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Camelia Kuhnen
Andrei Mui

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Human Capital and Economic Opportunity Global Working Group
Economics Research Center
University of Chicago
1126 E. 59th Street
Chicago IL 60637
www.hceconomics.org

Socioeconomic Status and Learning from Financial Information*

Camelia M. Kuhnen[†]

Andrei C. Miu[‡]

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Abstract

The majority of lower socioeconomic status (SES) households in the U.S. and Europe do not have any stock investments, which is detrimental to wealth accumulation. Here, we examine one explanation for this puzzling fact, namely, that economic adversity may influence how people learn from financial information. Using experimental and survey data from the U.S. and Romania, we find that lower SES individuals form more pessimistic beliefs about the distribution of stock returns and are less likely to invest in stocks. SES shapes people's beliefs about stocks, leading to large differences across households in their propensity to participate in financial markets.

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[†]University of North Carolina, Kenan-Flagler Business School & NBER, Finance Area, 300 Kenan Center Drive, MC #4407, Chapel Hill, NC 27599, USA. E-mail: camelia_kuhnen@kenan-flagler.unc.edu. (Corresponding author)

[‡]Babes-Bolyai University, Department of Psychology, Republicii St. #37, Cluj-Napoca 400015, Romania. E-mail: andreimiu@psychology.ro.

I. Introduction

A puzzling pattern in household finance is that more than 50% of people in the U.S. and Europe do not invest in the stock market (Campbell (2006), Calvet et al. (2007)). The avoidance of equity investments is particularly prevalent among those less well-off. Among households in the bottom quintile of the income distribution in the U.S., 89% have no stock holdings, while among those in the upper quintile, more than 82% have such holdings.¹ From a policy perspective, it is important to understand the drivers of these substantial differences in the investment choices of households across the socioeconomic spectrum.

Here we investigate a potential driver of these differences, which so far has received little attention in the literature, namely, that the beliefs held by people regarding the distribution of returns in equity markets may be shaped by these individuals' socioeconomic status. Specifically, we ask whether people's socioeconomic status change the way they learn from financial information and make investment decisions.

Recent evidence suggests that encountering economic adversity has a significant influence on how people make economic choices, in particular by changing the way they learn from new information and form beliefs about future outcomes. Chronic poverty and bad economic shocks have been shown to be detrimental to cognitive performance (Hackman and Farah (2009), Mani et al. (2013)). Early-life adversity in particular has long-lasting effects on brain development and function, for example by changing the brain's response to stress or by diminishing memory function (Evans and Schamberg (2009)). Poverty causes stress and negative affective states (Haushofer and Fehr (2014)), which may lead to suboptimal choices such as underinvestment in education, undersaving, or overborrowing (Banerjee and Duflo (2007), Shah et al. (2012)).

Aside from impeding decision-making in general, economic adversity is likely to also induce a pessimism bias in how people view the distribution of future outcomes they can attain.

¹Survey of Consumer Finances Chartbook, p. 507-510, issued by the Federal Reserve Board in September 2014, available at <http://www.federalreserve.gov/econresdata/scf/files/BulletinCharts.pdf>.

Specifically, neuroscience research has found that individuals who have experienced adversity exhibit a stronger brain response to negative outcomes, relative to positive outcomes. That is, those coming from more adverse environments display increased threat vigilance as well as a weaker response to rewarding outcomes (e.g., Nusslock and Miller (2015), Hanson et al. (2015)).

Therefore, the natural hypothesis that stems from these insights from neuroscience is that individuals coming from environments with more economic adversity, who are thus characterized by a lower socioeconomic status (SES), have more pessimistic beliefs about the outcomes of financial investment opportunities, and that these pessimistic beliefs arise from the fact that these lower SES individuals, unlike the rest of the population, will react less to good news relative to bad news about such investments. In other words, our current understanding about the effects of adversity on brain function suggests that economic adversity induces an asymmetry in how people learn from financial or economic news, such that those coming from lower SES environments will have a more pessimistic assessment of available economic or financial opportunities.

There is some indirect evidence from recent work in finance and economics that aligns with this prediction. Specifically, individuals who live through bad economic times subsequently avoid risky investments (Malmendier and Nagel (2011)), and those who experience sequences of negative financial outcomes form overly pessimistic beliefs about the future returns of risky assets (Kuhnen (2015)). Survey data indicates that people with less education have more pessimistic expectations about macroeconomic growth (Souleles (2004)).

In this paper, we use a controlled experimental setting to examine whether indeed people's socioeconomic background changes the way they learn from new financial information and make investment decisions. As hypothesized based on insights from neuroscience research, we find that lower SES participants form more pessimistic beliefs about the distribution of outcomes of risky financial assets – specifically, stocks – and are less likely to invest in these assets. The pessimism bias regarding stocks that is induced by coming from a low

SES environment is particularly strong in situations when, objectively, these assets are likely to have high payoffs, and when participants are actively investing, rather than passively learning, and financial losses are possible. Given our experimental design, we can isolate the role of SES on beliefs and investing decisions from confounding factors such as SES-based differences in opportunities to invest or in financial knowledge. We replicate these experimental findings in samples from two countries – Romania and the U.S. – and then test the external validity of our experimental results by collecting SES, beliefs and investment decisions data from a large non-laboratory sample of adults from all 50 states in the U.S. Across all these three populations, encompassing more than 1400 people, we consistently find that low SES individuals are more pessimistic about the distribution of stock returns and are less likely to invest in stocks.

As the first step in our study, we sought to investigate in a controlled experimental setting whether learning from new information depends on people’s socioeconomic background. To do so, we invited participants from a top public university in Romania to a financial decision making study, for which we used the same experimental design as in Kuhnen (2015). We ran the experiment at that university because there we can observe a large amount of variation in the socioeconomic status of the participant population, and, at the same time, a high degree of homogeneity in terms of scholastic achievement. Two institutional details lead to these features of our experimental setting: first, the students at this university are admitted based on their performance on a stringent, national-level exam; second, the Romanian government provides scholarships to all students who need financial assistance for covering the cost of attending this university, and 67% of those enrolled receive such aid.

We then checked whether the results from the original laboratory sample replicate in a different experimental pool of subjects, and conducted the experiment at a top public university in the U.S., where we verified that the findings from the original setting replicate out of sample, across the two countries.

Lastly, we sought to test the external validity of our laboratory results and collected

data regarding beliefs about stock market returns, and investment decisions from a large sample of U.S. adults across all 50 states. As expected based on the results of the laboratory experiments, we found that adults from lower SES backgrounds – namely those with lower income, lower education, faced with significant recent negative financial shocks, or living in counties with lower incomes, lower education or more unemployment – have a more pessimistic assessment of future stock market returns and invest a lower share of their income in stocks.

The controlled experiment done by our laboratory subjects required participants to complete two financial decision making tasks. In the Active task subjects made sixty decisions, split into ten separate blocks of six trials each, to invest in one of two securities: a stock with risky payoffs coming from one of two distributions (good and bad), one which was better than the other in the sense of first-order stochastic dominance, and a bond with a known payoff. In each trial, participants observed the dividend paid by the stock, after making their asset choice, and then were asked to provide an estimate of the probability that the stock was paying from the good distribution. Therefore, the stock dividend history seen by each participant does not depend on whether or not they chose the stock. In other words, the asset choice did not change the learning problem faced by participants. In the Passive task subjects were only asked to provide the probability estimate that the stock was paying from the good distribution, after observing its payoff in each of sixty trials, which were also split into ten separate learning blocks of six trials each. In either task, two types of conditions - gain or loss - were possible. In the gain condition, the two securities provided positive payoffs only. In the loss condition, the two securities provided negative payoffs only. Subjects were paid based on their investment payoffs and the accuracy of the probability estimates provided.

Importantly, the learning problem faced by subjects was exactly the same, irrespective of their socioeconomic status. Hence, people’s estimate regarding the probability that the stock was paying from the good dividend distribution, namely that distribution where the

high outcome for that condition was more likely to occur than the low outcome, should not depend on whether a participant has encountered more or less economic adversity in life.

However, we find that low SES participants form subjective estimates for the likelihood that the stock is paying from the good distribution that are 2.86% lower than those of mid or high SES participants, in situations where objectively the stock is likely to be the good one. If subjects are actively investing and they are in loss condition trials, this wedge in beliefs becomes 4.70%. These results are robust to multiple approaches through which the low, mid and high SES groups are constructed, and replicate out of the original Romanian sample, in a group of U.S. participants. This pessimism bias induced by low SES is not driven by differences in risk preferences or finance-relevant knowledge, but rather, by differences in updating from new information. In particular, we find that when high stock dividends are revealed, low SES participants update their beliefs less, by 3% to 5%, relative to mid or high SES participants. That is, lower SES participants are less likely to pay attention to good news about the available financial assets. We also show that while participants on average improve over time their ability to correctly estimate the probability that the stock is paying from the good distribution, the rate of improvement is slower for the low SES group relative to the others. Finally, we document that, relative to mid and high SES people, low SES individuals not only have a more pessimistic assessment of the stock outcome distribution, but they also are less likely to invest in the stock. We find that in cases when the stock is the optimal investment choice given the dividends observed so far, low SES participants are 5% less likely to choose the stock compared to their mid and high SES peers.

We checked whether our laboratory results have external validity by employing an outside company (Qualtrics) to recruit on our behalf a sample of approximately 1200 adults ages 18 to 65 across the U.S. and who were representative of the general population in terms of their income distribution. These adults resided in 591 different counties, across all 50 U.S. states. In line with the findings of our controlled experiments, in this non-laboratory sample we find that individuals from lower SES backgrounds are more pessimistic about the

stock market and invest a lower share of their income in stocks. For example, we find that people whose household income is in the lowest tercile in the sample (i.e., under \$35,000) on average estimate the probability that the aggregate U.S. stock market will have a positive return over the following year to be 47.70%, whereas the same subjective estimate is 58.69% for people whose household income is in the highest tercile (i.e., \$75,000 or higher). At the same time, we find that the share of income invested in stocks is on average 7.94% for people in the lowest income tertile and 21.59% for people in the top income tertile. College educated participants assess on average the probability that the U.S. stock market would have a positive return over the following year to be 55.46%, whereas the estimate provided by people without a college degree is 48.73%. Moreover, college educated participants invest on average 19.07% of their income in stocks, whereas people without a college degree invest on average only 9.24% of their income in stocks. Also, individuals who, as of early 2015, have not encountered significant financial difficulties since 2007 assess the probability that the U.S. stock market will have a positive return over the next year to be 53.05%, whereas the estimate of those who have encountered financial difficulties since 2007 is 49.65%. Those participants without financial difficulties invest on average 16.79% of their income in stocks, whereas those who have encountered financial trouble invest only 9.07% of their income in stocks. When instead of participants' self-reported own income, education or indicators of negative financial shocks we use objective U.S. Census county-level data regarding median household income, college education rates or unemployment rates, we continue to find the expected results: namely, people residing in counties with worse economic conditions are more pessimistic about the returns of the U.S. stock market, and invest a lower share of their income in stocks.

The results in this paper could help shed light on the empirical pattern documented by Campbell (2006) and Calvet et al. (2007), namely, that U.S. and European households with lower education, income or wealth are less likely to participate in the stock market. A potential driver of this pattern could be that lower SES households have more pessimistic

beliefs about the possible outcomes of risky investments, as suggested by the findings in our study. Thus, overly pessimistic beliefs about risky asset returns may help explain why lower SES households are less likely to invest in equities.

Our findings contribute to the recent experimental finance literature on learning in markets and to the household finance literature on stock market participation. Payzan-LeNestour and Bossaerts (forthcoming) show that people can learn about financial assets according to Bayes' rule, if changes in the outcome distributions of risky assets are made salient. If that is not the case, learning performance deteriorates significantly. Beshears et al. (2013) find that investors are unable to learn well from processes that mean-revert slowly. Investors' learning process depends, incorrectly, on their prior investment choices (Kuhnen et al. (2015)) and prior choices suboptimally influence future trading decisions (Frydman and Camerer (2015)). Beshears et al. (2015) find that low income individuals reduce their investment rates upon learning about the contributions to retirement accounts of their work peers, and suggest that discouragement from social comparisons may drive this effect.

We describe the experimental design in Section II. In Section III we present the main result, as well as robustness checks, tests of alternative explanations, and external validity tests. We discuss implications of the pessimism bias induced by encountering economic adversity and suggest avenues for future research building on this finding in Section IV.

