2016-12

Description and experience: How experimental investors learn about booms and busts affects their financial risk taking

Lejarraga, T

http://hdl.handle.net/10026.1/16577

10.1016/j.cognition.2016.10.001
Cognition
Elsevier BV

Published as:
Lejarraga, T., Woike, J. K., & Hertwig, R. (2016). Description and experience: How experimental investors learn about booms and busts affects their financial risk taking. *Cognition, 157*, 365-383.

Description and Experience: How Experimental Investors Learn About Booms and Busts Affects Their Financial Risk Taking

Tomás Lejarraga, Jan K. Woike, and Ralph Hertwig

Center for Adaptive Rationality

Max Planck Institute for Human Development, Berlin

Author Note

Tomás Lejarraga, Jan K. Woike, and Ralph Hertwig, Center for Adaptive Rationality, Max Planck Institute for Human Development, Berlin, Germany.

We are grateful to Leonidas Spiliopoulos and Robin Hogarth for helpful comments. We also thank Susannah Goss for editing the manuscript. This research was supported by the Swiss National Science Foundation grant CRSII1_136227.

Correspondence concerning this article should be addressed to Tomás Lejarraga, lejarraga@mpib-berlin.mpg.de

Abstract

A few years ago, the world experienced the most severe economic crisis since the Great Depression. According to the depression baby hypothesis, people who live through such macroeconomic shocks take less financial risk in their future lives (e.g., lower stock market participation). This hypothesis has previously been tested against survey data. Here, we tested it in a simulated experimental stock market (based on the Spanish stock index, IBEX-35), varying both the length of historical data available to participants (including or excluding a macroeconomic shock) and the mode of learning about macroeconomic events (through sequential experience or symbolic descriptions). Investors who learned about the market from personal experience took less financial risk than did those who learned from graphs, thus echoing the *description–experience gap* observed in risky choice. In a second experiment, we reversed the market, turning the crisis into a boom. The description–experience gap persisted, with investors who experienced the boom taking more risk than those who did not. The results of a third experiment suggest that the observed gap is not driven by a wealth effect, and modeling suggests that the description–experience gap is explained by the fact that participants who learn from experience are more risk averse after a negative shock. Our findings highlight the crucial role of the mode of learning for financial risk taking and, by extension, in the legally required provision of financial advice.

Keywords: description–experience gap, investment, financial risk taking, depression babies

Description and Experience: How Experimental Investors Learn About Booms and Busts Affects Their Financial Risk Taking

In the wake of the global financial crisis of 2008, the worst economic crisis since the Great Depression, U.S. households lost nearly $11 trillion in wealth, including life savings and retirement accounts, and about four million families lost their homes to foreclosure (Financial Crisis Inquiry Commission, 2011). The causes of the crisis were many, but most experts agree that important financial institutions failed to manage their exposure to risk. Financial firms were not alone in engaging in excessive borrowing and risky investments, however. In the years leading up to 2008, "many households borrowed to the hilt, leaving them vulnerable to financial distress or ruin if the value of their investments declined even modestly" (p. xix, Financial Crisis Inquiry Commission). What will people learn from this experience? How does exposure to economic turmoil change people's appetite for financial risk?

Borrowing is but one of several indicators of people's level of financial risk taking. Another is participation in the stock market. Standard models of portfolio choice do not consider how personal experiences of economic fluctuation affect individuals' willingness to take risks, and by extension, their stock market participation (e.g., Markowitz, 1952; Merton, 1969). Survey data, however, suggest that such a link is likely to exist. Using data from the Survey of Consumer Finances from 1960 to 2007, Malmendier and Nagel (2011, p. 373) found that individuals who had experienced macroeconomic shocks (e.g., during the Great Depression) reported that they were less likely to participate in the stock market. Those who did participate reported investing a lower proportion of their liquid assets in stocks. The analysis also showed a *recency* effect: more recent shocks were found to have stronger effects than less recent ones.

The results reported by Malmendier and Nagel (2011) have sparked interest in how macroeconomic experience influences financial risk taking. Weber, Weber, and Nosić (2013) surveyed a sample of UK online investors during the peak of the 2008 crisis. They found that investors reduced their risky investments in accordance with their expectations of lower returns and higher risk. Even subtle fluctuations within the business cycle seem to affect risk taking: Investors take less risk during the downside of the business cycle and more risk during the upside (Apergis, 2015).

These studies, including the influential investigation by Malmendier and Nagel (2011), share a common limitation: The use of survey data does not rule out potential cohort effects that may occur due to historic events other than the experience of interest. An alternative approach would be to experimentally examine the link between the experience of macroeconomic shocks and risk taking. The advantage of this approach is that investors can be randomly assigned to different market experiences, with these experiences being manipulated systematically. Admittedly, a disadvantage of experimentation is that the potential to systematically manipulate variables of interest typically comes at the expense of external validity and generalizability; we return to this limitation below.

Two lines of research have studied financial investing experimentally. One began with the economists Smith, Suchanek, and Williams (1988), who searched for experimental evidence on the efficiency of asset markets. To their surprise, their experimental market exhibited large pricing bubbles and subsequent crashes. Since then, several experiments have focused on understanding the causes of bubbles and crashes (Palan, 2013, provides a comprehensive review), but none have explored how the experience of bubbles and crashes affects present and future risk taking. The other line of research, more prominent in psychology, focused on how people actually invest, and the extent to which their investments correspond to the prescriptions of portfolio choice theory (Funk, Rapoport, & Jones, 1979;

Gordon, Paradis, & Rorke, 1972; Kroll, Levy, & Rapoport, 1988; Rapoport, 1984). Results suggest that people systematically select non-optimal portfolios, and that they adapt their investments in response to market fluctuations, that is, their most recent experience. However, how macroeconomic shocks influence risk taking has not been systematically examined within this line of research with perhaps one exception. Guerrero, Stone, and Sundali (2012) focused on the effects of fear on financial risk taking after exposing experimental investors to the market returns of the Great Crash of 1929. The authors found evidence that participants whose first allocation decisions overlapped with the start of the crash took less risk than those who made allocation decisions prior to the crash and who initially observed solid gains in stock returns. The authors concluded that during significant market downturns people "react by reducing their stock market allocations above and beyond what a rational response would suggest" (p. 62). This is interpreted to reflect a fear-based panic response, which in their data was exclusively due to the behavior of male participants. Our first goal is to build on the work of Guerrero et al., (2012); we aim to replicate it and extend it to the experience (or lack thereof) of a boom.

