivized. In the first part, participants were paid based on the accuracy of the probability estimate provided. Specifically, they received 10 cents for each probability estimate within 10 % (+/- 5%) of the objective Bayesian value. In the second part of the experiment, subjects received the amount not invested in the lottery plus the net earnings from their lottery investment. Both studies took approximately 9 minutes to complete and participants earned $1.93 on average.

B. Discussion of Important Aspects

Overall, our design allows us to test whether differential learning rules in boom and bust markets can account for time variation in risk taking. As it is imperative for our design to ensure that risk preferences remain constant and are unaffected by the forecasting task, a few aspects warrant a brief discussion. First, feedback regarding the accuracy of subjects' probability estimates was only provided at the very end of the experiment. This was done to not only avoid wealth effects, but also to ensure that subjects do not hedge the lottery investment against their earnings from the forecasting task, which would inevitably affect their risk-taking. Second, we abstract from using predisposed words like "boom", "bust", or similar financial jargon. This circumvents evoking negative or positive emotions (such as fear), experience effects, and other confounding factors, which would distort a clear identification of belief-induced risk-taking. Third, by exploiting the between-subject variation in the lottery tasks, we can directly investigate whether the forecasting task in different domains unintentionally affects risk preferences. More precisely, we can exclude that learning from adverse market conditions affects risk preferences.[2]

II. Hypotheses

We have two main hypotheses, one regarding the forecasting task and one regarding the investment task. First, we test whether forecasting in adverse learning environments systematically induces pessimism in subjects' belief formation. In the first experiment, we investigate the effect of domain-specific learning environments on subjects belief formation as tested by Kuhnen (2015). In the second experiment, we examine whether this effect is restricted to domain-specific learning or whether it generalizes to mixed-outcome learning environments as frequently observed in both boom markets and in recessions.

H1: Pessimism Bias

Subjects in the bust treatment are significantly more pessimistic in their average probability forecast both relative to the objective Bayesian forecast and relative to the subjects in the boom treatment.

Next, we investigate the main treatment effect of our study. In particular, we aim to examine whether asymmetric belief formation in boom and bust markets could explain

[2] Although we can directly control for the effect of positive and negative numbers on risk preferences in our design, Kuhnen (2015) concludes as well that risk preferences remain unaffected.

differences in risk-taking. To do so, we introduce a between-subject measure of belief- and preference-based risk taking. In the risky treatment, we have perfect control over subjects' return and risk expectations since both probabilities and outcomes are known and clearly communicated. As such, the risky treatment serves as a measurement tool for risk aversion. In the ambiguous treatment however, we intentionally give participants room to form subjective beliefs as there is uncertainty about the true probability. If the induced pessimism leads to more pessimistic expectations, we should observe a stronger treatment effect in the ambiguity treatment as the absence of perfect certainty about the success probability of the ambiguous lottery leaves more room for expectations (Klibanoff, Marinacci, & Mukerji, 2005).

H2a: Belief-Induced Risk-Taking

Subjects in the bust treatment invest significantly less in the ambiguous lottery than subjects in the boom treatment

H2b: Preference-Based Risk-Taking

Investments in the risky lottery should not significantly differ across treatments.

III. Summary Statistics and Randomization Checks

Table 1 presents summary statistics, Panel A for Experiment 1 and Panel B for Experiment 2. Overall 754 subjects participated in our studies, with an average age of 35.15 years in Experiment 1 (33.53 years in Experiment 2). Forty-five percent (thirty-four percent) were female. Subjects reported average statistic skills of 4.19 out of 7 (4.47) and are medium experienced in stock trading, with a self-reported average score of 3.64 out of 7 (3.94). Roughly thirty-nine percent (forty-four) were invested during the last financial crisis.

[INSERT TABLE 1 ABOUT HERE]

Additionally, we tested whether our randomization successfully resulted in a balanced sample. Table 1 also reports the mean and standard deviation of each variable split by treatment. Differences were tested using rank-sum tests, or χ^2-tests for binary variables. As we find no significant difference between our treatments for any variable, our randomization was successful. As such, we cannot reject the null hypothesis that the socio-economic background of the subjects is balanced between our boom and bust treatment.

IV. Results

We present answers to the following questions: 1) Do agents use the same learning rules when forming beliefs across market cycles?; 2) if learning rules are biased across market cycles, do they translate to systematic differences in risk taking?; 3) what is the mechanism behind the effect?; 4) who is most affected?; and 5) what are the boundaries?

A. Distorted Belief Formation

First, we examine whether employed learning rules in bust markets differ from learning rules in boom markets. Kuhnen (2015) shows that learning in the negative domain leads individuals to form overly pessimistic beliefs about available investment options, which resembles a pessimism bias. Yet, in financial market cycles, agents rarely observe exclusively positive or negative numbers. Instead, even in recessions agents occasionally observe positive returns, but the magnitude is on average smaller than the magnitude of observed negative returns. During the last two financial crises, the frequency of observing a negative monthly return was 66.67 % for the DotCom Crisis and 68.42 % for the 2008 Financial Crisis, while the average realized monthly return was -1.17 % and -2.11 %, respectively, as displayed in Figure 1.[3]

[INSERT FIGURE 1 ABOUT HERE]

To investigate the effect of biased belief formation rules on risk-taking, we consider both possibilities. While in Experiment 1 participants learn exclusively from either only positive or negative outcome lotteries (i.e. domain-specific learning), they learn from mixed outcome lotteries with either positive or negative expected value (i.e. mixed outcome-

[3] Business cycles are defined using the NBER Business Cycle Expansion and Contractions Classification.

dependent learning) in Experiment 2. Figure 2 displays the average probability estimate over eight rounds for good and bad distributions, separated by treatment and experiment.

[INSERT FIGURE 2 ABOUT HERE]

In the domain-specific learning environment (Experiment 1), we find that subjects who forecast the distribution of an asset from negative numbers only (i.e. Bust treatment) are significantly more pessimistic in their average probability estimate than those who forecast the identical distribution from positive numbers (i.e. Boom treatment). This finding is independent of the type of distribution subjects witnessed (good or bad) and in line with the results reported by Kuhnen (2015). Interestingly, and perhaps more importantly for market cycles, this finding is not limited to domain-specific learning environments. Instead, those subjects who forecast distributions from mixed outcome lotteries with negative expected value (i.e. Bust treatment), are also more pessimistic in their average probability assessment than those who learn from mixed lotteries with positive expected value (i.e. Boom treatment). That is, even though distributions are – as in Experiment 1 – completely identical. Overall, Figure 2 suggests that the pessimism bias is more general than previously anticipated. To control for the objective posterior probability, we also run regressions of subjects' probability estimates on a bust-indicator and the objective Bayesian probability that the stock is in the good state. Results are reported in Table 2.

[INSERT TABLE 2 ABOUT HERE]

We find that beliefs expressed by subjects in the bust treatment are on average 6.46% lower (i.e. more pessimistic) than in the boom treatment ($p < 0.001$). Remarkably, the magnitude of the pessimism bias does not significantly differ across experiments. In other words, our results suggest that the pessimism bias does not critically depend on domain-specific outcomes, which makes it even more general than previously thought.