II. Experimental design

For the controlled laboratory experiment we recruited 203 participants (53 males, 150 females, mean age 21.3 years, 2 years standard deviation) via on-campus flyers at the Babes-Bolyai University, which is a top higher-education institution in Romania. Participants gave written informed consent, as required by human subjects protection rules. All payments to participants for their performance in the experiment were provided in *RON*, which is the local currency. (1 *RON* is approximately equal to 0.3 *USD*.)

Following the same experimental protocol as in Kuhnen (2015), each participant completed two financial decision making tasks, referred to as the Active task and the Passive task, during which information about two securities, a stock and a bond, was presented. Whether a participant was presented with the Active task first, or the Passive task first, was determined at random. Each task included two types of conditions: gain or loss. In the gain condition, the two securities provided positive payoffs only. The stock payoffs were +10 *RON* or +2 *RON*, while the bond payoff was +6 *RON*. In the loss condition, the two securities provided negative payoffs only. The stock payoffs were -10 *RON* or -2 *RON*, while the bond payoff was -6 *RON*. The task included gain and loss blocks, in both the active and passive version, as learning may differ across these settings (Kuhnen (2015)).

In either the gain or the loss condition, the stock paid dividends from either a good distribution or from a bad distribution. The good distribution is that where the high outcome occurs with 70% probability in each trial, while the low outcome occurs with 30% probability. The bad distribution is that where these probabilities are reversed: the high outcome occurs with 30% probability, and the low outcome occurs with 70% probability in each trial.

Each participant went through 60 trials in the Active task, and 60 trials in the Passive task. Trials are split into "learning blocks" of six: for these six trials, the learning problem is the same. That is, the computer either pays dividends from the good stock distribution in each of these six trials, or it pays from the bad distribution in each of the six trials. At the beginning of each learning block, the computer randomly selects (with 50%-50% probabilities) whether the dividend distribution to be used in the following six trials will be the good or the bad one.

There are ten learning blocks in the Active task, and ten learning blocks in the Passive task. In either task, there are five blocks in the gain condition, and five blocks in the loss condition. The order of the blocks is randomized. An example of a sequence of loss or gain learning blocks the a subject may face during either the Active task or the Passive task, as well as a summary of the experimental design, are shown in Table I.

In the Active task participants made 60 decisions (six per each of the ten learning blocks) to invest in one of the two securities, the stock or the bond, then observed the stock payoff (irrespective of their choice) and provided an estimate of the probability that the stock was paying from the good distribution. Figure 1 shows the time line of a typical trial in the Active task, in either the gain and or the loss conditions (top and bottom panel, respectively).

In the Passive task participants were only asked to provide the probability estimate that the stock was paying from the good distribution, after observing its payoff in each of 60 trials (split into ten learning blocks of six trials each, as in the Active task). Figure 2 shows the time line of a typical trial in the Passive task, in either the gain or the loss conditions.

In the Active task participants were paid based on their investment payoffs and the accuracy of the probability estimates provided. Specifically, they received one tenth of accumulated dividends, plus ten cents for each probability estimate within 5% of the objective Bayesian value. In the Passive task, participants were paid based solely on the accuracy of the probability estimates provided, by receiving ten cents for each estimate within 5% of the correct value. Information regarding the accuracy of each subject's probability estimates and the corresponding payment was only provided at the end of each of the two tasks. This was done to avoid feedback effects that could have changed the participants' strategy or answers during the progression of each of the two tasks.

This information was presented to participants at the beginning of the experiment, and is summarized in the participant instructions sheet included in the Appendix. The experiment lasted 1.5 hours and the average payment per person was 28.69 *RON*.

The value of the objective Bayesian posterior that the stock is paying from the good distribution can be easily calculated. Specifically, after observing t high outcomes in n trials so far, the Bayesian posterior that the stock is the good one is: $\frac{1}{1 + \frac{1-p}{p} * (\frac{q}{1-q})^{n-2t}}$, where $p = 50\%$ is the prior that the stock is the good one (before any dividends are observed in that learning block) and $q = 70\%$ is the probability that a good stock pays the high (rather than the low) dividend in each trial. The Appendix provides the value of the objective Bayesian posterior

for all $\{n, t\}$ pairs possible in the experiment. This Bayesian posterior is our benchmark for measuring how close the subjects' expressed probability estimates are from the objectively correct beliefs.

For each participant we also obtained measures of their financial literacy and risk aversion. We obtained these two measures by asking subjects two questions regarding a portfolio allocation problem, after they completed the Active and Passive investment tasks. These questions are described in the Appendix. Briefly, the first question asked how much of a 10,000 *RON* portfolio the participant would allocate to the stock market and how much to a savings account. This answer provides a proxy for their risk preference, measured outside of the financial learning experiment. The second question asked the person to calculate the expected value of the portfolio they selected, and through multiple-choice answers could detect whether people lacked an understanding of probabilities, of the difference between net and gross returns, or of the difference between stocks and savings accounts. This yielded a financial knowledge score of 0 to 3, depending on whether the participant's answer showed an understanding of none, one, two or all three of these concepts.

Participants also completed an 11-item numeracy questionnaire as in Peters et al. (2006), which measured their ability to do simple algebraic calculations and use information about probabilities.

Our main measure of socioeconomic status for this sample of young adults is obtained as in Ensminger et al. (2000) by aggregating information we obtain from each participant regarding their parents' income and education, their family size, and closeness of family ties. We split the overall group of 203 participants into a low SES subsample (67 individuals), and a mid or high SES subsample (136 individuals), based on whether their aggregate SES score is in the low third or the upper two thirds of the SES scores distribution. As a second way to measure of SES, we split the sample depending on whether the parental income is below or above 1000 *RON*/month (approximately \$300), which is the minimum full-time wage in Romania. As a third way to measure of SES, we split the sample based on whether

the participants' subjective assessment of whether they rank in society on a scale from 1 to 10 is below 5. Finally, as a fourth way to measure of SES, we split the sample in based on whether neither of the participants' parents have a college degree.

III. Results

A. Main result

We find that low SES participants, relative to medium or high SES ones, form more pessimistic beliefs about the distribution of outcomes of financial investments when, objectively, these investments are likely to be good. This effect is shown in the simple univariate analysis in Figure 3, where we present the average subjective probability estimate that the stock is paying from the good distribution, for each level of the objective Bayesian posterior probability, separately for low SES participants, and for mid or high SES ones.

As the figure shows, there is no significant difference in the subjective posteriors of low SES individuals relative to the rest of the sample, in situations where the objective posterior that the stock is the good one is below 50%. However, when, objectively, the stock is likely to be the good one, we document that low SES participants have a significantly more pessimistic assessment of the quality of this stock, for every level of objective probability equal to or higher than 50%.

We also conduct regression analyses, as shown in Table II, where we estimate the effect of the low SES indicator on subjective probability estimates, while controlling for participants' gender and age, and including fixed effects for the level of the objective posterior probability. Standard errors in these regressions and throughout the rest of the analysis are clustered by participant.

In Table II we replicate the main result shown in Figure 3. We find that low SES participants have beliefs that are 2.86% ($p < 0.05$) more pessimistic relative to the mid or high SES participants, regarding the likelihood that the stock is paying from the good

distribution, when the objective probability that this is the good stock is greater or equal to 50%. When objectively the stock has a strictly less than 50% chance to be the good one, there is no SES difference in subjective probabilities. We can reject ($p < 0.05$) the hypothesis that the effect of low SES on the subjective estimate of the probability that the stock is the good one is the same for situations when objectively this probability is strictly below 50% (first column in Table II) as when it is equal to or higher than 50% (second column in Table II).²

Moreover, the regressions in the leftmost four columns in Table II show that the pessimism bias regarding risky investments that is induced by coming from a low SES environment is particularly strong if participants are actively investing, rather than passively learning, and if financial losses are possible. In these types of trials (i.e., in the Active task, in loss condition blocks), the beliefs expressed by low SES participants are on average 4.70% ($p < 0.05$) more pessimistic than those of mid or high SES participants. Unsurprisingly, in light of the prior literature on gender effects on investing (e.g., Barber and Odean (2001)), we also find that men have more optimistic assessments of the quality of the stock, relative to women, in most of the sample splits done in the analysis in Table II.

To check whether these findings are robust to our measure of low SES, in Table III we conduct the same type of regression analyses as in Table II using the other three ways to measure SES discussed in Section II. For ease of comparison, we present the coefficient estimates for our main low SES measure (obtained in Table II) in Panel A of Table III. We then assign participants to low socioeconomic status based on parental income (Panel B), subjective socioeconomic status evaluation (Panel C), or parental education (Panel D). The low SES measures in Panels A, B and C have similar effects: lower SES participants,

²In unreported models similar to the regression in the second column in Table II, we show that low SES has a significant and negative effect on the subjective probability that the stock is paying from the good distribution separately in situations when the objective probability is strictly below 50%, as well as when it is exactly equal to 50%. The estimated effects of low SES on the subjective probability in these two subsets of trials are -2.65% ($p < 0.1$) and -3.6% ($p < 0.05$), respectively. Hence we group these two subsets of trials together (i.e., these are the trials when the objective probability that the stock is the good one is equal or greater than 50%) in the main analysis.

categorized this way using either of these three approaches, have more pessimistic beliefs regarding the quality of the stock. However, if SES is assessed solely based on whether or not neither parent of a participant got a college education, we no longer observe a significant pessimism bias in the low SES participants (i.e., those whose parents do not have college degrees). This suggests a possibility that needs investigation in further work, namely, that pessimism in assessing financial investments may be triggered by aspects of SES related to low income or financial difficulties, and not necessarily by a lack of formal higher education of one's parents.

The evidence in Figure 3 and Tables II and III indicates that low SES individuals form pessimistic posterior beliefs about the likelihood that the stock they are presented with is paying dividends from the good distribution. A natural question is why these posterior beliefs are more pessimistic for the low SES group. All participants were carefully instructed at the beginning of each learning block of 6 trials that the probability that the stock would pay from the good distribution, not the bad one, was 50%. Thus, by the design of the experiment, the priors were set to 50%, for all participants, no matter their socioeconomic status. Therefore, the observed SES-related difference in posterior beliefs needs to be driven by the process by which individuals from different SES levels update their beliefs about the quality of the stock, after observing its dividends.

In the regressions in Table IV we find that indeed there is a difference in how low SES participants and the mid or high SES ones update beliefs after observing the stock outcome in a given trial. In particular, in the first column in the table we document that low SES participants' subjective probability estimates are 3.15% ($p < 0.06$) less sensitive relative to those of mid or high SES participants, to the presentation of high stock dividends. The second column in the table shows that updating after seeing low dividends does not significantly differ by SES level.

A particularly informative setting in which updating can be studied is that of the first trial in each of the 10 learning blocks completed by each person. In the first trial of each

learning block, everybody’s prior belief that the stock is the good one is set to 50%, by experimental design. In that first trial, the stock dividend is either high or low. If low SES participants update less from high dividends, we should observe that their subjective probability estimates after that first dividend in the learning block is revealed to be high will be lower than the estimates produced by mid or high SES participants who observe the same high dividend. The results in the third column of Table IV present evidence consistent with this prediction: after seeing a high dividend in the first trial of a new learning block, low SES participants produce subjective probability estimates that are 4.53% ($p < 0.08$) lower than those of their mid or high SES counterparts. The last column in the table shows that when the first dividend in a new learning block is low, there is no significant difference in the posterior beliefs of participants, depending on their SES level.

Therefore, the evidence in Table IV suggests that asymmetric updating is the likely mechanism through which low SES participants become pessimistic regarding the quality of the financial assets available to them: they do not update as much as the higher SES participants from news that would indicate that these assets are in fact of good quality. That is, low SES participants may have a skewed view of the financial investments surrounding them: more of a view akin to “the glass is half-empty” rather than “the glass is half-full”, consistent with neuroscience evidence that adverse environments predispose the brain to react relatively less to good outcomes compared to bad outcomes (e.g., Nusslock and Miller (2015)).