Our second objective relates to the mode of learning. Humans, unlike any other creature, are able to learn by means other than experience. Barely any aspect of modern life—from technology, science, commerce, and poetry to the World Wide Web—is conceivable without the human ability to read and produce symbolic descriptions (Schmandt-Besserat, 1996). Individuals are able to communicate and transmit their experiences to others through descriptions (e.g., statistics, text, and graphs). Yet Malmendier and Nagel's (2011) depression baby hypothesis implies that, when it comes to the experience of macroeconomic shocks, there is no substitute for personal experience. Retrospective symbolic descriptions, such as graphical representations of dramatic slumps in stock prices and returns, are available for those who were spared the experience of living through a crisis. These descriptions, however, can be expected to have less impact on financial risk taking than actually living through a macroeconomic crisis. But can the same be said about macroeconomic booms?

Again, these questions can be addressed by randomly exposing individuals to either the personal experience of drastic economic fluctuations or descriptions of them. Recent research on the description–experience gap (see Erev & Roth, 2014; Hertwig & Erev, 2009) suggests that learning about properties of payoff distributions via direct experience results in systematically different choices than does learning the same information via description. Furthermore, in line with the depression baby hypothesis, research on the description–experience gap has shown that more recent experiences are more influential than less recent ones (Hertwig, Barron, Weber, & Erev, 2004). Yet the studies on the description–experience gap have involved choices between relative simple monetary gambles—choices that differ from financial risk taking in at least four ways: (1) The description–experience gap is most prevalent when gambles include one clearly defined rare event—an outcome with a probability lower than .2 (see Hertwig et al., 2004). In the context of stock prices, rare events are difficult to define. Any such definition would depend critically on the time interval over which the history of prices is examined, during which multiple rare events may occur. (2) Furthermore, gambles are independent and identically distributed random variables, whereas the stock market is dynamic. (3) The choice between two gambles provides a discrete response measure, whereas the allocation of an investment budget is a continuous response measure. (4) In the stock market context, investors can estimate how much they would have earned if they had made different choices (i.e., they can estimate foregone payoffs).

Given these differences, it is unclear to what extent the description–experience gap—and, by extension, the systematically different choices arising from different modes of learning—will generalize to investment decisions in the stock market. If the description–experience gap does generalize, will experience lead to more or less risk taking? Kaufmann, Weber, and Haisley (2013) recently addressed a similar question. Exploring ways to boost people's investments in the stock market, they studied whether experiencing simulations of the stock market affected people's participation in it. Although these simulations had no consequences on participants' wealth, the authors found that participants who experienced multiple simulated outcomes of a hypothetical investment perceived risk more accurately and took more financial risk than did participants who learned from descriptive sources. Their results were subsequently corroborated by Bradbury, Hens, and Zeisberger (2014, 2016). None of these investigations, however, examined salient experiences of large market fluctuations. Yet their findings suggest that description and experience of stock market events may indeed lead to systematically different patterns of financial risk taking.

How will investment decisions change as a function of description versus experience? If Kaufmann et al.'s (2013) and Bradbury et al.'s (2014) finding of more risk taking under experience per se holds more generally (even in the context of macroeconomic shocks), direct experience of a crisis may result in more risk taking than being informed through a symbolic description (e.g., a graph of diminishing stock market returns). Yet research on myopic loss aversion suggests the opposite pattern. Myopic loss aversion refers to the combination of two regularities: the tendency to be more sensitive to losses than to gains, and the tendency to check one's investments too often (Benartzi & Thaler, 1995; Thaler, Tversky, Kahneman, & Schwartz, 1997). Someone who evaluates their investments frequently will be exposed to losses more often than someone who evaluates them rarely, because the natural fluctuations of the market produce frequent instances of losses (i.e., each time the price drops). Consequently, people who check their investments often are less willing to bear risk. This observation is important for the distinction between learning from description and learning from experience. Participants who learn from experience are—inevitably—frequently exposed to losses produced by each downturn of the market, whereas participants who learn from description are shielded from such frequent exposure to losses. Findings on myopic loss aversion in combination with results on the description–experience gap thus suggest that experiencing a crisis may result in less financial risk taking than learning about that crisis from a description. At the same time, the experience of a boom may be as persuasive as directly experiencing it.

To what extent descriptions of economic fluctuations have a systematically different impact on the willingness to take financial risk than does the direct experience of those fluctuations is thus an open question with potentially far-reaching implications (e.g., for financial advice giving). According to Erev and Roth (2014), descriptions of risks such as a major economic shock "might not be enough" (p. 10822) to warn people as effectively as experience does. In other words, descriptions of a threat may not have the same power to alter behavior as experiencing the real thing.

In this article, we experimentally address the following questions about how the mode of learning about macroeconomic events is associated with financial risk taking:

1. Does experiencing a crisis reduce financial risk taking (as found in Guerrero et al., 2012)?
2. Does the willingness to take financial risk depend on whether large market fluctuations (crises and booms) are experienced or learned from symbolic descriptions?
3. Do participants' investments exhibit recency effects? And do they depend on the mode of learning or on the particular market fluctuations (crises or booms)?
4. Does experiencing a boom increase financial risk taking?
5. If there is a description–experience gap in investment decisions, what are the likely drivers of this effect (e.g., beliefs, risk preferences, wealth effects)?