B. Belief Formation and Risk Taking

So far, we have shown that learning rules are systematically distorted by whether subjects learn during boom periods or during bust periods. Next, we investigate whether the induced pessimism resulting from biased belief formation rules in bust markets translates to lower risk taking, without altering risk preferences. To test our main hypotheses, we specify the following regression model:

$$Investment_i = \beta_0 + \beta_1 Bust_i + \beta_2 Ambiguous_i + \beta_3 Bust_i \; x \; Ambiguous_i + \sum_{j=1}^{n} \beta_j \boldsymbol{X_{ij}} + \epsilon_i,$$

where the dependent variable $Investment_i$ is the amount individual i invested in the risky/ambiguous asset. $Bust_i$ is a dummy that denotes if a subject learned to form beliefs in the Bust treatment, while $Ambiguous_i$ is a dummy that denotes that the investment decision was made under uncertainty (i.e. unknown probabilities in the investment task). The interaction $Bust_i \; x \; Ambiguous_i$ allows us to examine our main hypothesis, i.e. that subjects who learned to form beliefs in the negative domain invest significantly less in the ambiguous lottery where they have room to form subjective expectations. Finally, $\boldsymbol{X_{ij}}$ is a set of control variables including gender, age, statistic skills, stock trading experience, a life orientation test, the order of good and bad distributions in the forecasting task, and an indicator whether subjects were invested in the last financial crisis. We estimate our regression model using OLS with robust standard errors. However, results remain stable if we use a Tobit model instead.

[INSERT TABLE 3 ABOUT HERE]

Table 3 reports our main finding for each experiment separately and pooled. In the pooled data, it becomes evident that individuals in the Bust treatment invested on average 47 % less in the ambiguous lottery compared to those in the Boom treatment (*p* = 0.011, t-test), confirming Hypothesis **H2a**. In the risky lottery, when expectations are fixed, we can directly test the effect of our forecasting task on subjects' risk aversion. However, we do not find any significant difference between treatments on subjects' investment in the risky lottery (*p* = 0.47, t-test), confirming Hypothesis **H2b**. This means that we cannot reject the null hypothesis that risk aversion is similar for subjects who learned to form beliefs in different domains.

When looking at the results of each experiment separately, we find a strong and similar-sized effect for the domain-specific learning environment and a weaker – albeit statistically insignificant – effect for the mixed-outcome learning environment. Moreover, and consistent with the pooled data, we find no effect on subjects' risk preferences in neither the domain-specific nor the mixed-outcome learning environment. To better understand whether the effect in the pooled sample is primarily driven by domain-specific outcomes, or whether other factors are at play, we will run further regressions in Section D.

C. Mechanism

In this section, we test whether expectations are indeed the driving mechanism behind our main effect. We designed the ambiguous treatment in such a way that we can assess participants' subjective beliefs about the success probability of the lottery and directly relate them to their investment decision. If expectations are the main driver of differences in risk taking, we should observe that subjects who learned to form beliefs in either the negative domain-specific or in the negative expected value mixed-outcome learning environment are more pessimistic about the success probability of the ambiguous lottery. Additionally, we would expect a positive correlation between the subjective probability estimate of the success chance of the ambiguous lottery and the amount invested in the ambiguous lottery. In order to directly test the implied mechanism, we estimate the following two OLS regression models for our pooled sample and for each experiment separately:

$$(1)\ \ Probability_i = \beta_0 + \beta_1 Bust_i + \sum_{j=1}^{n} \beta_j \boldsymbol{X_{ij}} + \epsilon_i$$

$$(2)\ Investment\_Ambiguous_i = \beta_0 + \beta_1 Probability_i + \sum_{j=1}^{n} \beta_j \boldsymbol{X_{ij}} + \epsilon_i,$$

where $Probability_i$ is the subjective success probability of the ambiguous lottery of subject i, and $Investment\_Ambiguous_i$ is the investment of subject i in the ambiguous lottery. Findings for the first model are reported in Table 4 and for the second model in Table 5.

[INSERT TABLE 4 ABOUT HERE]

In the pooled data, we find a strong and highly significant effect of our treatment indicator on the subjective success probability of the ambiguous lottery. In particular, those subjects who learned to form expectations in the Bust-treatment are about 19 percentage points ($p < 0.001$) more pessimistic about the success probability than subjects who learned to form beliefs in the Boom-treatment. The finding remains stable and highly statistically significant for each learning environment separately, even though the effect seems to be stronger in the mixed-outcome learning environment. As such, the induced pessimism resulting from distorted belief formation rules translates to other – independent – investment environments.

[INSERT TABLE 5 ABOUT HERE]

In Table 5, we test whether differences in subjective expectations regarding the success probability of the ambiguous lottery also translate to changes in risk-taking. In essence, we test whether subjects adhere to a basic economic principle: keeping everything else constant, do subjects increase their investment amount in an ambiguous asset when their beliefs about the outcome distribution are more optimistic? Results across all specifications confirm that subjects act upon their beliefs. In other words, the more optimistic they are about the success probability of the ambiguous asset, the more they invest ($p < 0.01$). In addition, in Columns (2), (4), and (6), we include the Bust indicator as an additional control variable to exclude the possibility that our manipulation affects factors unrelated to expectations. Even after including the Bust indicator, the effect of subjective probability estimates on investments remains of similar magnitude and statistical significance. Moreover, we find no additional effect of our manipulation on the investment decision. Effectively, this means while our manipulation does induce pessimism, it does not affect factors unrelated to expectations.

Taken together, our findings suggest that: 1) Learning to form beliefs in adverse market environments induces pessimism caused by systematic errors in the belief updating process. 2) This pessimism translates to lower risk taking even in independent investment environments when there is room to form beliefs. 3) Pessimism causes agents to assign lower probabilities to high outcomes in uncertain future states. 4) Learning in adverse market environments and the resulting errors in the belief updating process do not affect risk preferences.

D. Who is Most Affected?

In this section, we seek to establish a more profound understanding of how subjects' forecasting abilities in the first part of the experiments affect their subsequent risk-taking. To investigate this relation, we define the squared deviation of subjects' subjective probability forecast in each round from the objective posterior probability as a measure of forecasting quality. Next, we conduct median splits with respect to this measure to distinguish above-median forecasters from below-median forecasters. To assess the validity of our measure, we compare the number of correct forecasts (defined in the payment scheme by being in the range of 10 % of the objective forecast) between below- and above-median forecasters. Across both experiments, those subjects who are classified as "above-median" have on average 3 more correct forecasts than those classified as "below-median" ($p < 0.001$, t-test). Moreover, both measures are highly correlated (Pearson correlation of 0.57, $p < 0.001$).

To better understand to what extent the resulting pessimism through learning from adverse market outcomes is a necessary condition for belief-induced changes in risk-taking, we repeat the previous analyses and split by the forecasting ability of our participants. Table 6 reports our main finding.

[INSERT TABLE 6 ABOUT HERE]

Interestingly, we find that the previously reported effect is both stronger in absolute terms and in terms of statistical significance but only for participants with above-median forecasting ability. In other words, the risk-taking of those agents who achieve more correct forecasts is stronger affect by the learning environment than the risk-taking of agents who achieve less correct forecasts. While this effect is roughly twice as big as for the full sample, it is also independent of the initial learning environment and even slightly stronger for the mixed-outcome learning environment.

In a next step, we investigate whether the learning environment affects the estimated success probability of the ambiguous asset differently depending on the forecasting ability. Results are reported in Table 7.