Aside from being more pessimistic in their beliefs regarding the stocks presented during the experiment, low SES participants also differ from the mid or high SES ones in terms of the rate at which they improve their probability estimation performance over time. Specifically, while on average participants improve their probability estimation over time, during the 20 blocks of the experiment, the rate of improvement is lower among low SES individuals, compared to mid and high SES individuals. Figure 4 shows that for low SES subjects, probability estimates are on average 31.87% away from Bayesian posteriors in the first learn-

ing block they encounter, and then these subjects' estimation errors decrease at an average rate of 0.2% per block. For mid or high SES subjects, probability estimates are on average 31.18% away from Bayesian posteriors in the first learning block they encounter, and then their estimation errors decrease at an average rate of 0.35% per block. The rate of improvement in probability estimation for low SES participants is significantly lower than that for mid or high SES participants ($p < 0.05$).

B. Replication study in a different experimental sample

To examine whether the results obtained in the original sample of participants replicate in other populations, we recruited 33 participants from the University of North Carolina at Chapel Hill. These U.S.-based individuals completed the Active version of the experiment only, as the original Romanian sample results indicated no SES effects in the Passive version. The Active task was identical to that used in the Romanian sample, except for having the stock and bond payoffs expressed in U.S. dollars, instead of RON. As done in the original sample, in the replication sample we assign participants to the low SES category if they have SES scores which are in the bottom third of the distribution.

We find that in the U.S. sample, people from a low SES background form more pessimistic estimates of the probability that they are faced with the good stock, relative to those from middle or high SES backgrounds. This result, which replicates the main finding from the Romanian sample documented in Table II, is shown in Table V. As in the original sample, in the replication sample we find that the effect of low SES on subjective beliefs about the stock is particularly large when objectively, the stock is likely to be the good one, and during loss condition trials, when participants face negative outcomes.

Thus, across two samples in two different countries, we document that coming from more economically disadvantaged backgrounds predicts that people will have a more pessimistic assessment regarding the outcomes of financial investments available to them in our experimental setting.

C. Alternative explanations

C.1. Do risk aversion and finance knowledge differ across SES categories?

While the evidence so far suggests that low SES participants form opinions about the quality of investment opportunities differently from mid or high SES participants, it is possible that there are other SES-related factors, unrelated to updating, that would lead to these differences in subjective probability estimates in the low SES versus the mid or high SES group. For example, it could be that low SES participants are not more pessimistic in how they update their view about investments, but they have lower levels of finance-related knowledge that would allow them to do well in this learning task. We find that this is not the case in our sample. We use four measures of finance-relevant knowledge: the subjects' scores on the financial knowledge questions detailed in Section II, their numeracy score calculated as in Peters et al. (2006), the type of college major they pursued (technical or not), and the average confidence they reported when expressing their probability estimate every trial.

Table VI presents averages of these four variables related to the subjects' understanding of finance-relevant concepts, separately for the low SES subsample, and the mid or high SES subsample. We find that neither one of these four dimensions of finance-relevant knowledge differs significantly across the two subsamples, as shown by the p -values in the last column in the table.

Another potential explanation for our main effect is that perhaps low SES participants are more risk averse than the mid or high SES participants, and their subjective probability estimates reflect their increased risk aversion, and not pessimism in their true beliefs. We analyze four measures of risk aversion to see whether they are different for the low SES group relative to the rest of participants.

First, for each person we calculate the frequency with which they chose the stock, rather than the bond, in the first trial in each learning block. In this trial the choice is solely driven by risk preferences and not by new information, since no dividend of the stock has yet been

observed, and thus participants only know the 50% prior that the stock is the good one. As shown in the first row of Table VII, the difference in the propensity to chose the stock in the first trial between the low SES group and the other participants is not significantly different from 0 at conventional levels. Second, we compare the amount, out of a hypothetical 10,000 *RON* endowment, that subjects would invest in the stock market, for the low SES group and the mid or high SES group, and again find no significant difference, as shown in the second row of the table. The third and fourth measures of risk attitudes shown in the bottom two rows of Table VII are given by subjects' scores on two surveys used widely in the psychology literature, the State-Trait Anxiety Inventory (Spielberger et al. (1983)) and the Behavioral Inhibition Scale (Carver and White (1994)). We do not find any differences between the low SES and the mid or high SES groups on these anxiety-related proxies for risk avoidance.

Furthermore, as a robustness check we include the personal characteristics from Tables VI and VII, such as finance knowledge and risk aversion, as additional explanatory variables in our main analysis in Table II and continue to find that the effect of low SES on the subjective probability that the stock is the good one is negative and significant (full estimation results omitted here for brevity). For example, after adding financial knowledge, numeracy, an indicator for whether the participant pursues a technical college major, and the state and trait anxiety measures to the regression in column 2 of Table II, the effect of low SES on the subjective probability estimate is -3.43% (t -stat = -2.34), similar to the effect found without these additional explanatory variables (-2.85%, t -stat=1.98).

C.2. Do low SES participants exhibit pessimism or are they in general less able to update correctly?

If low SES participants were simply less able to update, their probability estimates would be significantly higher than those of mid and high SES participants in situations when the objective probability that the stock is the good one is less than 50%. However, as Figure 3 shows, this is not the case. That is, when the stock is unlikely to be the good one, the

estimates of both types of participants are equally far from the correct, objective probability (the 45° grey line in the figure). The same conclusion can be drawn when comparing the first two columns in Tables II, III and V. Specifically, across the original Romanian sample and the replication sample in the US, using various measures of SES, the evidence points to relative pessimism on behalf of low SES participants relative to mid and high SES ones when the stock is likely to be the good one, but not to relative optimism when the stock is unlikely to be good. Hence, we do not find evidence of a general lack of updating ability among low SES participants, but rather, we find evidence consistent with belief errors in a specific direction, namely, that of pessimism about the stock return distribution in situations when objectively the stock is likely to have good outcomes.

D. Consequences for investment choices

The pessimistic assessment of the quality of the stock payoff distribution observed among the low SES participants has consequences for these individuals' investment choices. Specifically, as shown in Figure 5, low SES individuals are significantly less likely to choose the stock, particularly in trials when the objective probability that the stock is paying from the good dividend distribution is greater than 50%. In such trials, risk-neutral expected value maximizing investors would choose to hold the stock rather than the bond.

However, we find that in these situations low SES participants choose the stock, rather than the bond, in 74% of the trials, whereas the mid and high SES participants choose the stock in 79% of the trials (the difference is significant at $p < 0.05$). That is, in cases when the stock is the optimal investment choice given the dividends observed so far, low SES participants are less likely to choose the stock compared to their mid and high SES peers, and thus get a smaller payoff by choosing the bond.³

³In the Romanian laboratory sample we observed that subjects sometimes chose the stock instead of the bond even in situations when the objective probability that the stock was the good one was strictly less than 50%, and hence the bond would have been the optimal choice for a risk-neutral agent, as can be inferred from Figure 5. This tendency was reduced, yet not completely, in the U.S. laboratory sample, which may indicate an interesting cultural difference in people's approach to investment decisions, something which we

E. External validity test: Large sample evidence from the U.S.

The evidence from our laboratory experiment run in Romania and replicated in the U.S. indicates that lower SES experiment participants are more pessimistic in their assessment of the available stock investment and less willing to choose the stock over the bond. The natural next step is to inquire whether these findings are also present among populations outside of college laboratory samples, in situations when people are considering actual stocks instead of experimental assets, and whether our findings are robust to other ways in which a person's SES is measured.

Since the participants in the experimental task in the laboratory were all college students (thus young and not yet fully employed or fully educated), for these individuals we measured their SES based on the demographic characteristics (e.g., income and education) of their parents. It is thus important to check whether in older samples of individuals, who vary in SES because of their own (not their parents') income, education or other circumstances, we still observe that lower SES people view stocks in a more pessimistic manner and are less likely to invest in them.

To test the external validity of the findings of our experiment, we contracted with Qualtrics, a well-known provider of on-line survey services, to recruit on our behalf approximately 1200 individuals across all 50 U.S. states, across ages 18-65, and across all income levels such as to be representative of the income distribution according to the U.S. Census. Each of the 1207 individuals who were in the final sample provided by Qualtrics, recruited during April-May 2015 from 591 different counties across all U.S. states, answered several demographics questions. These questions, which are detailed in Appendix D, included asking participants about their age, gender, education, income level, zipcode of residence and history of financial difficulties since 2007, the beginning of the recent economic turmoil.

The sample characteristics are presented in Table VIII and indicate that the individuals recruited by Qualtrics are indeed very diverse and representative of the U.S. population.

leave for future research to examine in depth.

Household income is below \$15,000 for 13.12% of participants and above \$100,000 for 18.89% of participants, with other income levels being also very well represented in the sample. In terms of education, 41.34% of participants have a college degree. Males represent 51.20% of the sample. Participants' ages vary from 18 to 65, with middle-aged people being the most represented – for example, people with ages between 30-39 years old make up 21.96% of the sample, and those with ages 40-49 years old make up 22.45% of the sample. About 45.15% of the sample reported having at least one of seven types of financial difficulties since 2007. The seven types of financial difficulties we asked participants about are: bankruptcy, foreclosure of property, loss of employment, the inability to pay debts on time, difficulty getting approved for loans, for example to buy a car or a house, having accounts in collection, or borrowing from a payday lender.

After the demographics-related questions, participants were asked two additional questions, to elicit their beliefs about the possible outcomes of investing in the U.S. stock market, and their actual investment choices. These two questions were worded as in the Michigan Survey of Consumers, which has provided an aggregate index of consumer sentiment for many years, and are as follows: (1) *“What do you think is the percent chance that a \$1000 investment in a diversified stock mutual fund will increase in value in the year ahead, so that it is worth more than \$1000 one year from now?”*; and (2) *“Currently, what percentage of your income do you invest in the stock market? Include investments in directly-owned stocks, stocks in mutual funds and stocks in retirement accounts, such as 401(K)s or IRAs.”*

Question (1) above reveals the subjective probability of the individual that the aggregate U.S. stock market will have a positive return over the following year, and this quantity is a good real-life parallel to the subjective probability estimate that the participants in the laboratory experiment had to provide. That is, both in the sample of experimental subjects and in the regular adult sample surveyed by Qualtrics, we obtain a measure of people's belief that stocks are good investments. Question (2) above measures the individual's actual investment behavior, in terms of their decision to invest in stocks, and it is the real-life

parallel of the measure we used in the laboratory experiment, which referred to people's decision to choose the stock instead of the bond in any given trial.

If our laboratory findings have external validity, then we should observe that in the sample of 1207 adults surveyed by Qualtrics on our behalf, the lower SES individuals would have a more pessimistic assessment of the probability that the U.S. stock market would have a positive return over the subsequent year, and would invest a lower fraction of their income in stocks. As shown in Figure 6 the data provide strong support for these predictions. In the figure we present the participants' answers to questions (1) and (2) above – namely, their belief about stock investments, and the share of income they invest in stocks – for different subsamples of individuals based on their SES level. As our measure of participants' SES, we use their household income in the top panel of Figure 6, education in the middle panel of Figure 6, and whether or not since 2007 they encountered any of the seven types of financial difficulties listed above.

No matter which SES measure we use, we find that adults with lower SES indeed have more pessimistic beliefs about the U.S. stock market and they invest a lower percentage of their income in stocks. For example, the data in the top panel of Figure 6 shows that people whose household income is in the lowest tercile in the sample (i.e., under \$35,000) on average estimate the probability that the U.S. stock market will have a positive return over the following year to be 47.70%, whereas the same subjective estimate is 58.69% for people whose household income is in the highest tercile (i.e., \$75,000 or higher). These probability estimates are significantly different at $p < 0.01$. People in the middle tertile of income also report significantly lower probability estimates than those in the top tertile (49.33% vs. 58.69%, $p < 0.01$). Importantly, not only do those earning less have a more pessimistic assessment of the U.S. stock market, but they also invest a lower share of their income in stocks. Specifically, we find that the average share of income invested in stocks is 7.94% for people in the lowest income tertile, 11.89% for people in the middle income tertile, and 21.59% for people in the top income tertile. The differences between the income share

invested in stocks of individuals in the top income tertile and those in the lowest two income tertiles are significant at $p < 0.01$.