Experiment 1

We used an experimental investment task to examine financial risk taking. Participants were assigned a hypothetical portfolio of €100 and asked to allocate this amount between a risky and a safe option across a number of monthly periods (as in Guerrero et al., 2012). The safe option was a cash deposit account offering a .25% rate of return each month (i.e., a 3% annual rate of return; relative to 4% in Guerrero et al.). The risky option was the Spanish stock index fund, IBEX-35, offering the monthly rates of return actually obtained from July 1999 to September 2013. Participants were informed that the rates of return were based on real data; however, we used virtual dates (adding 25 years to each actual year) so that they would not be able to infer the market (and thus the long-term returns). Between 1999 and 2013, the IBEX-35 experienced two macroeconomic shocks—the first from 1999 to 2002 (resulting in a 57% drop in stock price); the second, from late 2007 to 2009 (resulting in a 52% drop in stock price). This experimental investment task is only an approximation of real-world investments. For example, the .25% monthly rate of return is only representative of some periods during the experimental period, but we kept it constant for simplicity's sake and to provide a stable benchmark against which the highly volatile risky option could be compared.[1]

For each monthly period, participants determined the portion of their portfolio to be invested in stocks (i.e., the index fund) and the complementary portion to be invested in the cash deposit account. The return on their investment was added to (or subtracted from) their current portfolio balance. The full portfolio amount was invested in each period. Return feedback was given in a table (amounts earned from stock investment and from the cash deposit account) and in three graphs (Figures A1–A3 in the Appendix). One graph showed

[1] Our research question concerns differences between experimental conditions in which investment options were the same; thus, keeping the safe option constant across investment periods—even in periods where it would have been unrealistic—does not weaken our experimental design.

the price of the index fund. Another showed the rates of return on the index fund, the cash deposit account, and the portfolio. A third showed the portfolio balance. The three graphs were updated period-by-period, after each investment was realized.

To begin, participants read the instructions on the computer screen and completed 10 periods as practice trials. They were informed that the return data in the practice trials were randomly generated. They were also given a printed booklet of instructions (which included definitions of all concepts in the investment task) that they could consult at any time. All instruction materials are available as supplementary material.

Conditions. Because there was no basis for an a priori estimate of the effect size, we pre-set the sample size to 200. Participants (40% male, mean age 25 years, SD = 3.5) were randomly assigned to one of four conditions that varied with respect to the *length* of historical data available and the *mode* of learning. Fifty participants in the *shock experience* condition made investments across all 172 periods in the experiment (i.e., the 172 months between July 1999 and September 2013). These participants experienced an initially decreasing stock market until about period 40. Another 50 participants, who were assigned to the *no-shock experience* condition, entered the market in period 40 and made decisions in 133 periods (note that Guerrero et al.'s participants made only 20 allocation decisions). These participants experienced a market that initially increased for around 60 periods; they were unaware of the previous downward trend.

The remaining 100 participants entered the market in period 100 and made 73 investment decisions. Of these participants, 50 were assigned to the *shock description* condition and were shown a graph plotting the price of the index fund since the first period. These participants thus learned from the graph what participants in the shock experience condition learned from experience (i.e., the development of the price of the index fund and, by extension, its return across periods 1–99). The remaining 50 participants were assigned to the *no-shock description* condition and were shown a graph plotting the price of the index fund since period 40. Like their counterparts in the no-shock experience condition, participants in the no-shock description condition were not aware of the market's initial downward trend, but learned about the later upward trend from the graph. One final distinction between participants in the two experience and the two description conditions is that those who learned from experience were able to observe the outcome of their individual investments while they learned, something participants learning from description could not do (because they were not invested in the past). Participants were not told in advance how many investment decisions they would make. Figure 1 (upper panel) summarizes the four experimental conditions.

Compensation. Participants were paid according to the performance of their portfolio at the end of period 172. We calculated the maximum and minimum possible returns in the task (assuming perfectly right or perfectly wrong foresight) and linearly rescaled those amounts to a maximum of €13 and a minimum of €7. Participants' returns in the experiment we converted using the same linear function. Participants were informed that their compensation would depend on the return on their investments. On average, participants earned €7.60 (range: €7.10–€8.95).

Results

To analyze how the length of available historical data and the mode of learning affected risk taking, we evaluated participants' investment behavior during the evaluation window (period 100–172), in which participants in all four conditions made portfolio choices and experienced their financial consequences. We used the "new statistics" (Cumming, 2012) to compare conditions, reporting the difference in mean risk taking as a measure of effect size and the 95% confidence interval of that difference.

What is the impact of a shock on risk taking? The measure of risk taking *R* is defined as the proportion of a person's investment in the index fund (vs. the safe cash deposit). The lower panel of Figure 1 shows the average trends in risk taking as a function of each condition. Figure 2 shows the average *R* measure (collapsed across all periods). Recall that some participants learned about the initial downward trend from either experience or description. Those participants took similar financial risks (shock condition; $R_s = 29.7\%$) as did participants who were unaware of the trend (no-shock condition; $R_{ns} = 32.5\%$), $R_{s–ns} = −2.8\%$, 95% CI [−7.2%, 1.6%].[2] However, awareness of the shock affected participants who learned from description differently than it did those who learned from experience. Participants who learned from description took almost identical risk in the shock ($R_{sd} = 37.1\%$) and no-shock conditions ($R_{nsd} = 38.1\%$), $R_{sd–nsd} = −1\%$ [−7%, 5%]. However, historical prices had a small but discernible effect on the investment behavior of participants who experienced the market: Participants in the shock experience condition took less risk ($R_{se} = 22.4\%$) than did participants in the no-shock experience condition ($R_{nse} = 26.9\%$). Although this difference in the average *R* may not indicate a true population difference, $R_{se–nse} = −4.5\%$ [−11%, 1.7%], Figure 3 shows that in 82% of the periods of the evaluation window, participants who did not experience the shock took more financial risk than participants who did. This 4.5% absolute difference translates into a relative difference in risk taking of 20% in participants who did not experience the shock. Importantly, participants who experienced the