[INSERT TABLE 7 ABOUT HERE]

Across all specifications, we consistently find that subjects in the Bust-treatment are significantly more pessimistic in their assessment of the success probability of the ambiguous asset. For the mixed-outcome learning environment, we find that above-median forecasters are even more pessimistic in their probability assessment than below-median forecasters, which is consistent with our previous findings. Across both experiments, above-median forecasters rate the success probability on average 25 percentage points lower if they are in the Bust-treatment than their peers in the Boom-treatment. This effect shrinks substantially to only 15 percentage points for below-median forecasters. Similar to previous analyses, we also find that subjects – independent of their forecasting ability – act upon their beliefs by investing more in the ambiguous asset if they rate the success probability to be higher (see Table A1 in the Appendix).

But how is it possible that the risk-taking of the seemingly smarter agents (i.e. the better forecasters) is more affected by the learning environment? One possible explanation could be that our proxy of forecasting ability is related to other factors such as socio-demographic background. Alternatively, our proxy might capture participants' involvement in the experimental task. Effectively, this would suggest that the documented effect is more generalizable outside of the experimental environment but limited by the difficulty of the Bayesian updating task. To test the first explanation, we investigate whether agents with above-median forecasting ability share specific socio-demographic characteristics. Results are reported in Table 8.

[INSERT TABLE 8 ABOUT HERE]

Overall, neither gender nor age can explain differences in participants' forecasting abilities. Additionally, and importantly, we find no treatment differences between both groups. As such, the share of above-median forecasters is rather evenly distributed among our boom and bust treatment. Somehow surprisingly, we find differences in subjects' self-reported statistic skills. However, the sign of the coefficient is rather unexpected as the group of above-median forecasters self-reports on average lower statistic skills, which might hint at overconfidence. Similar findings can be observed for subjects' self-reported experience in stock trading. Taken together, our results – while not conclusive – provide no basis to support the first explanation.

To test whether subjects with above-median forecasting ability are more involved in the experiment, we investigate the time it took to finish the experiment and the strength of the pessimism bias. Interestingly, we find that above-median forecasters spent on average 112 seconds to read the instructions of the forecasting task, while below-median forecasters only spent roughly 86 seconds ($p < 0.05$). Additionally, the overall time to finish the experiment is roughly 580 seconds for above-median forecasters, and about 553 seconds for below-median forecasters ($p < 0.10$). The difference is largely driven by the additional time above-median forecasters spent to read the instructions more carefully.

We also investigate the strength of the pessimism bias in both groups. Results are reported in Table 9.

[INSERT TABLE 9 ABOUT HERE]

As expected the bias is less pronounced for those subjects with above-median forecasting ability (who also have more correct forecasts). However, and more importantly, the pessimism bias still persists and is highly statistically significant. Across all experiments, we consistently find that above-median forecasters exhibit a 29 % less pronounced pessimism bias. Nevertheless, these findings show that even the above-median forecasts suffer from a pessimism bias which subsequently translates to lower risk-taking. One indication of this might be that the above-median forecasters are more involved in the overall experiment and in particular the forecasting task given the additional time they need to finish the experiment. Given the strength of the pessimism bias even in the group of more sophisticated forecasters paired with the higher involvement of the aforementioned group in our experiment, we believe that the effect of different learning environments on risk-taking might be even more generalizable in the real economy.

E. Boundaries and External Validity

To test both the external validity and the boundaries of the induced pessimism resulting from asymmetric learning in boom and bust markets, we analyze subjects' responses to two additional set of questions, which deal with expectations outside the experimental setting. The first question tests to which extent the induced pessimism even translates to expectations in the real economy. We gave subjects the at the time current level of the Dow Jones Industrial Average, and asked them to provide a 6-month return forecast on a balanced 12-point Likert scale (see Appendix B). The second set of questions tests to which degree the induced pessimism from the underlying learning environment permeates to different contexts. As a measure of dispositional optimism/pessimism across different life situations, we included a 10-item general Life Orientation Test borrowed from Scheier, Carver, and Bridges (1994), which is frequently used in psychological research (see Appendix B). Results are reported in Figure 3. Panels A and B show results for the Dow Jones return estimates (for entire sample and split by forecast quality), while Panels C and D show results for the Life Orientation Test (for entire sample and split by forecast quality).

[INSERT FIGURE 3 ABOUT HERE]

For the Dow Jones return estimates, we consistently find across all learning environments that subjects in the bust treatment are significantly more pessimistic in their return expectations. More strikingly, subjects in the bust treatment provide not only lower return estimates but negative return estimates, while those in the boom treatment provide positive return estimates on average. Moreover, the effect seems to be stronger in absolute magnitude for the negative return estimates, consistent with a pessimism bias. When split by forecast quality, we observe that the effect is again mainly driven by subjects with above-median forecasting ability. As such, even while above-median forecasters show a less pronounced pessimism bias overall (see previous section), their pessimism still translates to lower return expectations in the real economy and thus outside the experimental setting. For the below-median forecasters however, we do not find significant differences even though they also suffer from a pessimism bias. This fact paired with a potentially lower involvement may explain why we cannot observe differences in risk-taking in the ambiguous lottery between treatments for this subgroup. It remains to stress, that even in such a simple and short-learning environment as in our experiment, we are able to systematically manipulate return expectations for real world market indices.

Finally, we investigate the boundaries of how the pessimism induced by adverse learning environments affects subjects overall psychological well-being. Across all experiments and splits we do not find any significant difference in dispositional optimism/pessimism depending on whether subjects were in the Boom or Bust treatment. Taken together, our results suggest that the environment in which subjects learn strongly affects their return expectations for even unrelated financial investments, but does not affect subjects' inherent psychological traits such as neuroticism, anxiety, self-mastery, or self-esteem as assessed by the Life Orientation Test.

V. Conclusion

This paper presents experimental evidence on an alternative channel to countercyclical risk aversion for time-varying risk-taking. While rational expectations models introduce modifications in the representative agent's utility, we test whether systematic deviations from rational expectations can cause the same observed investment pattern without assuming time-varying degrees of risk aversion.

We place subjects in a learning environment which resembles key characteristics of boom and bust markets and measure their risk taking under risk (i.e. known probabilities) or under uncertainty (i.e. unknown probabilities) in an independent investment task. Subjects who learned to form beliefs from adverse outcomes (resembling a bust market) take significantly less risk in investments under uncertainty. However, we do not find any significant difference in their level of risk aversion.

Overall, the mechanism described in our experiment implies that agents may form pro-cyclical return expectations, i.e. they are more optimistic in boom markets and more pessimistic in recessions. These results are consistent with recent survey evidence on investors' return expectations. While traditional models (i.e. rational expectations models) assume that agents are fully aware of the implied counter-cyclical nature of the equity premium (Nagel & Xu, 2019), these surveys find that – if anything – investors form rather pro-cyclical expectations.

Additionally, the investigated systematic deviation from rational expectations can produce similar self-reinforcing processes as countercyclical risk aversion. The countercyclical nature of risk preferences implies that investors are more risk averse during recessions, which leads investors to reduce their equity share. This process then generates additional downward momentum for prices. Yet, similar dynamics can also be generated assuming time-varying changes in expectations. If bust markets systematically induce pessimistic expectations about future returns for a substantial subset of investors, this may reduce the aggregate share invested in risky assets of an economy, which in turn generates downward pressure on prices due to excess supply.