The same pattern emerges when we measure SES by education, or by the presence of financial difficulties in the recent recession since 2007. The middle panel of Figure 6 shows that college educated participants assess on average the probability that the U.S. stock market would have a positive return over the following year to be 55.46%, whereas the estimate provided by people without a college degree is 48.73% (the difference is significant at $p < 0.01$). Moreover, college educated participants invest on average 19.07% of their income in stocks, whereas people without a college degree invest on average only 9.24% of their income in stocks (the difference is significant at $p < 0.0$). The data in the bottom panel of Figure 6 shows that individuals who have not encountered financial difficulties since 2007 assess on average the probability that U.S. stock market will have a positive return over the next year to be 53.05%, whereas the estimate of those who have encountered financial difficulties since 2007 is 49.65% (the p -value of the difference is 0.08). Those participants without financial difficulties invest on average 16.79% of their income in stocks, whereas those who have encountered financial trouble invest only 9.07% of their income in stocks (the difference is significant at $p < 0.01$).

This evidence strongly indicates that the survey participants with lower SES are more pessimistic about the stock market and less inclined to invest in stocks, thus supporting the findings from our experimental laboratory setting. However, there exists the concern that perhaps those individuals we surveyed were not truthful about their income, education or financial troubles and biased their answers in such a way that we ended up observing those reporting lower SES also reporting more pessimistic beliefs about stocks and a reluctance to invest in stocks. While we have no reason to believe that misreporting happened, and that it happened in this very specific manner that would drive all the results in Figure 6, it is important to investigate if our results disappear once we have objective measures of these individuals' SES. Luckily, we can do this, as in the survey we asked participants (before they

saw any questions about their income, financial troubles or the stock market) to tell us the five-digit zipcode in which they reside.⁴ We then identified the county to which each zipcode belongs.⁵ This allows us to obtain county-level data from the American Community Survey conducted by U.S. Census regarding each county’s demographics and economic conditions. The data are from the 2013 release (the latest available at the time this paper is written) and provide county-level measurements of income, education or unemployment as 5-year averages over the 2009-2013 window (one-year estimates are also available but only for the very largest of counties in the US). These objective county-level measures can therefore provide us with instruments for our survey participants’ income, education and economic adversity in general, and thus will alleviate the concern that the self-reported SES measures we get from these individuals are biased or mismeasured in general.

With these objective, county-level SES measurements in hand, in the analysis presented in Figure 7 we conduct the same type of comparisons as in Figure 6, but instead of the participants’ self-reported SES measures we use the county-level measures from the U.S. Census. The results in the two figures are very similar. Even when instrumenting the participants’ SES with county-level SES indicators, we continue to find that people in worse economic situations, namely, people living in counties with lower income, lower education or higher unemployment, have a more pessimistic assessment about the U.S. stock market return over the following year and invest less of their income in stocks. Specifically, the top panel of Figure 7 shows that participants in the bottom tercile in terms of county-level median household income assess the probability that the U.S. stock market will have a positive return in the next year to be 48.91%, whereas those in the top tercile assess that probability to be 54.24% (the difference is significant at $p < 0.05$). These groups also invest differently: those in the bottom tercile, namely, living in counties with a low median

⁴This information can be verified using the geolocation information provided by Qualtrics based on the IP address of each survey participant.

⁵To map zipcodes to counties, we used the HUD USPS ZIP Code Crosswalk Files available at www.huduser.gov. If a zipcode stretches across multiple counties, which happens rarely, we assigned to that zipcode the county where more than 50% of the zipcode’s residents live.

household income, invest 11.02% of their income in stocks, whereas those in the top tercile invest 15.86% of their income in stocks (the difference is significant at $p < 0.01$). The middle panel of Figure 7 shows that people living in counties with below-median college education rates express lower probabilities about the stock market having a positive return, relative to those living in counties with above-median college education (48.98% vs. 54.15%, difference significant at $p < 0.01$), and also invest less of their income in stocks (10.74% vs. 16.03%, difference significant at $p < 0.01$). The bottom panel of Figure 7 shows that county-level unemployment is also a predictor of people’s beliefs about the stock market, as we find that among participants in counties with above-median unemployment, the average subjective probability that the U.S. stock market will have a positive return over the next year is 49.50%, whereas among those in counties with below-median unemployment the average subjective probability is 53.54% (the difference is significant at $p < 0.05$).

Overall, therefore, we find consistent evidence in support of the hypothesis of the paper, which is that people from lower SES environments, or those characterized by more economic adversity, have a more pessimistic assessment of the stock market and are more reluctant to invest in stocks. This evidence comes from both controlled experimental settings in two different countries, as well as from a large sample of participants from all of 50 states in the U.S., which suggests that these results are robust, have external validity, and describe actual households’ beliefs and investment decisions.

IV. Implications and conclusion

Building on insights from neuroscience which suggest that encountering adversity biases the brain to respond less to positive outcomes relative to negative ones, we test the hypothesis that individuals who have faced more economic adversity will have more pessimistic beliefs regarding the possible returns of financial investments and will be less inclined to invest in risky assets such as stocks.

In line with this hypothesis, we find that individuals with lower socioeconomic status are more pessimistic compared to their more economically advantaged peers when assessing the distribution of stock investment outcomes and invest less in stocks. SES-related differences in beliefs are robust to several ways of measuring one’s socioeconomic standing and do not arise from differences in risk preferences or finance-relevant knowledge. Rather, we document that SES induces an asymmetry in how people learn from new stock outcomes. Specifically, we find that low SES participants are less likely to update their beliefs about the quality of the distribution of stock outcomes when good news about stocks is revealed. We replicate these results in two different controlled experimental settings in Romania and the U.S. and then also show their external validity in a large sample of adults across all 50 U.S. states. Namely, we find that adults with lower income, lower education, who have faced significant negative financial shocks during the recent economic downturn, or live in counties with worse economic conditions, assess a lower probability that the aggregate U.S. stock market will have a positive return over the following year, and invest a lower share of their income in stocks.

It would be useful for future work to investigate the importance of the effect of SES on beliefs about stocks for investment decisions of households measured over a long horizon, and for the evolution of wealth inequality in the population. Furthermore, it remains to be established which aspects of economic adversity matter more for the beliefs that households form regarding financial investments, and how this may vary in different age groups. As Cronqvist and Siegel (2015) show that the influence of the early-life environment on people’s savings behavior is highest among people in their twenties, it is thus possible that among older adults, beliefs about financial asset returns may be driven more by their own, rather than their parents’, socioeconomic status.

The findings in our study are important for understanding the low rates of stock market participation observed among low SES households (Campbell (2006) and Calvet et al. (2007)). Our results indicate that coming from a background characterized by high economic adversity induces people to view financial matters through a pessimistic, “glass is

half-empty”, lens rather than in an unbiased manner, which may have negative consequences on wealth accumulation. Hence another avenue for future work is to examine interventions that can help reduce the SES-induced bias in people’s beliefs about the distribution of outcomes of risky investments.

REFERENCES

- Banerjee, A. V. and Duflo, E.: 2007, The economic lives of the poor, *Journal of Economic Perspectives* **21**, 141–167.
- Barber, B. M. and Odean, T.: 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *Quarterly Journal of Economics* **116**(1), 261–292.
- Beshears, J., Choi, J., Fuster, A., Laibson, D. and Madrian, B. C.: 2013, What goes up must come down? Experimental evidence on intuitive forecasting, *American Economic Review: Papers and Proceedings* **103**(3), 570–574.
- Beshears, J., Choi, J., Laibson, D., Madrian, B. C. and Milkman, K. L.: 2015, The effect of providing peer information on retirement savings decisions, *Journal of Finance* **70**(3), 1161–1201.
- Calvet, L. E., Campbell, J. Y. and Sodini, P.: 2007, Down or out: Assessing the welfare costs of household investment mistakes, *Journal of Political Economy* **115**(5), 707–747.
- Campbell, J. Y.: 2006, Household finance, *Journal of Finance* **61**(4), 1553–1604.
- Carver, C. S. and White, T. L.: 1994, Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: The BIS/BAS scales, *Journal of Personality and Social Psychology* **67**, 319–333.
- Cronqvist, H. and Siegel, S.: 2015, The origins of savings behavior, *Journal of Political Economy* **123**(1), 123–169.
- Ensminger, M. E., Forrest, C. B., Riley, A. W., Kang, M., Green, B. F., Starfield, B. and Ryan, S. A.: 2000, The validity of measures of socioeconomic status of adolescents, *Journal of Adolescent Research* **15**(3), 392–418.
- Evans, G. W. and Schamberg, M. A.: 2009, Childhood poverty, chronic stress, and adult working memory, *Proceedings of the National Academy of Sciences* **106**, 6545–6549.

- Frydman, C. and Camerer, C.: 2015, Neural evidence of regret and its implications for investor behavior, *Working paper* .
- Hackman, D. A. and Farah, M. J.: 2009, Socioeconomic status and the developing brain, *Trends in Cognitive Sciences* **13**, 65–73.
- Hanson, J. L., Albert, W. D., Iselin, A.-M. R., Carr, J. M., Dodge, K. A. and Hariri, A. R.: 2015, Cumulative stress in childhood is associated with blunted reward-related brain activity in adulthood, *Social Cognitive and Affective Neuroscience* doi:10.1093/scan/nsv124.
- Haushofer, J. and Fehr, E.: 2014, On the psychology of poverty, *Science* **344**(6186), 862–867.
- Kuhnen, C. M.: 2015, Asymmetric learning from financial information, *Journal of Finance* **70**(5), 2029–2062.
- Kuhnen, C., Rudolf, S. and Weber, B.: 2015, Stock ownership and learning from financial information, *Working paper* .
- Malmendier, U. and Nagel, S.: 2011, Depression babies: Do macroeconomic experiences affect risk-taking?, *Quarterly Journal of Economics* **126**(1), 373–416.
- Mani, A., Mullainathan, S., Shafir, E. and Zhao, J.: 2013, Poverty impedes cognitive function, *Science* **341**, 976–980.
- Nusslock, R. and Miller, G. E.: 2015, Early-life adversity and physical and emotional health across the lifespan: A neuroimmune network hypothesis, *Biological Psychiatry* doi:10.1016/j.biopsych.2015.05.017.
- Payzan-LeNestour, E. and Bossaerts, P.: forthcoming, Learning about unstable, publicly unobservable payoffs, *Review of Financial Studies* .
- Peters, E., Vastfjall, D., Slovic, P., Mertz, C., Mazzocco, K. and Dickert, S.: 2006, Numeracy and decision making, *Psychological Science* **17**(5), 407–413.

Shah, A. K., Mullainathan, S. and Shafir, E.: 2012, Some consequences of having too little, *Science* **338**, 682–685.

Souleles, N. S.: 2004, Expectations, heterogeneous forecast errors, and consumption: Micro evidence from the Michigan Consumer Sentiment Surveys, *Journal of Money, Credit, and Banking* **36**(1), 39–72.

Spielberger, C. D., Gorsuch, R. L., Lushene, R., Vagg, P. R. and Jacobs, G. A.: 1983, *Manual for the State-Trait Anxiety Inventory*, Consulting Psychologists Press, Palo Alto, CA.

APPENDIX

A. Participant Instructions (English Translation)

Welcome to our financial decision making study!

In this study you will work on two investment tasks. In one task you will repeatedly invest in one of two securities: a risky security (i.e., a stock with risky payoffs) and a riskless security (i.e., a bond with a known payoff), and will provide estimates as to how good an investment the risky security is. In the other task you are only asked to provide estimates as to how good an investment the risky security is, after observing its payoffs.

In either task, there are two types of conditions you can face: the GAIN and the LOSS conditions. In the GAIN condition, the two securities will only provide POSITIVE payoffs. In the LOSS condition, the two securities will only provide NEGATIVE payoffs.

Details for the Investment Choice and Investment Evaluation Task:

Specific details for the GAIN condition:

In the GAIN condition, on any trial, if you choose to invest in the bond, you get a payoff of 6 *RON* for sure at the end of the trial. If you choose to invest in the stock, you will receive a dividend which can be either 10 *RON* or 2 *RON*.

The stock can either be good or bad, and this will determine the likelihood of its dividend being high or low. If the stock is good then the probability of receiving the 10 *RON* dividend is 70% and the probability of receiving the 2 *RON* dividend is 30%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is good, then on each trial the odds of the dividend being 10 *RON* are 70%, and the odds of it being 2 *RON* are 30%. If the stock is bad then the probability of receiving the 10 *RON* dividend is 30% and the probability of receiving the 2 *RON* dividend is 70%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is bad, then on each trial the odds of the dividend being 10 *RON* are 30%, and the odds of it being 2 *RON* are 70%.

Specific details for the LOSS condition:

In the LOSS condition, on any trial, if you choose to invest in the bond, you get a payoff of -6 *RON* for sure at the end of the trial. If you choose to invest in the stock, you will receive a dividend which can be either -10 *RON* or -2 *RON*.