[2] Confidence intervals on mean risk taking were calculated using the following margin of error:
$t_{.95}(N_A + N_B - 2) \times S_p\sqrt{\frac{1}{N_A} + \frac{1}{N_B}}$, where N_A is the number of participants of the first proportion; N_B is the number of participants of the second proportion; $t_{.95}(N_A + N_B - 2)$ is the critical value of *t* for a 95% confidence level and $(N_A + N_B - 2)$ degrees of freedom; and S_p is the pooled estimate of the within-group standard deviation: $S_p = \sqrt{\frac{(N_A-1)s_A^2+(N_B-1)s_B^2}{N_A+N_B-2}}$.

shock also took less risk than participants who learned about it from description, R_{se-sd} = −14.7% [−20%, −0.1%].

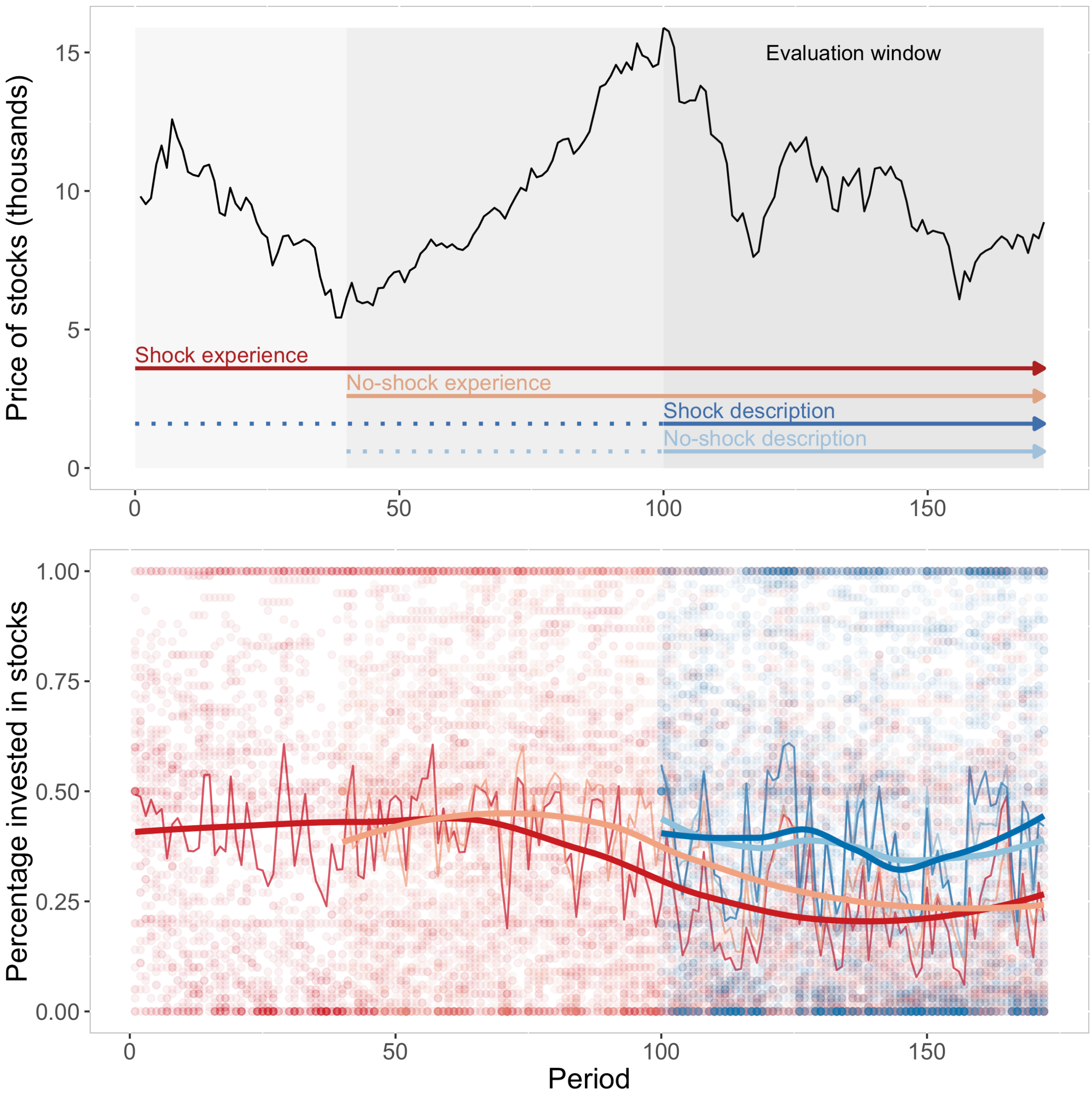


Figure 1. Upper panel. Experimental conditions and price of stocks (i.e., index fund) across 172 monthly periods. Solid arrow segments indicate periods with actual investment decisions. Dotted arrow segments indicate those periods learned from a graph. The four conditions were compared over the evaluation window from period 100 to period 172.
Lower panel. Percentage invested in stocks by condition. Dots indicate individuals' allocations. The thin lines show the mean percentage; the thicker lines show the data smoothed by local polynomial regression fitting (Cleveland, Grosse, & Shyu, 1992).