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Figures

Figure 1:

Figure 1 documents both the relative frequency of observing a negative monthly return of the MSCI All Country World Index as well as the average monthly return for the last two financial recessions. Recessions are defined according to the NBER US Business Cycle Contraction classification. The left y-axis refers to the relative frequency of negative returns. The right y-axis (reversed scale) refers to the average monthly realized returns.

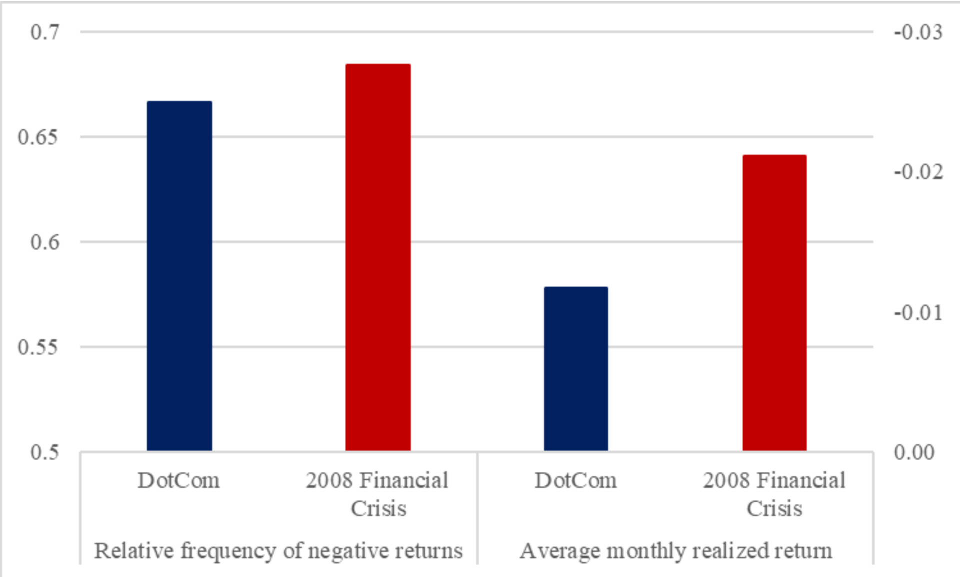


Figure 2:

Figure 2 documents the pessimism bias. It depicts participants' average probability forecasts split by the underlying distribution they had to forecast (good or bad), the treatment they were in (boom or bust), and the experiment in which they participated (domain-specific forecasting or mixed-outcome forecasting). Displayed are 95 % confidence intervals.

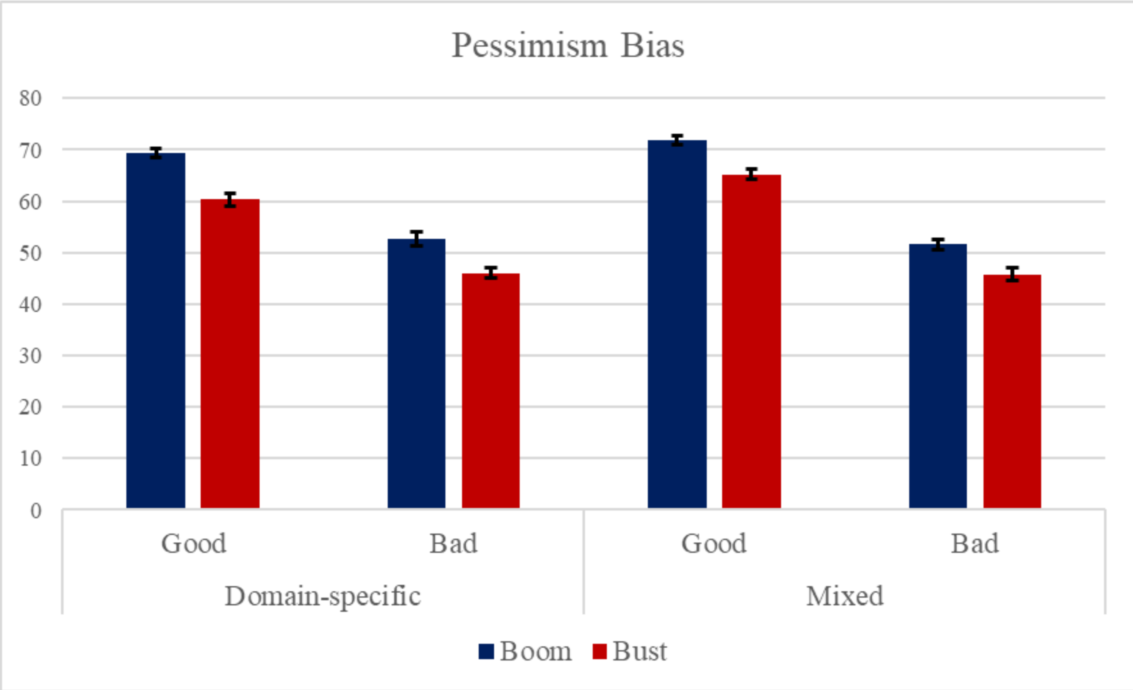
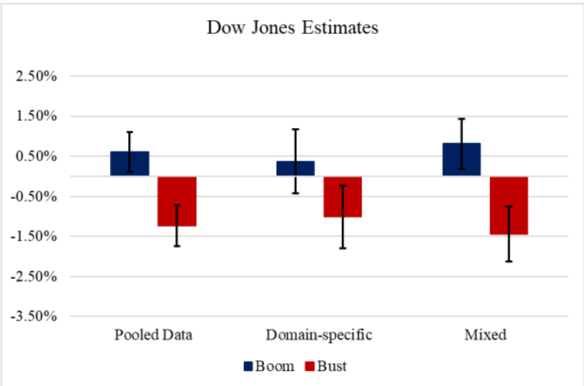


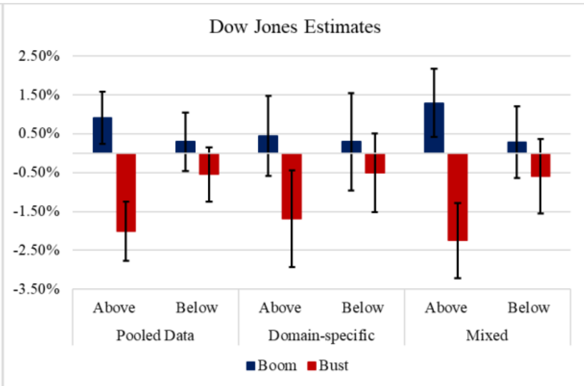
Figure 3:

Figure 3 displays subjects' self-reported return expectations of the Dow Jones Industrial average (Panels A and B) and their answers to a general life orientation test (Panels C and D). Dow Jones return expectations were assessed on a 12-point Likert scale and are displayed separately for subjects across treatments (boom / bust) and across experiments. Panel B displays return expectations split by above- and below-forecasting ability. The life orientation test (Scheier, Carver, & Bridges, 1994) is a 10-item inventory where subjects rate statements on a 7-point Likert scale. Displayed is the cumulated score separated by treatment (boom / bust) and by experiment. Panel D displays the cumulated score split by above- and below-forecasting ability.