The stock can either be good or bad, and this will determine the likelihood of its dividend being high or low. If the stock is good then the probability of receiving the -10 *RON* dividend is 30% and the probability of receiving the -2 *RON* dividend is 70%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is good, then on each trial the odds of the dividend being -10 *RON* are 30%, and the odds of it being -2 *RON* are 70%. If the stock is bad then the probability of receiving the -10 *RON* dividend is 70% and the probability of receiving the -2 *RON* dividend is 30%. The dividends paid by this stock are independent from trial to trial, but come from this exact distribution. In other words, once it is determined by the computer that the stock is bad, then on each trial the odds of the dividend being -10 *RON* are 70%, and the odds of it being -2 *RON* are 30%.

In both GAIN and LOSS conditions:

In each condition, at the beginning of each block of 6 trials, you do not know which type of stock the computer selected for that block. You may be facing the good stock, or the bad stock, with equal probability.

On each trial in the block you will decide whether you want to invest in the stock for that trial and accumulate the dividend paid by the stock, or invest in the riskless security and add the known payoff to your task earnings.

You will then see the dividend paid by the stock, no matter if you chose the stock or the bond.

After that we will ask you to tell us two things: (1) what you think is the probability that the stock is the good one (the answer must be a number between 0 and 100 - do not add the % sign, just type in the value); (2) how much you trust your ability to come up with the correct probability estimate that the stock is good. In other words, we want to know how confident you are that the probability you estimated is correct. (The answer is between 1 and 9, with 1 meaning you have the lowest amount of confidence in your estimate, and 9 meaning you have the highest level of

confidence in your ability to come up with the right probability estimate.)

There is always an objective, correct, probability that the stock is good, which depends on the history of dividends paid by the stock already. For instance, at the beginning of each block of trials, the probability that the stock is good is exactly 50%, and there is no doubt about this value.

As you observe the dividends paid by the stock you will update your belief whether or not the stock is good. It may be that after a series of good dividends, you think the probability of the stock being good is 75%. However, how much you trust your ability to calculate this probability could vary. Sometimes you may not be too confident in the probability estimate you calculated and some times you may be highly confident in this estimate. For instance, at the very beginning of each block, the probability of the stock being good is 50% and you should be highly confident in this number because you are told that the computer just picked at random the type of stock you will see in the block, and nothing else has happened since then.

Every time you provide us with a probability estimate that is within 5% of the correct value (e.g. correct probability is 80% and you say 84% , or 75%) we will add 10 cents to your payment for taking part in this study.

Throughout the task you will be told how much you have accumulated through dividends paid by the stock or bond you chose up to that point.

Details for the Investment Evaluation Task:

This task is exactly as the task described above, except for the fact that you will not be making any investment choices. You will observe the dividends paid by the stock in either the GAIN or the LOSS conditions, and you will be asked to provide us with your probability estimate that the stock is good, and your confidence in this estimate. In this task, therefore, your payment only depends on the accuracy of your probability estimates.

You final pay for completing the investment tasks will be:

$27 \text{ RON} + 1/10 * \text{Investment Payoffs} + 1/10 * \text{Number of accurate probability estimates,}$

where Investment Payoffs = Dividends of securities you chose in the experiment, in both the GAIN and the LOSS conditions.

B. Objective Bayesian Posterior Beliefs

The table below provides all possible values for the objectively correct Bayesian posterior that the stock is paying from the good dividend distribution, starting with a 50%-50% prior, and after observing each possible dividend history path in a learning block. Every trial a new dividend (high or low) is revealed. There are six trials in each learning block.

The objective Bayesian posterior that the stock is the good one, after observing t high outcomes in n trials so far is given by: $\frac{1}{1 + \frac{1-p}{p} * (\frac{q}{1-q})^{n-2t}}$, where $p = 50\%$ is the prior that the stock is good (before any dividends are observed in that learning block) and $q = 70\%$ is the probability that a good stock pays the high (rather than the low) dividend in each trial.

n trials so far	t high outcomes so far	Probability{stock is good t high outcomes in n trials}
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%

C. Measures of Financial Literacy and Risk Preferences

To get measures of financial literacy and risk preferences, each participant was asked the following questions after the completion of the experimental tasks: “Imagine you have saved 10,000

RON. You can now invest this money over the next year using two investment options: a stock index mutual fund which tracks the performance of the stock market, and a savings account. The annual return per dollar invested in the stock index fund will be either +40% or -20%, with equal probability. In other words, it is equally likely that for each *RON* you invest in the stock market, at the end of the one year investment period, you will have either gained 40 cents, or lost 20 cents. For the savings account, the known and certain rate of return for a one year investment is 5%. In other words, for each *RON* you put in the savings account today, for sure you will gain 5 cents at the end of the one year investment period. We assume that whatever amount you do not invest in stocks will be invested in the savings account and will earn the risk free rate of return. Given this information, how much of the 10,000 *RON* will you invest in the stock index fund? Choose an answer that you would be comfortable with if this was a real-life investment decision. The answer should be a number between 0 and 10,000 *RON*.”

After each participant wrote their answer to this question, they were asked the following: ”Let’s say that when you answered the prior question you decided to invest x *RON* out of the 10,000 *RON* amount in the stock index fund, and therefore you put $(10,000 - x)$ *RON* in the savings account. Recall that over the next year the rate of return on the stock index fund will be +40% or -20%, with equal probability. For the savings account, the rate of return is 5% for sure. What is the amount of money you expect to have at the end of this one year investment period? Please choose one of the answers below. If you choose the correct answer, you will get a 5 *RON* bonus added to your pay for this experiment. [A]. $0.5 (0.4 x - 0.2 x) + 0.05 (10,000 - x)$; [B]. $1.4 x + 0.8 x + 1.05 (10,000 - x)$; [C]. $0.4 (10,000 - x) - 0.2 (10,000 - x) + 0.05 x$; [D]. $0.5 [0.4 (10,000 - x) - 0.2 (10,000 - x)] + 0.05 x$; [E]. $0.4 x - 0.2 x + 0.05 (10,000 - x)$; [F]. $0.5 (1.4 x + 0.8 x) + 1.05 (10,000 - x)$; [G]. $1.4 (10,000 - x) + 0.8 (10,000 - x) + 1.05 x$; [H]. $0.5 [1.4 (10,000 - x) + 0.8 (10,000 - x)] + 1.05 x$.”

The correct answer to this question is [F]. The actual choices (if other than [F]) made by participants indicate three different types of errors that can occur when calculating the expected value of their portfolio holdings: the lack of understanding of statements regarding probabilities (answers [B], [C], [E], [G]); the lack of understanding of the difference between net and gross returns (answers [A],[C], [D] and [E]); and confusing the stock versus risk-free asset investments (answers

[C], [D], [G] and [H]). Therefore, a financial knowledge score varying between zero and three can be constructed, based on the number of different types of errors contained in the answer provided by each participant (i.e., zero errors for answer [F], one error for answers [A], [B] and [H], two errors for answers [D], [E] and [G], and three for answer [C]). Hence a financial knowledge score of 3 indicates a perfect answer, while a score of 0 indicates that the participant's answer included all three possible types of errors.

D. Large Sample Survey (Qualtrics) Questions

We contracted with the outside firm Qualtrics, using their Panels service, for them to recruit on our behalf approximately 1200 individuals ages 18-65 from across the U.S.A. and across income levels such as to have the income distribution be representative of the population according to the U.S. Census. These individuals were invited by Qualtrics Panels to take part in our short survey, during April-May 2015. The survey questions were as follows:

What is your age? 18-22 years old/23-29 years old/30-39 years old/40-49 years old/50-59 years old/60-65 years old

What is your gender? Male/Female

What is the highest level of education you have completed? some high school/GED/completed high school/some college/technical and/or associates degree/college degree/some post-graduate work/post-graduate degree/Other (please specify)

To which racial or ethnic group do you most identify?

African-American (non-Hispanic)/Asian/Pacific Islanders/Caucasian (non-Hispanic)/Latino or Hispanic/ Native American or American Indian/Other (please specify)

In which zipcode do you currently reside? Please enter your 5-digit zipcode: _____

Which of the following best describes your current employment status? Employed for wages/Self-employed/Unemployed and looking for work/Unemployed and not looking for work/Stay-at-home caregiver/Student/Military/Retired/Unable to work due to disability/Other (please specify)

Follow up question if unemployed: *For how many months have you been unemployed?*

If student: *What is your family's annual income?* Under \$15,000/\$15,000-\$24,999/\$25,000-\$34,999/\$35,000-\$49,999/\$50,000-\$74,999/\$75,000-\$99,999/\$100,000 and over

If not student: *What is your household's annual income?* Under \$15,000/\$15,000-\$24,999/\$25,000-\$34,999/\$35,000-\$49,999/\$50,000-\$74,999 /\$75,000-\$99,999/\$100,000 and over

If not student: *How many individuals are in your household? (including yourself)*

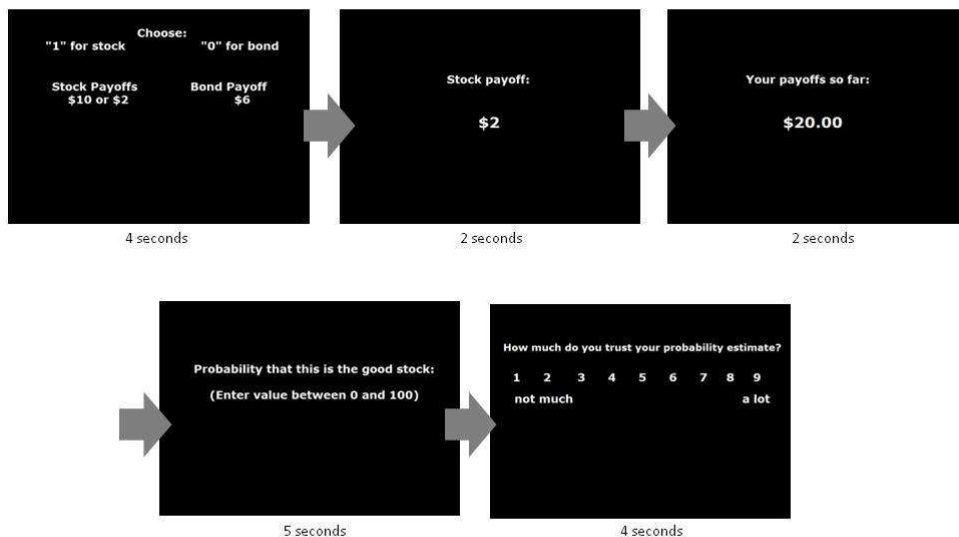
If not student: *How many of those individuals are children under the age of 18?*

Since 2007, have you or your immediate family personally experienced any of the following? (Please check all that apply): Bankruptcy/Foreclosure of property/Loss of employment/Inability to pay your debts on time/Difficulty getting approved for loans, for example to buy a car or a house/Having accounts in collection/Borrowing from a payday lender/None of the above

What do you think is the percent chance that a \$1000 investment in a diversified stock mutual fund will increase in value in the year ahead, so that it is worth more than \$1000 one year from now? Your answer, which is a percentage, should be a number between 0 and 100.

Currently, what percentage of your income do you invest in the stock market? Include investments in directly-owned stocks, stocks in mutual funds and stocks in retirement accounts, such as 401(K)s or IRAs. Your answer, which is a percentage, should be a number between 0 and 100.