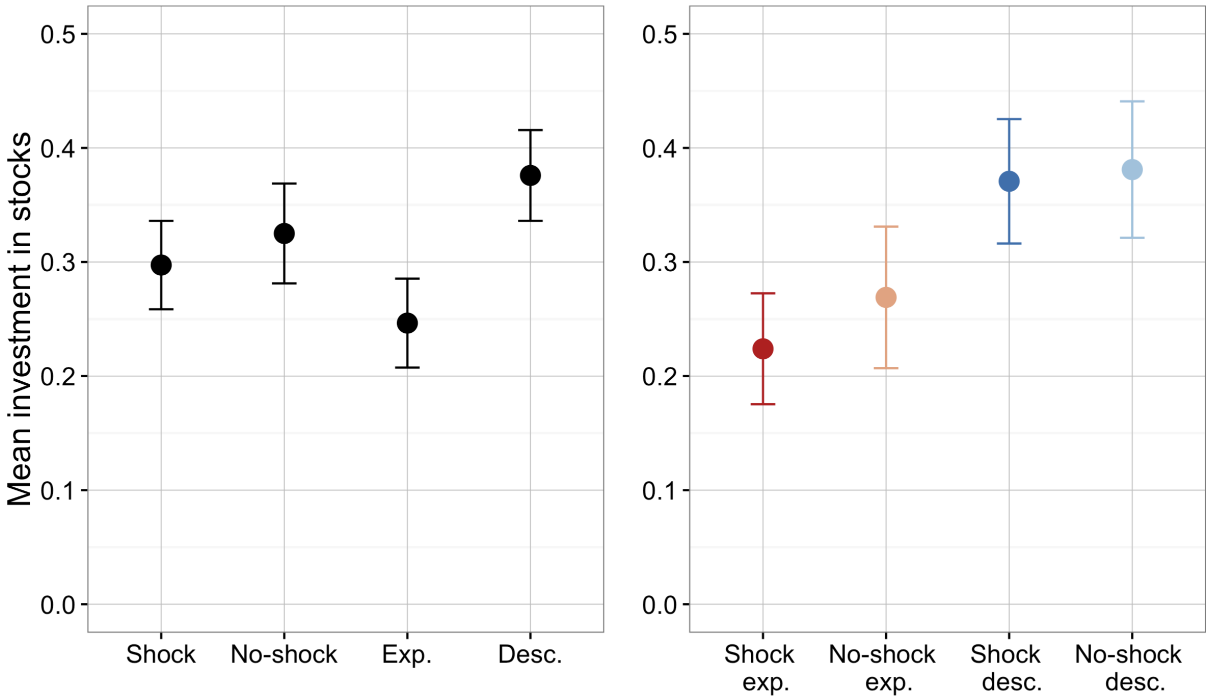


Figure 2. Investment in stocks by condition. Error bars indicate the 95% confidence interval. Means and confidence intervals were calculated by averaging risk taking for each individual across periods and computing the mean across individuals (i.e., means and CIs reflect independent observations). The left panel shows the mean investment in stocks by condition (shock, no-shock, experience, and description). The right panel shows the same measure for the resulting four interactions (shock experience, no-shock experience, shock description, and no-shock description).

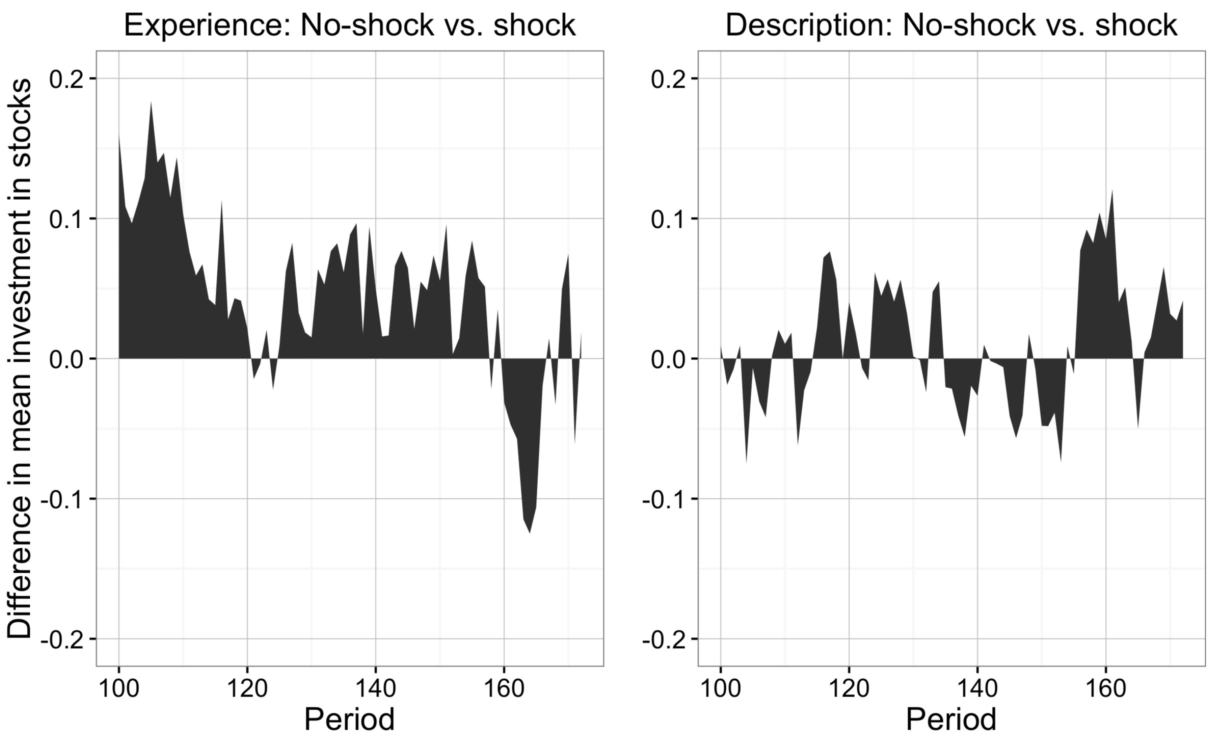


Figure 3. Difference in average financial risk taking (i.e., allocations to the index fund) between no-shock and shock experience and description conditions. Positive values indicate

that investors in the no-shock conditions took, on average, more financial risk than investors in the shock conditions; negative values indicate the opposite.