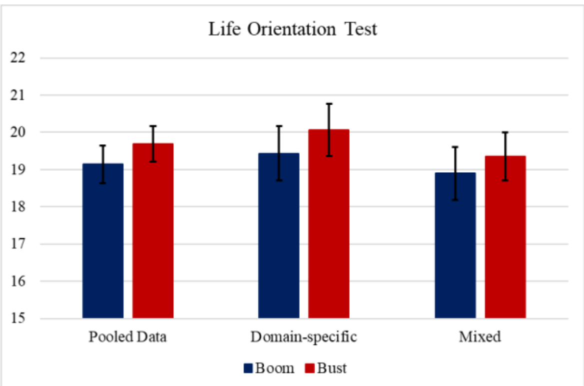
Panel A



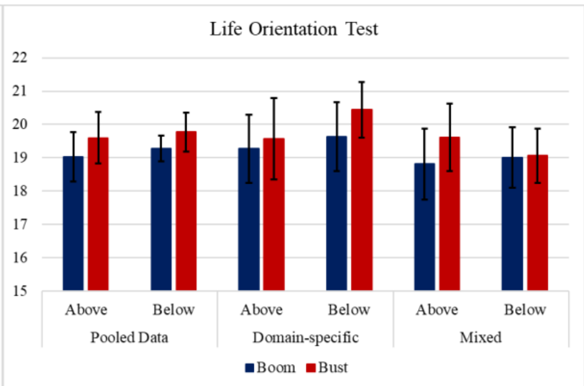
Panel B



Panel C



Panel D



Tables

Table 1: Summary statistics

This table shows summary statistics for our experimental data. Reported are the mean and the standard deviation (in parentheses) for the whole sample (Column 1) and split across treatments (Column 2 and 3). Column 4 presents randomization checks. Differences in mean were tested using rank-sum tests, or χ^2-tests for binary variables. The p-value is reported in Column 5. *Female* is an indicator variable that equals 1 if a participant is female. *Statistic skills* denotes participants' self-assed statistical skills on a 7-point Likert scale. *Experience in stock trading* is the self-reported experience participants have in stock trading, assessed by a 7-point Likert scale. *Invested financial crisis* is an indicator that equals 1 if participants were invested in the stock market during the last financial crisis.

Panel A **Variable**	**Full sample (N = 350)**	**Boom (N = 174)**	**Bust (N = 176)**	**Difference**	**p-value**
Age	35.15	34.76	35.54	0.78	0.76
	(11.52)	(11.18)	(11.86)		
Female	0.45	0.47	0.43	0.04	0.44
	(0.50)	(0.50)	(0.50)		
Statistic Skills (1-7)	4.19	4.22	4.16	0.06	0.91
	(1.62)	(1.51)	(1.72)		
Experience in Stock Trading (1 - 7)	3.64	3.73	3.56	0.17	0.42
	(1.88)	(1.84)	(1.92)		
Invested Financial Crisis (1 = Yes)	0.39	0.39	0.39	0	1
	(0.49)	(0.49)	(0.49)		

Panel B **Variable**	**Full sample (N = 403)**	**Boom (N = 207)**	**Bust (N = 196)**	**Difference**	**p-value**
Age	33.53	32.73	34.37	1.63	0.07
	(9.03)	(8.46)	(9.55)		
Female	0.34	0.33	0.35	0.02	0.69
	(0.48)	(0.47)	(0.48)		
Statistic Skills (1-7)	4.47	4.40	4.55	0.15	0.42
	(1.67)	(1.69)	(1.65)		
Experience in Stock Trading (1 - 7)	3.94	3.89	3.98	0.09	0.52
	(1.99)	(1.95)	(2.03)		
Invested Financial Crisis (1 = Yes)	0.44	0.41	0.47	0.06	0.24
	(0.50)	(0.49)	(0.50)		

Table 2: Pessimism Bias

This table reports the results of three OLS regressions on how subjective posterior beliefs about the distribution of the lottery depend on the treatment. The dependent variable in the regression model, *Probability Estimate*, is the subjective posterior belief that the asset is paying from the good distribution. Independent variables include the *Bust* dummy, an indicator variable that equals 1 if participants were in the bust treatment and zero otherwise, as well as *Objective Posterior,* which is the correct Bayesian probability that the stock is good, given the information seen by the participant up to trial *t* in the learning block. Controls include age, gender, statistical skills, self-reported experience in stock trading, whether subjects were invested in the stock market during the last financial crisis, and the order of outcomes they experienced in the forecasting task. Reported are coefficients and t-statistics (in parentheses) using robust standard errors. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	*Probability Estimate (Subjective Posterior)*		
	Pooled Data	Domain-specific	Mixed
Bust	-6.425***	-6.218***	-6.742***
	(-6.16)	(-3.86)	(-4.88)
Objective Posterior	0.378***	0.370***	0.384***
	(23.94)	(17.21)	(17.09)
Constant	46.31***	45.96***	47.01***
	(10.82)	(7.02)	(8.24)
Observations	12048	5600	6448
R^2	0.262	0.244	0.279

Table 3: Risk taking across macroeconomic cycles

This table examines subjects' risk-taking across treatments. We report the results of OLS regressions for the whole sample, and for each experiment individually. The dependent variable is *Investment*, which denotes participants' invested amount (0 – 100) in the lottery they were assigned to. *Bust* is an indicator variable that equals 1 if participants were in the bust treatment. *Ambiguous* is an indicator variable that equals 1 if participants were asked to invest in the ambiguous lottery, and 0 if they invested in the risky lottery. Controls include age, gender, statistical skills, self-reported experience in stock trading, whether subjects were invested in the stock market during the last financial crisis, and the order of outcomes they experienced in the forecasting task. Reported are coefficients and t-statistics (in parentheses) using robust standard errors. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable		*Investment*	
	Pooled Data	Domain-specific	Mixed
Bust	2.271	3.948	-0.948
	(0.72)	(0.86)	(-0.21)
Ambiguous	5.149*	5.540	4.473
	(1.71)	(1.26)	(1.04)
Bust x Ambiguous	-11.23**	-13.57**	-8.229
	(-2.54)	(-2.21)	(-1.25)
Constant	15.82*	20.32*	10.69
	(1.70)	(1.67)	(0.74)
Observations	753	350	403
R^2	0.060	0.080	0.069

Table 4: Relation between treatment variable and probability estimates

This table examines the underlying mechanism of how our treatment variable affects subjects' beliefs about the success probability of the ambiguous lottery. Dependent variable is *Success Probability*, which denotes participants' beliefs about the success probability of the ambiguous lottery. *Bust* is an indicator variable that equals 1 if participants were in the bust treatment. Controls include age, gender, statistical skills, self-reported experience in stock trading and whether subjects were invested in the stock market during the last financial crisis. Reported are coefficients and t-statistics (in parentheses) using robust standard errors. *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	*Success Probability Estimate of Ambiguous Asset*		
	Pooled Data	Domain-specific	Mixed
Bust	-18.86***	-11.83***	-25.59***
	(-8.59)	(-3.74)	(-8.57)
Constant	55.83***	68.72***	41.10***
	(6.15)	(5.25)	(3.59)
Observations	377	177	200
R^2	0.241	0.176	0.349