Gain Condition - Active Involvement



Loss Condition - Active Involvement

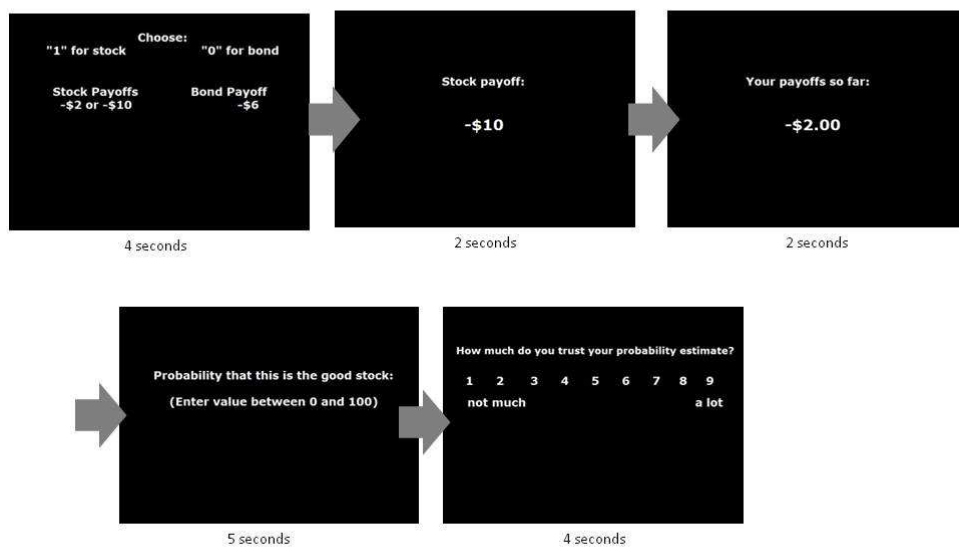


Figure 1: Active task: An example, translated in English, of a gain condition trial (top panel) and a loss condition trial (bottom panel). In either type of trial, subjects first choose between the stock and the bond. Then they observe the dividend paid by the stock that trial, no matter which asset they chose, and then are reminded of how much they have earned so far from the payoffs of the assets chosen so far in the Active investment task. Lastly, they are asked to provide an estimate for the probability that the stock is paying from the good dividend distribution, and their confidence in this estimate.

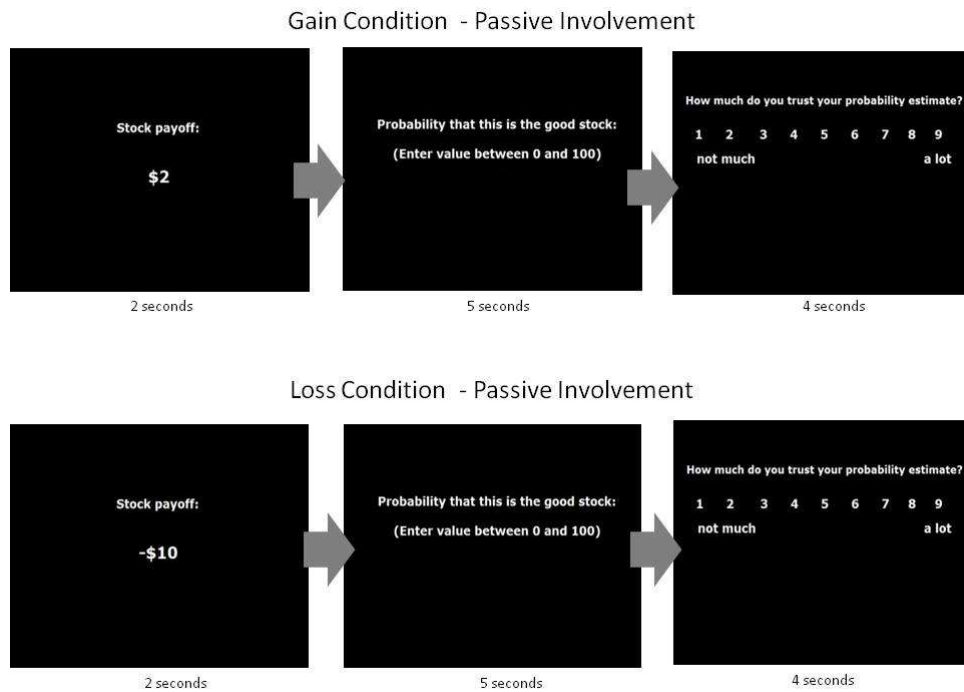


Figure 2: Passive task: An example, translated in English, of a gain condition trial (top panel) and a loss condition trial (bottom panel). In either type of trial, subjects observe the dividend paid by the stock that trial. Then they are asked to provide an estimate for the probability that the stock is paying from the good dividend distribution, and their confidence in this estimate.

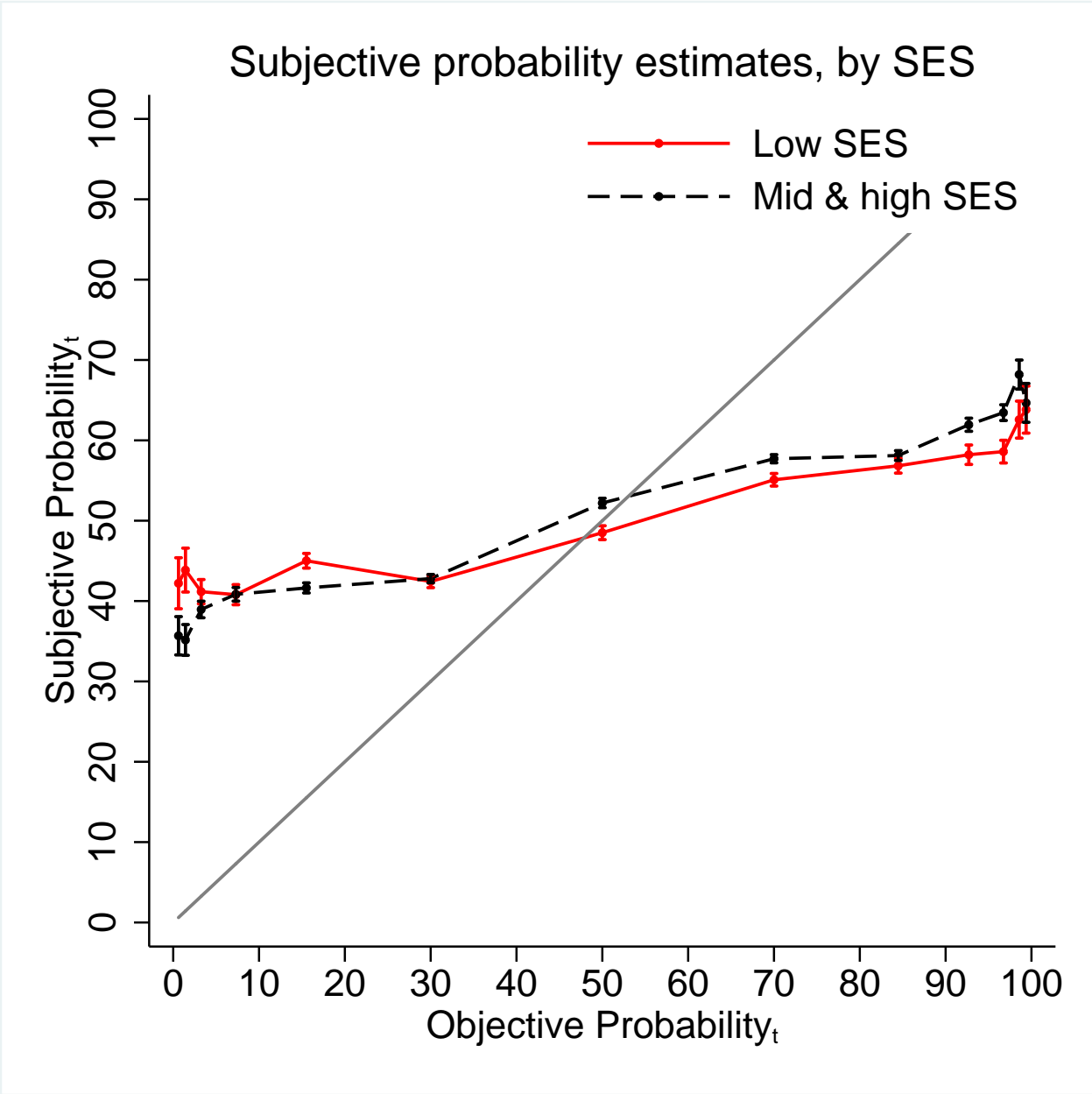


Figure 3: Average subjective estimates for the probability that the stock is paying from the good dividend distribution, as a function of the objective Bayesian probability. The objective Bayesian posteriors that the stock is good which are possible in the experiment are listed in the Appendix, together with the various combinations of high and low outcomes observed during a learning block that lead to such posteriors. If subjective posteriors were Bayesian, they would equal the objective probabilities and thus would line up on the grey 45° line. Subjective probability estimates provided by participants for each level of the objectively correct Bayesian posterior, along with their standard errors, are shown in red (solid line) for low SES participants (i.e., those in the bottom third of the SES score distribution), and in black (dashed line) for medium and high SES participants.

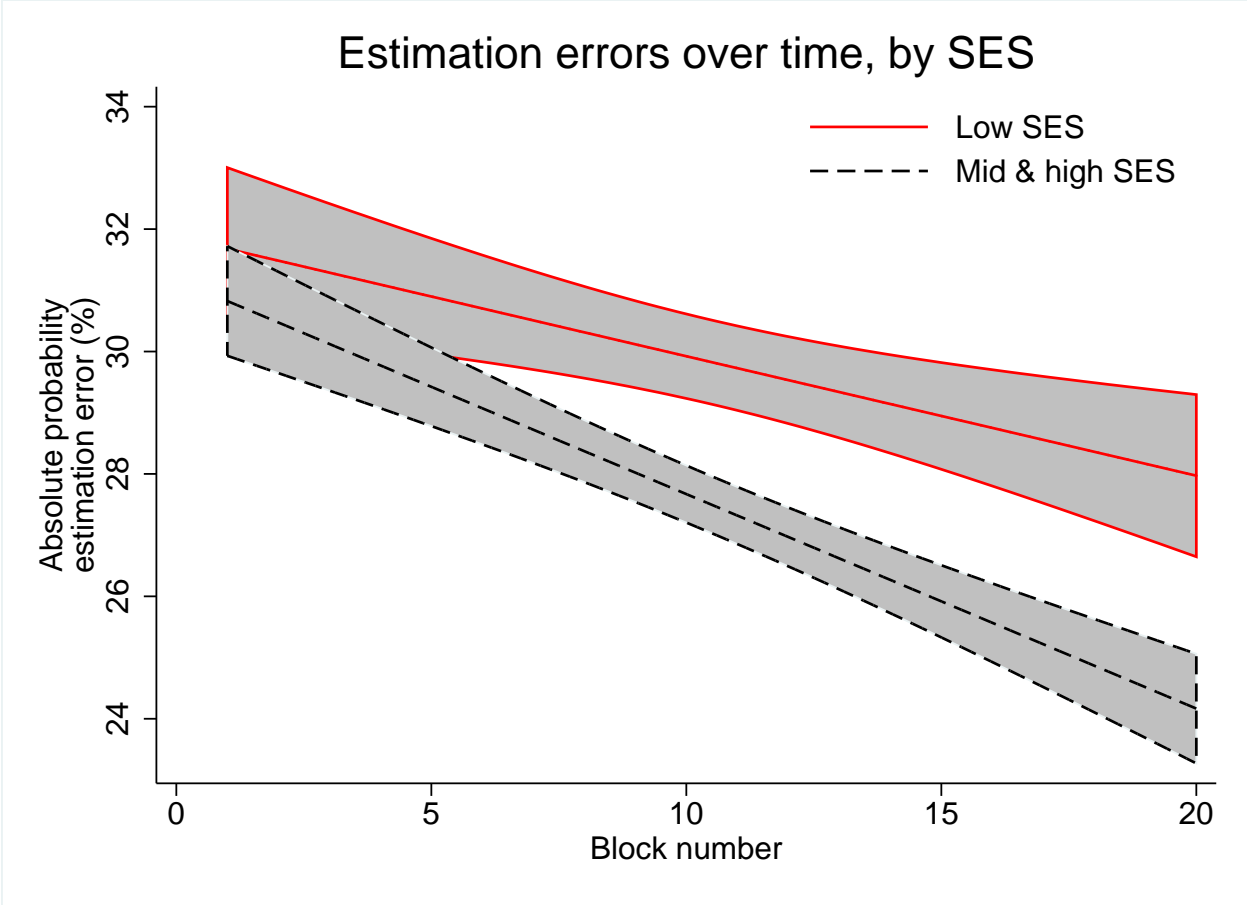


Figure 4: Absolute probability estimation errors, over the 20 learning blocks played by each subject (10 active and 10 passive learning blocks), by SES level. For low SES subjects, probability estimates are on average 31.87% away from Bayesian posteriors in the first learning block they encounter. These subjects' estimation errors decrease at an average rate of 0.2% per block. For mid or high SES subjects, probability estimates are on average 31.18% away from Bayesian posteriors in the first learning block they encounter. These subjects' estimation errors decrease at an average rate of 0.35% per block. The rate of improvement in probability estimation (shown here along with the 95% confidence interval) is significantly lower for low SES participants than that for mid or high SES participants ($p < 0.05$).