Does risk taking change as a function of experience or description? Averaged across the shock and no-shock conditions, investors who learned about a window of stock market fluctuations from a graph took more risk (R_d = 37.6%) than did participants who actually experienced the market during the same window (R_e = 24.6%), R_{d-e} = 13% [9%, 17%]. Moreover, those who learned about past market performance from a graph proved practically insensitive to the type of market history observed. Note, however, that the percentage invested in stocks in the four conditions (i.e., the thin curves in Figure 1, lower panel) is highly volatile across periods. Consistent with previous studies (Funk et al., 1979; Gordon et al., 1972; Kroll et al., 1988; Rapoport, 1984), this pattern indicates that investment decisions may be reactive to recent experiences.

Did the recency of experience influence risk taking? To determine the extent to which individuals reacted to the most recent change in stock prices in each period, we calculated the individual-specific correlation between the change in price of the index fund (stock price$_t$/stock price$_{t-1}$) and change in investment in the following period (proportion in stock$_{t+1}$ – proportion in stock$_t$). This measure of reactivity to price changes is conservative, because the proportion invested in the index fund is bounded within 0 and 1, and a participant who is fully invested in stocks cannot increase the level of risk taking following an increase in stock prices. Figure 4 shows positive and almost equivalent correlations across all conditions, indicating high reactivity to recent changes both in description and in experience and to whether or not participants were exposed to a shock.

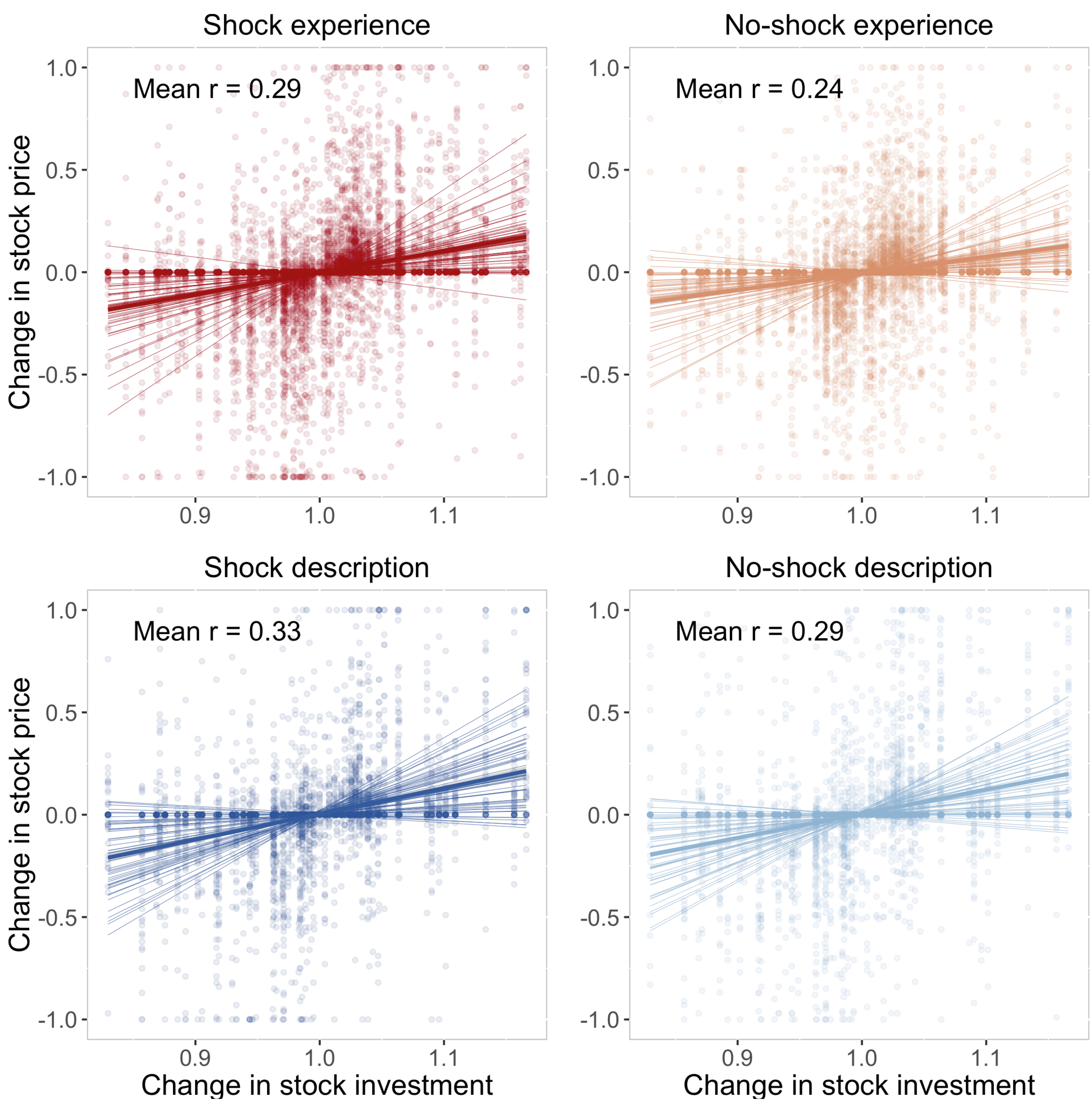


Figure 4. Correlation between the change in stock price in period t and the change in stock investment in period $t + 1$. Each thin line denotes the correlation for each investor; the thicker line denotes the correlation across investors.