Table 5: Relation between beliefs about success probability and investment

This table examines whether subjects in our experiment act upon their beliefs about the success probability of the ambiguous asset. Dependent variable is *Investment Ambiguous*, which captures subjects' invested amount in the ambiguous lottery. *Success Probability* denotes participants' beliefs about the success probability of the ambiguous lottery. *Bust* is an indicator variable that equals 1 if participants were in the bust treatment. Controls include age, gender, statistical skills, self-reported experience in stock trading and whether subjects were invested in the stock market during the last financial crisis. Reported are coefficients and t-statistics (in parentheses) using robust standard errors. *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	*Investment in Ambiguous Asset*					
	Pooled Data	Pooled Data	Domain-specific	Domain-specific	Mixed	Mixed
Success Probability	0.412***	0.409***	0.365***	0.341***	0.470***	0.521***
	(6.45)	(5.70)	(3.88)	(3.42)	(5.47)	(4.83)
Bust		-0.372		-3.846		4.571
		(-0.11)		(-0.93)		(0.82)
Constant	-3.304	-2.985	-5.350	-2.458	2.166	0.00936
	(-0.26)	(-0.23)	(-0.36)	(-0.16)	(0.10)	(0.00)
Observations	377	377	177	177	200	200
R^2	0.146	0.146	0.162	0.166	0.157	0.160

Table 6: Risk taking across macroeconomic cycles split by forecasting quality

This table examines subjects' risk-taking across treatments split by above and below median forecasting ability as defined in the text. We report the results of OLS regressions for the whole sample, and for each experiment individually. The dependent variable is *Investment*, which denotes participants' invested amount (0 – 100) in the lottery they were assigned to. *Bust* is an indicator variable that equals 1 if participants were in the bust treatment. *Ambiguous* is an indicator variable that equals 1 if participants were asked to invest in the ambiguous lottery, and 0 if they invested in the risky lottery. Controls include age, gender, statistical skills, self-reported experience in stock trading, whether subjects were invested in the stock market during the last financial crisis, and the order of outcomes they experienced in the forecasting task. Reported are coefficients and t-statistics (in parentheses) using robust standard errors. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	*Investment*					
	Pooled Data		**Domain-specific**		**Mixed**	
	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median
Bust	6.126	-1.109	6.424	0.652	3.437	-2.713
	(1.38)	(-0.25)	(0.86)	(0.11)	(0.59)	(-0.41)
Ambiguous	10.94***	-1.448	11.48*	-1.582	10.56*	-2.073
	(2.65)	(-0.33)	(1.92)	(-0.24)	(1.75)	(-0.34)
Bust # Ambiguous	-21.49***	-1.454	-22.15**	-4.501	-19.14**	1.881
	(-3.54)	(-0.23)	(-2.44)	(-0.52)	(-2.25)	(0.19)
Constant	1.238	22.65	1.822	37.77**	5.365	4.365
	(0.10)	(1.58)	(0.11)	(2.09)	(0.29)	(0.20)
Observations	377	376	169	181	208	195
R^2	0.095	0.072	0.139	0.070	0.119	0.114

Table 7: Relation between treatment and probability estimates split by forecasting quality

This table examines the underlying mechanism of how our treatment variable affects subjects' beliefs about the success probability of the ambiguous lottery split by above and below median forecasting ability as defined in the text. Dependent variable is *Success Probability*, which denotes participants' beliefs about the success probability of the ambiguous lottery. *Bust* is an indicator variable that equals 1 if participants were in the bust treatment. Controls include age, gender, statistical skills, self-reported experience in stock trading and whether subjects were invested in the stock market during the last financial crisis. Reported are coefficients and t-statistics (in parentheses) using robust standard errors. *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	*Success Probability Estimate of Ambiguous Asset*					
	Pooled Data		**Domain-specific**		**Mixed**	
	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median
Bust	-25.58***	-13.38***	-13.55***	-11.40**	-35.34***	-15.48***
	(-8.20)	(-4.50)	(-3.09)	(-2.51)	(-8.57)	(-3.75)
Constant	57.97***	53.54***	84.00***	50.75**	33.84**	54.92***
	(4.19)	(4.33)	(4.75)	(2.57)	(2.14)	(3.40)
Observations	187	190	85	92	102	98
R^2	0.333	0.194	0.228	0.185	0.516	0.244

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Socio demographic determinants of forecasting ability

This table shows demographics for our sample split by above- and below-median forecasting ability. Reported are the mean and the standard deviation (in parentheses) for the whole sample (Column 1) and split by median (Column 2 and 3). Column 4 presents randomization checks. Differences in mean were tested using rank-sum tests, or χ^2-tests for binary variables. The p-value is reported in Column 5. *Female* is an indicator variable that equals 1 if a participant is female. *Statistic skills* denotes participants' self-assed statistical skills on a 7-point Likert scale. *Experience in stock trading* is the self-reported experience participants have in stock trading, assessed by a 7-point Likert scale. *Invested financial crisis* is an indicator that equals 1 if participants were invested in the stock market during the last financial crisis. *Bust* is an indicator variable that equals 1 if participants were in the bust treatment.

Variable	**Full sample (N = 753)**	**Above median (N = 377)**	**Below median (N = 376)**	**Difference**	**p-value**
Age	34.72	34.32	34.23	0.09	0.90
	(10.28)	(9.79)	(10.77)		
Female	0.39	0.39	0.40	0.01	0.77
	(0.49)	(0.49)	(0.49)		
Statistic Skills (1-7)	4.35	4.14	4.56	0.42	< 0.01
	(1.65)	(1.56)	(1.71)		
Experience in Stock Trading (1 - 7)	3.80	3.29	4.31	1.02	< 0.01
	(1.94)	(1.92)	(1.83)		
Invested Financial Crisis (1 = Yes)	0.41	0.33	0.50	0.17	< 0.01
	(0.49)	(0.47)	(0.50)		
Bust	0.50	0.47	0.53	0.06	0.11
	(0.50)	(0.50)	(0.50)		

Table 9: Pessimism bias split by forecasting quality

This table reports the results of three OLS regressions on how subjective posterior beliefs about the distribution of the lottery depend on the treatment split by above and below median forecasting ability as defined in the text. The dependent variable *Probability Estimate* is the subjective posterior belief that the asset is paying from the good distribution. Independent variables include the *Bust* dummy, an indicator variable that equals 1 if participants were in the bust treatment and zero otherwise, as well as *Objective Posterior*, which is the correct Bayesian probability that the stock is good, given the information seen by the participant up to trial *t* in the learning block. Controls include age, gender, statistical skills, self-reported experience in stock trading, whether subjects were invested in the stock market during the last financial crisis, and the order of outcomes they experienced in the forecasting task. Reported are coefficients and t-statistics (in parentheses) using robust standard errors. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	*Probability Estimate (Subjective Posterior)*					
	Pooled Data		**Domain-specific**		**Mixed**	
	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median
Bust	-4.529***	-6.813***	-4.261***	-7.247***	-4.997***	-5.661***
	(-6.13)	(-4.54)	(-3.72)	(-3.11)	(-5.18)	(-2.86)
Objective Posterior	0.671***	0.133***	0.641***	0.165***	0.693***	0.107***
	(48.14)	(7.46)	(34.13)	(6.33)	(35.46)	(4.37)
Constant	20.92***	58.92***	14.88***	66.86***	27.49***	50.78***
	(6.75)	(9.62)	(3.22)	(6.82)	(6.38)	(6.60)
Observations	6032	6016	2704	2896	3328	3120
R^2	0.69	0.10	0.68	0.08	0.70	0.12