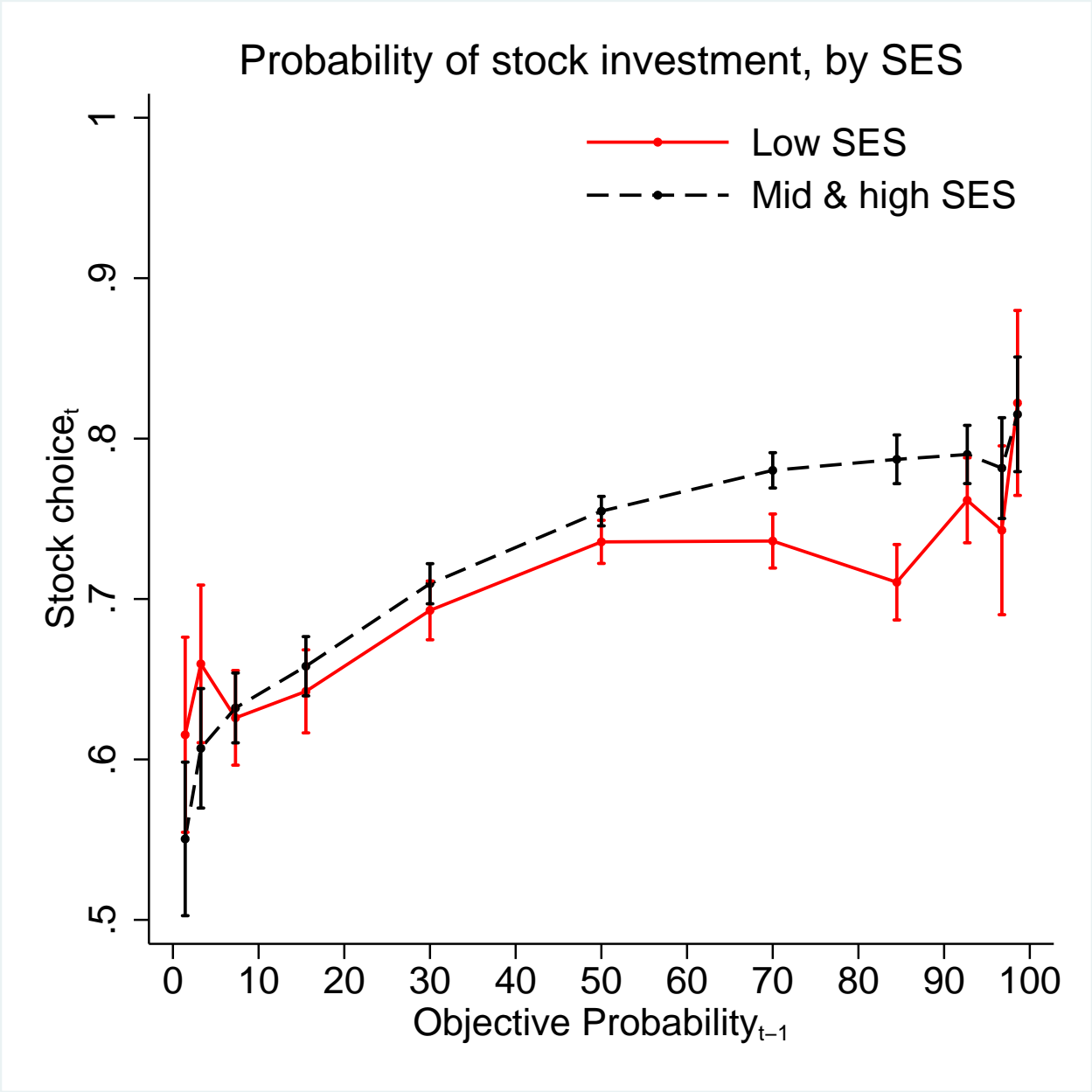


Figure 5: The mean and standard error of the frequency of decisions to pick the stock, rather than the bond, are shown in red (solid line) for low SES participants (i.e., those in the bottom third of the SES score distribution), and in black (dashed line) for medium and high SES participants, for all levels of objective probability that the stock pays form the good dividend distribution. A risk neutral expected value maximizing investor would choose to invest in the stock (rather than the bond) in trials when the probability that the stock is the good one is 50% or higher.

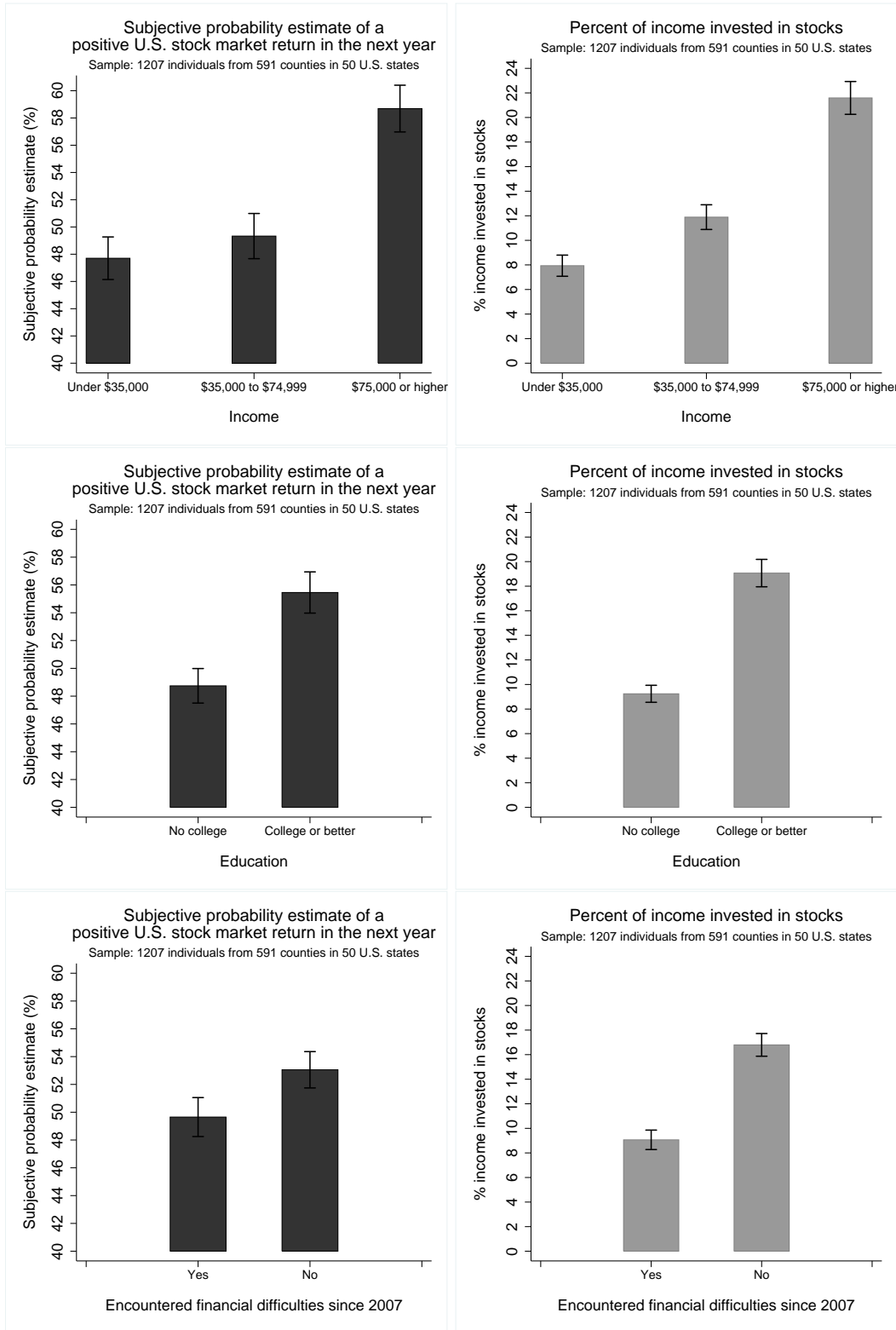


Figure 6: External validity check using a large U.S. survey sample. Data is split by the participants' tercile of self-reported income (top panel), education level (middle panel) and the experience of recent financial difficulties (bottom panel). Means and standard errors are shown for each subsample.

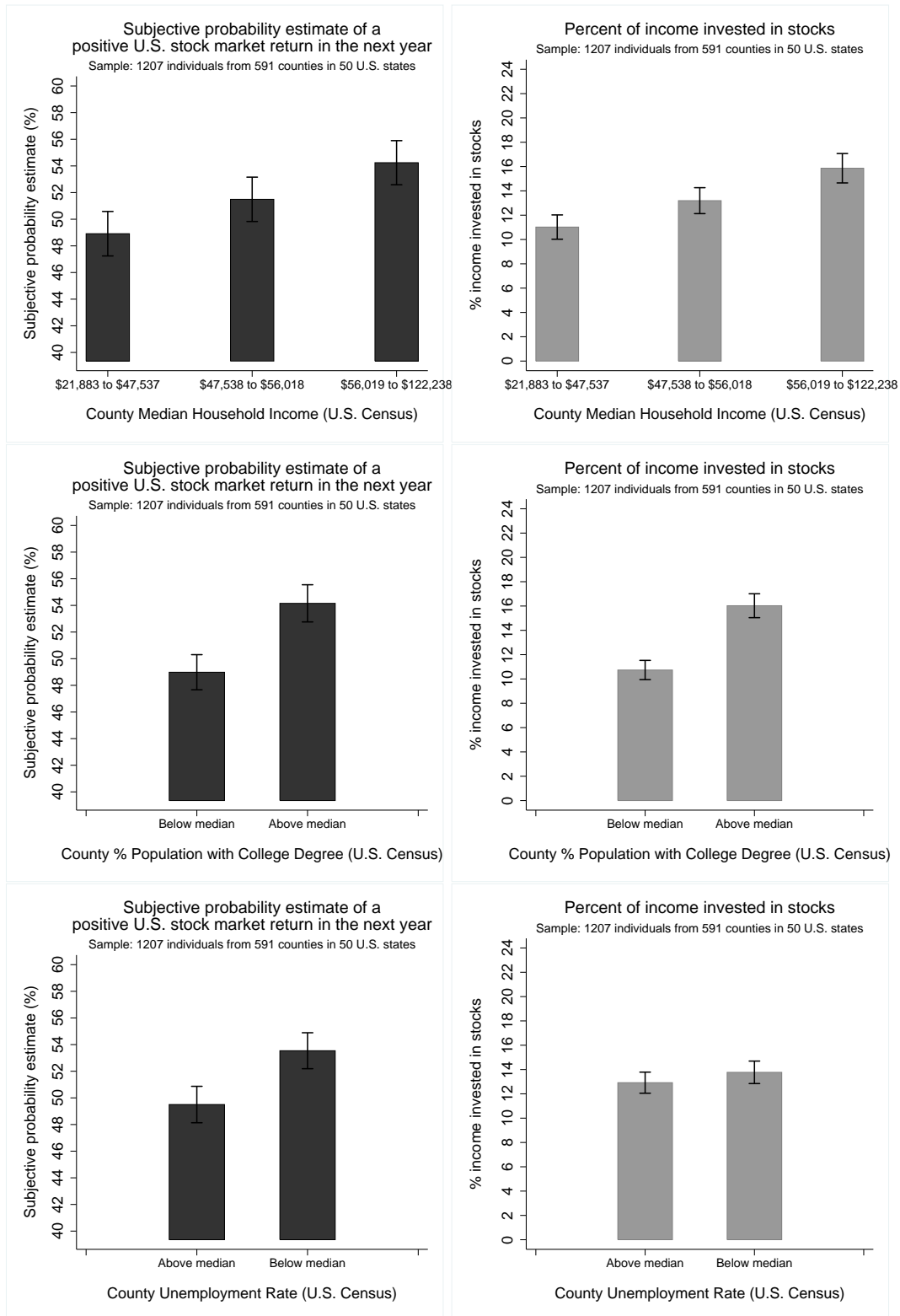


Figure 7: External validity check using a large U.S. survey sample, corroborated with U.S. Census data. Data is split by the participants' tertile of county median household income (top panel), county education level (middle panel) and county unemployment rate (bottom panel). County data are from the U.S. Census American Community Survey and refer to 5-year averages calculated for each county during 2009-2013. Means and standard errors are shown for each subsample.