Summary

We observed three key results. First, participants who learned about the market from experience differed considerably in their risk taking from those who learned from descriptive displays. This result echoes the description–experience gap commonly observed in research with described and experienced gambles (Hertwig, 2016). Participants who experienced the market took less financial risk than those who learned from a graph. This pattern of behavior is consistent with investors being “myopically loss averse” (Benartzi & Thaler, 1995).

Second, the impact of the market shock differed as a function of the mode of learning. Participants who learned about the market from a graph were largely unreactive to the past shock. In the experience condition, however, those who entered the market in a downward trend were generally more cautious. Although the difference was small (4.5%), participants who lacked direct experience of the shock took more financial risk in the large majority of investment periods in the evaluation window, amounting to, on average, a relative increase of allocation in stocks of 20% compared with participants who experienced the shock. Our experimental results are therefore consistent with the survey data of Malmendier and Nagel (2011) and the experimental results obtained by Guerrero et al. (2012). The effects of macroeconomic experiences on financial risk taking can thus be replicated in an experimental microworld.

Third, investors were highly reactive to their most recent experience, irrespective of the mode of learning and whether or not they were aware of a past shock. The investment behavior of nearly all participants (91%) correlated positively with stock prices. This result is consistent with other studies finding strong sequential dependencies in investments (Kroll et al., 1988).

The potential limitation of using of real stock market data in Experiment 1 is that the results may provide insights into investors’ response to a particularly pronounced macroeconomic shock in recent Spanish financial history, but say little about their behavior in other market situations. In Experiment 2, we therefore explored a different market. Specifically, we examined two questions. First, does the description–experience gap in financial risk taking persist when the initial macroeconomic event is a boom rather than a shock? If so, does experiencing the market still lead to lower risk taking than learning from a graphical description? Second, does a financial boom have the opposite effect than a shock? In other words, do participants who experience a boom subsequently take more financial risk than those who lack this experience?

Experiment 2

Experiment 2 was identical to Experiment 1, with the exception that we reversed the sign of the changes in stock prices while keeping the mean price constant (5).[3] Reversing the stock prices creates two distinct boom periods, one corresponding to the 1999–2002 crisis and the other to the 2007–2009 crisis. The long period between the two booms now represents a lengthy downward trend. Keeping the mean price constant does not guarantee that the mean rate of return remains the same as in Experiment 1, however. In fact, reversing the stock prices creates a market where the mean rate of return is lower than in Experiment 1. Experiment 2 therefore represents a strong test of the description–experience gap, because it leaves less room for differences between conditions to emerge.

Based on a power analysis (G*Power software, version 3.1.9.2), we recruited 161 participants (46% male, mean age 25, SD = 3.5) and assigned them randomly to each of the four conditions. Forty participants were allocated to the *shock experience* condition, 41 to the *no-shock experience* condition, 40 to the *shock description* condition, and 40 to the *no-shock description* condition. As before, we paid participants by comparing their performance with maximum and minimum benchmarks. This time, however, the benchmarks were taken from the best and worst performances in Experiment 1. The mean payoff was €10.80 (range: €7.20–€13).

[3] The reversed stock price for a given period was twice the mean stock price of the whole range, minus the stock price in the same period.