Appendix

A. Further Analyses

Table A1: Relation between beliefs about success probability and investment

This table examines whether subjects in our experiment act upon their beliefs about the success probability of the ambiguous asset, split by above- and below-median forecasting ability as defined in the text. Dependent variable is *Investment Ambiguous*, which captures subjects' invested amount in the ambiguous lottery. *Success Probability* denotes participants' beliefs about the success probability of the ambiguous lottery. *Bust* is an indicator variable that equals 1 if participants were in the bust treatment. Controls include age, gender, statistical skills, self-reported experience in stock trading and whether subjects were invested in the stock market during the last financial crisis. Reported are coefficients and t-statistics (in parentheses) using robust standard errors. *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	*Investment in Ambiguous Asset*					
	Pooled Data		**Domain-specific**		**Mixed**	
	Above Median	Below Median	Above Median	Below Median	Above Median	Below Median
Success Probability	0.387***	0.364***	0.356***	0.369***	0.515***	0.437**
	(4.07)	(3.39)	(2.73)	(2.67)	(3.31)	(2.57)
Bust	-6.384	3.036	-10.71*	1.334	-0.186	5.905
	(-1.42)	(0.63)	(-1.98)	(0.21)	(-0.02)	(0.76)
Constant	-20.72	13.96	-43.07**	27.90	11.33	-3.123
	(-1.21)	(0.75)	(-2.22)	(1.33)	(0.39)	(-0.09)
Observations	187	190	85	92	102	98
R^2	0.22	0.11	0.27	0.18	0.24	0.11

B. Experimental Instructions and Screenshots

Instructions Bayesian Updating (Exemplary for Boom Treatment of Experiment 1)

In this part, we would like to test your forecasting abilities. You will make forecasting decisions in two consecutive blocks each consisting of 8 rounds.

Suppose you find yourself in an environment, in which the value of a risky asset can either increase by 2 or by 15. The probability of either outcome (2 or 15) depends on the state in which the asset is (**good** state or **bad** state). If the risky asset is in the **good** state, then the probability that the risky asset increases in value by 15 is 70% and the probability that it increases in value by 2 is 30%. If the risky asset is in the **bad** state, then the probability that the risky asset increases in value by 15 is 30% and the probability that it increases in value by 2 is 70%.

The computer determines the state at the beginning of each block (consisting of 8 rounds). Within a block, the state does not change and remains fixed. At the beginning of each block, you do not know which state the risky asset is in. The risky asset may be in the good state or in the bad state with equal probability.

At the beginning of each round, you will observe the payoff of the risky asset (2 or 15). After that, we will ask you to provide a probability estimate that the risky asset is in the good state and ask you how sure you are about your probability estimate. While answering these questions, you can observe the price development in a chart next to the question.

There is always an objective correct probability that the risky asset is in the good state. This probability depends on the history of payoffs of the risky asset already. As you observe the payoffs of the risky asset, you will update your beliefs whether or not the risky asset is in the good state.

Every time you provide us with a probability estimate that is within 5% of the correct value (e.g., correct probability is 70% and your answer is between 65% and 75%) we will add 10 Cents to your payment.

Objective Bayesian Posterior Probabilities

This table provides all possible values for the objectively correct probability that the asset is in the good state for every possible combination of trials and outcomes. The initial prior for good and bad distribution is set to 50%. The objective Bayesian posterior probability that the asset is in the good state, after observing t high outcomes in n trials so far is given by: $\frac{1}{1+\frac{1-p}{p}\cdot(\frac{q}{1-q})^{n-2t}}$, where p is the initial prior before any outcome is observed that the stock is in the good state (50% here), and q is the probability that the value increase of the asset is the higher one (70% here).

n (number of trials so far)	**t (number of high outcomes so far)**	**Probability [stock is good t high outcomes in n trials]**
0	0	50.00%
1	0	30.00%
1	1	70.00%
2	0	15.52%
2	1	50.00%
2	2	84.48%
3	0	7.30%
3	1	30.00%
3	2	70.00%
3	3	92.70%
4	0	3.26%
4	1	15.52%
4	2	50.00%
4	3	84.48%
4	4	96.74%
5	0	1.43%
5	1	7.30%
5	2	30.00%
5	3	70.00%
5	4	92.70%
5	5	98.57%
6	0	0.62%
6	1	3.26%
6	2	15.52%
6	3	50.00%
6	4	84.48%
6	5	96.74%
6	6	99.38%
7	0	0.26%
7	1	1.43%
7	2	7.30%
7	3	30.00%
7	4	70.00%
7	5	92.70%
7	6	98.57%
7	7	99.74%
8	0	0.11%
8	1	0.62%
8	2	3.26%
8	3	15.52%
8	4	50.00%
8	5	84.48%
8	6	96.74%
8	7	99.38%
8	8	99.89%

Screenshots of Experiment 1

Figures B1 to B3 present the screens of the forecasting task as seen by subjects in the experiment (example block 1, round 5). One round consists of three sequential screens. First, subjects saw the payoff of the risky asset in the respective round. Second, the cumulated payoffs of the risky asset are shown in a price-line-chart and subjects are asked to provide a probability estimate that the risky asset pays from the good distribution. Finally, subjects are asked on a 9-point Likert scale how confident they are in their probability estimate.