Table I: Experimental design. Each participant goes through 60 trials in the Active task, and 60 trials in the Passive task. Whether the participant does the Active task first, or the Passive task first, is determined at random. Trials are split into "learning blocks" of six: for these six trials, the learning problem is the same. That is, the computer either pays dividends from the good stock distribution in each of these six trials, or it pays from the bad distribution in each of the six trials. The good distribution is that where the high dividend occurs with 70% probability in each trial, while the low outcome occurs with 30% probability. The bad distribution is that where these probabilities are reversed: the high outcome occurs with 30% probability, and the low outcome occurs with 70% probability in each trial. At the beginning of each learning block, the computer randomly selects (with 50%-50% probabilities) whether the dividend distribution to be used in the following six trials will be the good or the bad one. There are ten learning blocks in the Active task, and ten learning blocks in the Passive task. In either task, there are five blocks in the gain condition, and five blocks in the loss condition. The order of the blocks is randomized. An example of a sequence of loss or gain blocks that a participant may face is shown below.

Active Task	See Figure 1 for examples of trials	Condition
Block 1	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Loss
Block 2	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Gain
Block 3	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Gain
.	.	.
.	.	.
.	.	.
Block 9	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Gain
Block 10	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Loss

Passive Task	See Figure 2 for examples of trials	Condition
Block 1	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Gain
Block 2	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Loss
Block 3	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Gain
.	.	.
.	.	.
.	.	.
Block 9	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Loss
Block 10	Trial 1; Trial 2; Trial 3; Trial 4; Trial 5; Trial 6	Loss

Table II: Probability estimates and the SES aggregate score

The dependent variable in the OLS regressions in the table is *Probability Estimate_{it}*, which is the subjective estimate for the probability that the stock pays from the good dividend distribution, given the dividend history seen by participant *i* up to and including trial *t*. The variable *Low SES_i* is an indicator equal to 1 for participants in the bottom third of the aggregate SES score distribution. Control variables *Male_i* and *Age_i* indicate the gender and age of participant *i*. Also included as controls are fixed effects for each level of the objective Bayesian posterior probability that the stock pays from the good distribution, given the 50% prior and the history of stock dividends observed by participant *i* up to and including trial *t* (*Objective Probability_{it}*). Standard errors are robust to heteroskedasticity and are clustered by subject.

Dependent variable	<i>Probability Estimate_{it}</i>					
	Objective Probability <50%	Objective Probability ≥50%	Objective Probability ≥50% Passive Task	Objective Probability ≥50% Active Task	Objective Probability ≥50% Active Task Gain Condition	Objective Probability ≥50% Active Task Loss Condition
<i>Low SES_i</i>	1.65 (0.92)	-2.86 (-1.98)**	-1.71 (-0.94)	-4.07 (-2.28)**	-3.17 (-1.71)*	-4.70 (-1.98)**
<i>Male_i</i>	1.31 (0.66)	5.39 (3.79)***	4.96 (3.02)***	5.87 (3.32)***	2.08 (1.12)	10.10 (4.12)***
<i>Age_i</i>	-0.38 (-0.94)	0.50 (2.18)**	0.54 (1.70)*	0.42 (1.58)	0.49 (1.27)	0.40 (1.15)
<i>Objective Probability_{it}</i>						
FEs	Yes	Yes	Yes	Yes	Yes	Yes
<i>R</i> ²	0.004	0.033	0.027	0.039	0.043	0.048
Observations	10135	13669	6813	6856	3476	3380

Table III: Probability estimates and different measures of socioeconomic status

The regressions in the four panels of the table are estimated as in Table II. A different measure of socioeconomic status is used in each panel. The dependent variable in the OLS regressions in the table is *Probability Estimate_{it}*, which is the subjective estimate for the probability that the stock pays from the good dividend distribution, given the dividend history seen by participant *i* up to and including trial *t*. The variable *Low SES_i* is an indicator equal to 1 for participants in the bottom third of the SES score distribution. The variable *Low Parental Income_i* is an indicator equal to 1 for participants whose parents have a combine income of less than 1000 RON (approx. \$300) per month. The variable *Low SSS_i* is an indicator equal to 1 if the person's subjective assessment of their socioeconomic status is less than 5, on a scale from 1 to 10. The variable *Low Parental Education_i* is an indicator equal to 1 for participants for whom neither parent has a college degree. Standard errors are robust to heteroskedasticity and are clustered by subject.

Dependent variable	<i>Probability Estimate_{it}</i>					
	Objective Probability <50%	Objective Probability ≥50%	Objective Probability ≥50% Passive Task	Objective Probability ≥50% Active Task	Objective Probability ≥50% Active Task Gain Condition	Objective Probability ≥50% Active Task Loss Condition
Panel A						
<i>Low SES_i</i>	1.65 (0.92)	-2.86 (-1.98)**	-1.71 (-0.94)	-4.07 (-2.28)**	-3.17 (-1.71)*	-4.70 (-1.98)**
Panel B						
<i>Low Parental Income_i</i>	1.69 (0.70)	-5.39 (-2.58)**	-5.03 (-1.80)*	-5.83 (-2.21)**	-4.58 (-1.81)*	-6.66 (-2.20)**
Panel C						
<i>Low SSS_i</i>	-1.00 (-0.59)	-3.28 (-2.29)**	-3.52 (-2.04)**	-3.11 (-1.85)*	-2.65 (-1.45)	-3.54 (-1.52)
Panel D						
<i>Low Parental Education_i</i>	0.46 (0.27)	-0.95 (-0.69)	-1.54 (-0.94)	-0.32 (-0.19)	2.02 (1.13)	-3.34 (-1.50)

Table IV: SES and differences in probability updating after high and after low dividends.

The dependent variable in the OLS regressions in the table is *Probability Estimate_{it}*, which is the subjective estimate for the probability that the stock pays from the good dividend distribution, given the dividend history seen by participant *i* up to and including trial *t*, in the Active version of the task. The variable *Low SES_i* is an indicator equal to 1 for participants in the bottom third of the SES score distribution. Control variables *Male_i* and *Age_i* indicate the gender and age of participant *i*. Also included as a control in the first two columns is the subjective probability, expressed in trial *t* – 1, that the stock pays from the good distribution. The regressions in the last two columns include only data from the first trial in each learning block (i.e., 10 trials per subject), for which the prior belief that the stock is the good one is 50%, as indicated to subjects in the experimental instructions. That is, for observations in the last two columns, *Probability Estimate_{it-1}*=50% by experimental design. Standard errors are robust to heteroskedasticity and are clustered by subject.

Dependent variable	<i>Probability Estimate_{it}</i>			
	High dividend in trial <i>t</i>	Low dividend in trial <i>t</i>	High dividend in 1 st trial	Low dividend in 1 st trial
<i>Low SES_i</i>	-3.15 (-1.95)*	0.69 (0.35)	-4.53 (-1.77)*	0.66 (0.23)
<i>Male_i</i>	5.67 (3.56)***	-0.22 (-0.11)	6.29 (2.48)**	-0.82 (-0.25)
<i>Age_i</i>	0.69 (2.26)**	-0.47 (-1.00)	1.54 (3.03)***	-0.60 (-0.96)
<i>Probability Estimate_{it-1}</i>				
<i>Fixed Effects</i>	Yes	Yes		
<i>R</i> ²	0.196	0.122	0.035	0.002
Observations	5864	5866	1027	943

Table V: Probability estimates and SES - U.S. experimental laboratory replication sample

The dependent variable in the OLS regressions in the table is $Probability\ Estimate_{it}$, which is the subjective estimate for the probability that the stock pays from the good dividend distribution, given the dividend history seen by participant i up to and including trial t . The variable $Low\ SES_i$ is an indicator equal to 1 for participants in the bottom third of the SES score distribution in the replication sample of U.S.-based participants. These individuals completed the Active version of the task only. Control variables $Male_i$ and Age_i indicate the gender and age of participant i . Also included as controls are fixed effects for each level of the objective Bayesian posterior probability that the stock pays from the good distribution, given the 50% prior and the history of stock dividends observed by participant i up to and including trial t ($Objective\ Probability_{it}$). Standard errors are robust to heteroskedasticity and are clustered by subject.

Dependent variable	$Probability\ Estimate_{it}$			
	Objective Probability <50%	Objective Probability \geq 50%	Objective Probability \geq 50% Gain Condition	Objective Probability \geq 50% Loss Condition
$Low\ SES_i$	-7.66 (-1.50)	-9.90 (-2.00)*	-4.54 (-0.87)	-15.60 (-2.24)**
$Male_i$	-3.70 (-0.73)	-3.25 (-0.80)	-5.82 (-1.48)	-1.56 (-0.30)
Age_i	-2.42 (-0.90)	-0.88 (-0.34)	-2.40 (-0.76)	0.29 (0.11)
$Objective\ Probability_{it}$ FEs	Yes	Yes	Yes	Yes
R^2	0.080	0.163	0.180	0.183
Observations	813	1124	589	535

Table VI: Finance-relevant knowledge and SES

The table presents averages of four variables related to the subjects' understanding of finance-relevant concepts, separately for the low SES subsample, and the mid or high SES subsample. Neither one of these four dimensions of finance-relevant knowledge differs significantly across the two subsamples, as shown by the p -values in the last column.

	Low SES participants ($N=67$)	Mid or high SES participants ($N=136$)	p -value for Difference $\neq 0$
Financial knowledge score (0-3 scale) as in Kuhnen (2015)	1.03	1.06	0.83
Numeracy score (0-11 scale) as in Peters et al. (2006)	7.94	8.16	0.45
Technical major (0=No, 1=Yes)	0.48	0.56	0.28
Confidence in subjective beliefs (1-9 scale)	6.42	6.59	0.38

Table VII: Risk aversion and SES

The table presents averages of measures related to the subjects' risk aversion, separately for the low SES subsample, and the mid or high SES subsample. The State Anxiety score, based on the State-Trait Anxiety Inventory (Spielberger et al. (1983)), measures state or current anxiety, whereas the Behavioral Inhibition score (Carver and White (1994)) measures more stable trait anxiety. Neither one of these proxies for risk aversion differs significantly across the two subsamples at conventional levels, as shown by the p -values in the last column.

	Low SES participants ($N=67$)	Mid or high SES participants ($N=136$)	p -value for Difference $\neq 0$
% trials stock chosen in 1st trial in block	73.48%	78.84%	0.11
% of 10,000 <i>RON</i> invested in stocks	66.11%	47.70%	0.09
State Anxiety score	32.25	31.77	0.70
Behavioral Inhibition Score	19.90	19.99	0.88

Table VIII: External validity check: Characteristics of U.S. large survey sample

The table presents the characteristics of the individuals surveyed in the U.S. by Qualtrics Panels during April-May 2015 for the purpose of testing the external validity of the findings from the experimental laboratory samples in Romania (i.e., data collected at Babes-Bolyai University) and the U.S. (i.e., data collected at University of North Carolina). Panel A presents self-reported participant level data, and Panel B presents data from the U.S. Census American Community Survey regarding characteristics (measured as of the end of 2013, the latest available) of the counties where our survey participants reside.

Panel A: Survey participants in the sample	
<i>N</i> =1207 individuals in 591 counties in 50 U.S. states	
Income category	Under \$15,000: 13.42%
	\$15,000-\$24,999: 12.43%
	\$25,000-\$34,999: 11.43%
	\$35,000-\$49,999: 15.24%
	\$50,000-\$74,999: 17.73%
	\$75,000-\$99,999: 10.85%
	\$100,000 and over: 18.89%
Education	Without college degree: 58.66%
	With college degree or better: 41.34%
Gender	Males: 51.20%; Females: 48.80%
Age category	18-22 years old: 2.24%
	23-29 years old: 10.44%
	30-39 years old: 21.96%
	40-49 years old: 22.45%
	50-59 years old: 27.17%
	60-65 years old: 15.74%
Financial difficulties since 2007	45.15% Yes; 54.85% No

Panel B: Counties represented in the sample					
<i>N</i> =591 counties in 50 U.S. states					
	Mean	St. Dev.	Median	Min	Max
Median household income	\$51,300	\$13,887	\$48,493	\$21,883	\$122,238
% population with college degree	25.37%	10.59%	23.20%	7.84%	59.98%
Unemployment rate	9.76%	2.95%	9.45%	2.79%	27.11%