Figure B1: Payoff screen

Figure B2: Probability estimate screen

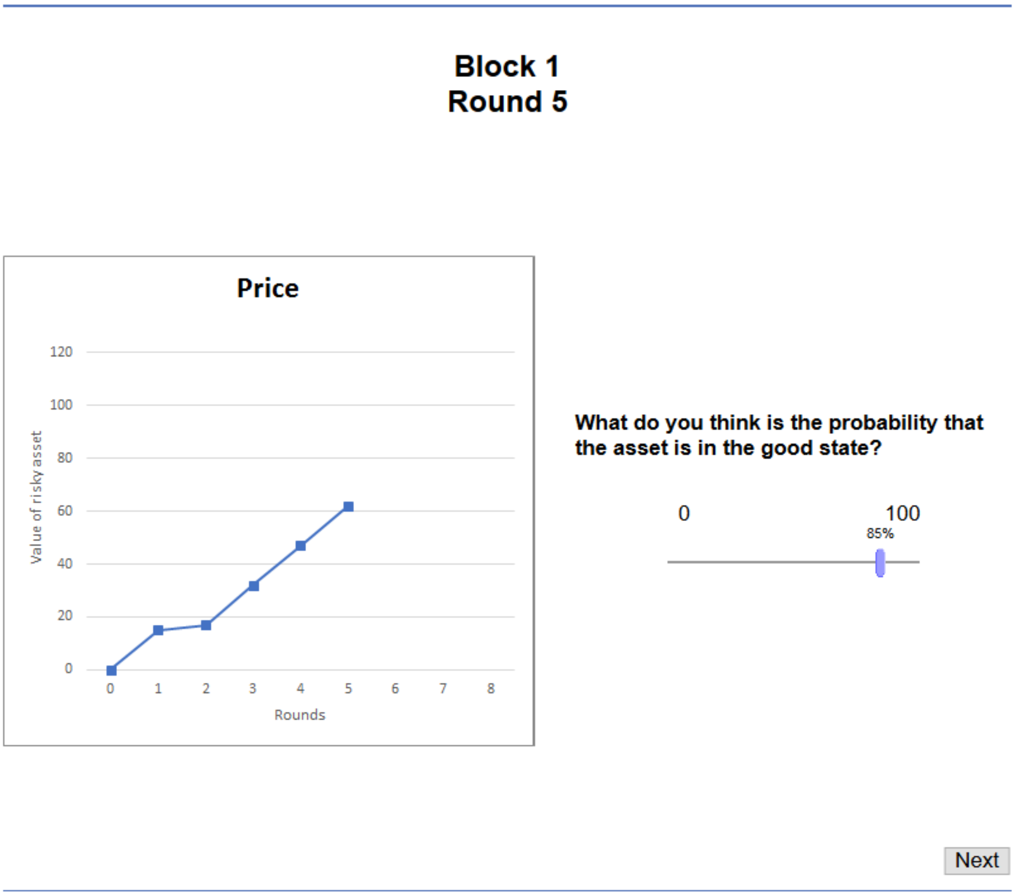
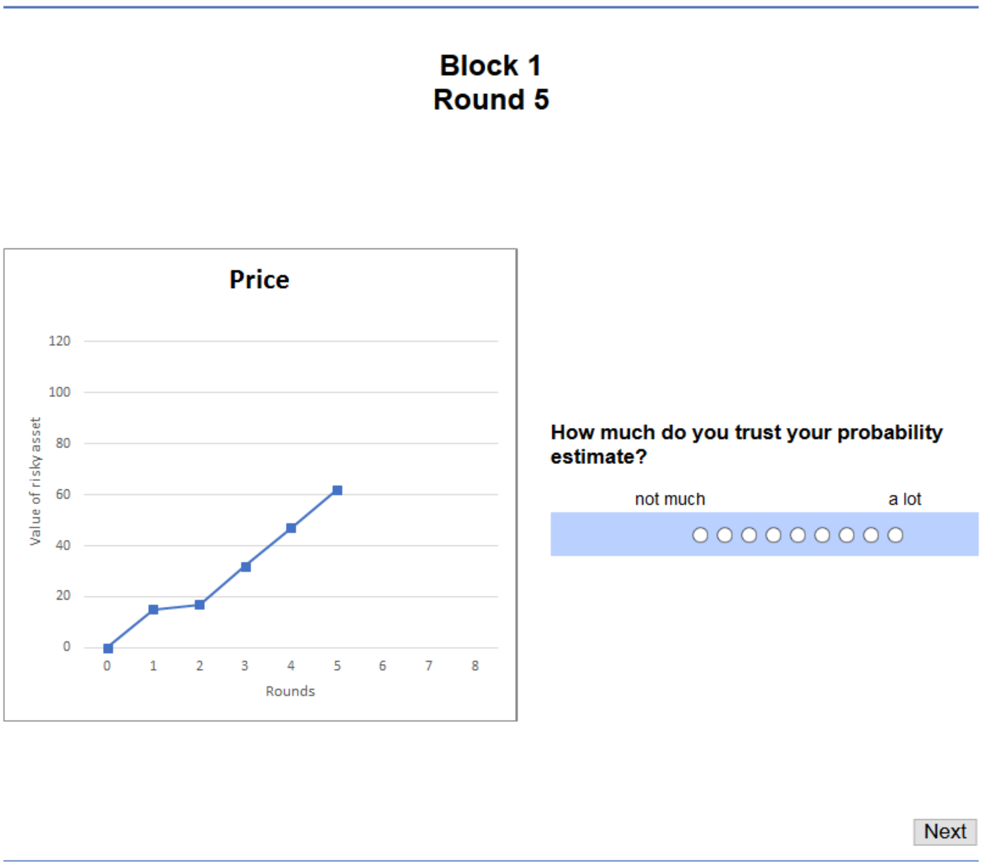


Figure B3: Confidence level screen



C. Experimental Measures in Experiment 1 and 2

Risky Lottery

Imagine in the stock market there is a risky asset, in which you can invest 100 Cent now. The asset pays you either 2.5 times the amount you invest or it becomes valueless, i.e. your invested amount is lost. **The probability of either outcome is exactly 50%**.

You can keep whatever amount you decide not to invest in the risky asset.

How much of your endowment do you want to invest in the risky asset?

[Dropdown Menu of all possible combinations in 5 Cent steps]

Ambiguous Lottery

Imagine in the stock market there is a risky asset, in which you can invest 100 Cent now. The asset pays you either 2.5 times the amount you invest or it becomes valueless, i.e. your invested amount is lost. **However, the probability of either outcome is unknown**.

You can keep whatever amount you decide not to invest in the risky asset.

How much of your endowment do you want to invest in the risky asset?

[Dropdown Menu of all possible combinations in 5 Cent steps]

Life Orientation Test

Below we report the questions used in the revised version of the Life Orientation Test developed by Scheier, Carver, and Bridges (1994). All questions were answered on a 5-point Likert scale from “do not agree at all” to “fully agree”. Reverse-coded items are indicated by [R]. Filler-items are indicated by [F]. The non-filler items were added to a final score.

1. In uncertain times, I usually expect the best.
2. It’s easy for me to relax. [F]
3. If something can go wrong, it will. [R]
4. I’m always optimistic about my future.
5. I enjoy my friends a lot. [F]
6. It’s important for me to keep busy. [F]
7. I hardly ever expect things to go my way. [R]
8. I don’t get upset too easily. [F]
9. I rarely count on good things happening to me. [R]
10. Overall, I expect more good things to happen to me than bad.

Comprehension Question for Bayesian Updating Task

Below we report the comprehension questions that participants had to answer correctly after reading the instructions to proceed to the Bayesian Updating task. Correct responses are displayed in italic.

1. If you see a series of +15 [-2 for Bust treatment], what is more likely?
    a. *The risky asset is in the good state.*
    b. The risky asset is in the bad state.

2. The correct probability estimate is let's say 0.70. Which probability estimate(s) would be in the range such that you earn 10 cents? [Note: You can check multiple boxes.]
    a. 0.55
    b. *0.67*
    c. *0.75*
    d. 0.85
    e. 0.87

3. At the beginning of each block, the probability that the risky asset is in the good state is 50%.
    a. *True*
    b. False

Dow Jones Return Expectations Question in Experiment 1

The Dow Jones Industrial Average (Stock Market Index of the 30 largest US companies) is currently trading at around 25,343.

In which price range would you expect this index to trade in 6 months from now?

[Dropdown]

- < 23,000
- 23,000 – 23,500
- 23,501 – 24,000
- 24,001 – 24,500
- 24,501 – 25,000
- 25,001 – 25,500
- 25,501 – 26,000
- 26,001 – 26,500
- 26,501 – 27,000
- 27,001 – 27,500
- 27,501 – 28,000
- > 28,000

Dow Jones Return Expectations Question in Experiment 2

The Dow Jones Industrial Average (Stock Market Index of the 30 largest US companies) is currently trading at around 26,770.

In which price range would you expect this index to trade in 6 months from now?

[Dropdown]

- < 24,500
- 24,500 – 25,000
- 25,001 – 25,500
- 25,501 – 26,000
- 26,001 – 26,500
- 26,501 – 27,000
- 27,001 – 27,500
- 27,501 – 28,000
- 28,001 – 28,500
- 28,501 – 29,000
- 29,001 – 29,500
- > 29,500