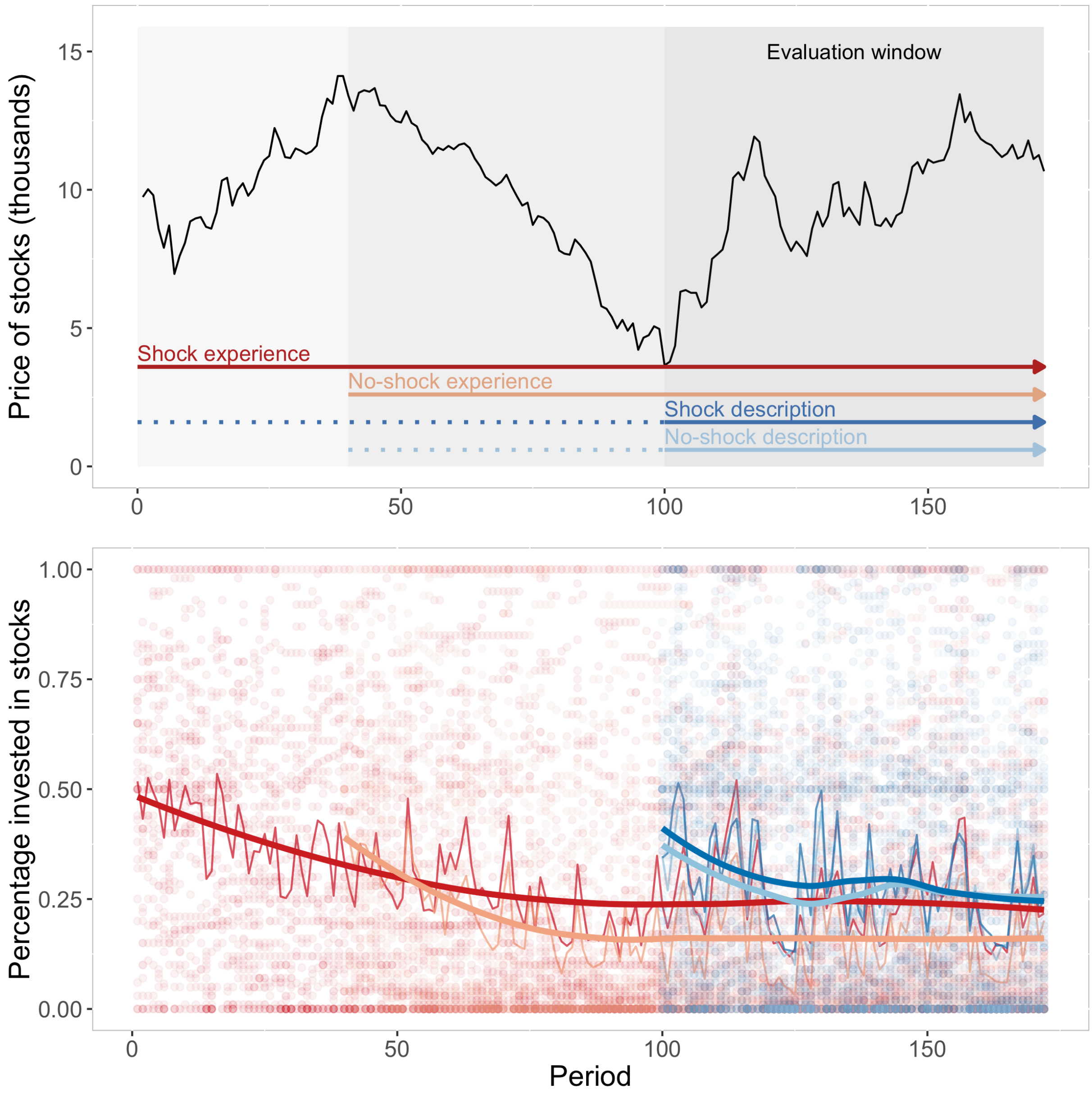


Figure 5. Upper panel. Experimental conditions and price of stocks (i.e., index fund) across 172 monthly periods. Solid arrow segments indicate periods with investment decisions. Dotted arrow segments indicate periods learned from a graph. The four conditions were compared over the evaluation window from period 100 to period 172.
Lower panel. Percentage invested in stocks by condition. Dots indicate individuals' allocations. The thin lines show the mean percentage; the thicker lines show the data smoothed by local polynomial regression fitting (Cleveland et al., 1992).

Results

Although Experiment 2 made risk taking less profitable than Experiment 1, the observed financial risk taking again revealed a description–experience gap (Figure 6, left panel). Participants who learned from a graph took more financial risk (R_d = 28.3%) than did participants who experienced the market (R_e = 20.4%), $R_{d–e}$ = 7.9% [4%, 12%]. This difference was particularly pronounced during the early periods of the evaluation window, when the effect of freshly accumulated experience was still minimal (Figure 5, up to approximately period 100).

As in Experiment 1, having experienced a particularly salient financial period influenced risk taking for many periods thereafter. As Figure 6 shows (right panel), investors who had experienced the positive shock were generally more inclined to take financial risk (R_{se} = 24.8%) than were those who had not (no-shock experience) (R_{nse} = 16.2%), $R_{se–nse}$ = 8.7% [4%, 13%]. Supporting and extending the results of Experiment 1, the findings of Experiment 2 showed that there was no difference in risk taking between investors in the description condition who had learned about the shock from a graph (R_{sd} = 29.3%) and those who had not (R_{nsd} = 27.3%), $R_{sd–nsd}$ = 2.0% [–3%, 7%] (right panel of Figure 7).

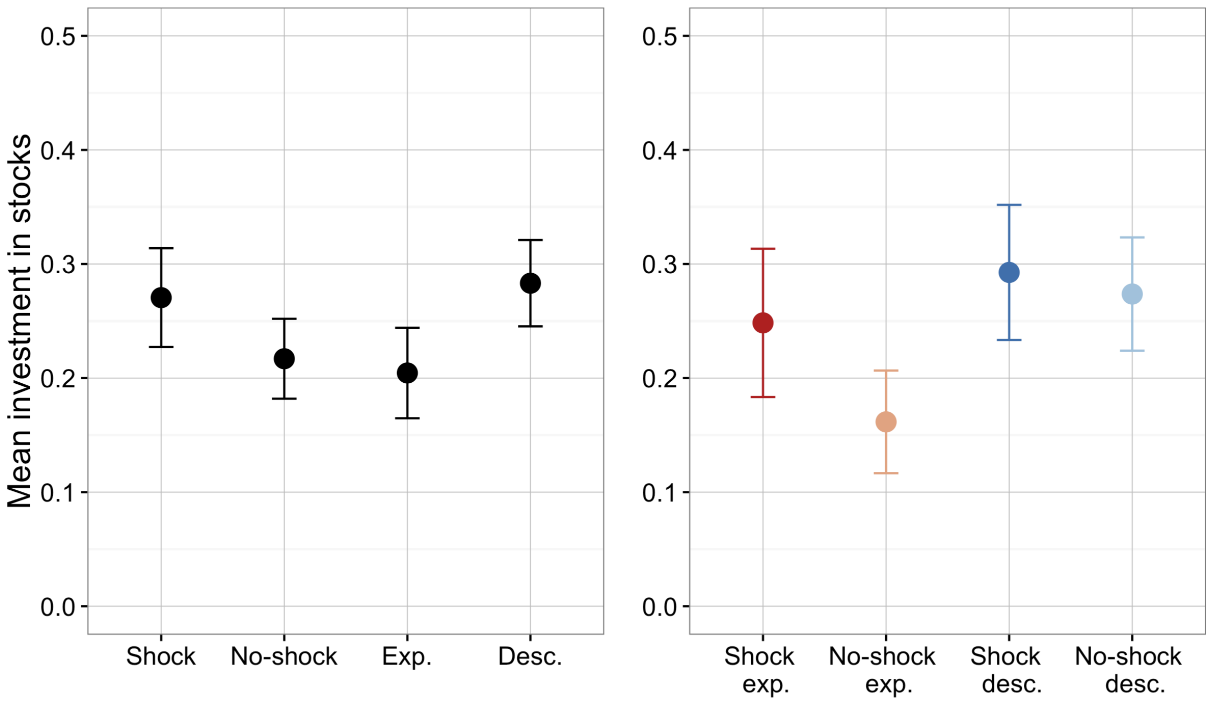


Figure 6. Investment in stocks by condition. Error bars indicate the 95% confidence interval. Means and confidence intervals were calculated by averaging risk taking for each individual across periods and computing the mean across individuals (i.e., means and CIs reflect independent observations).

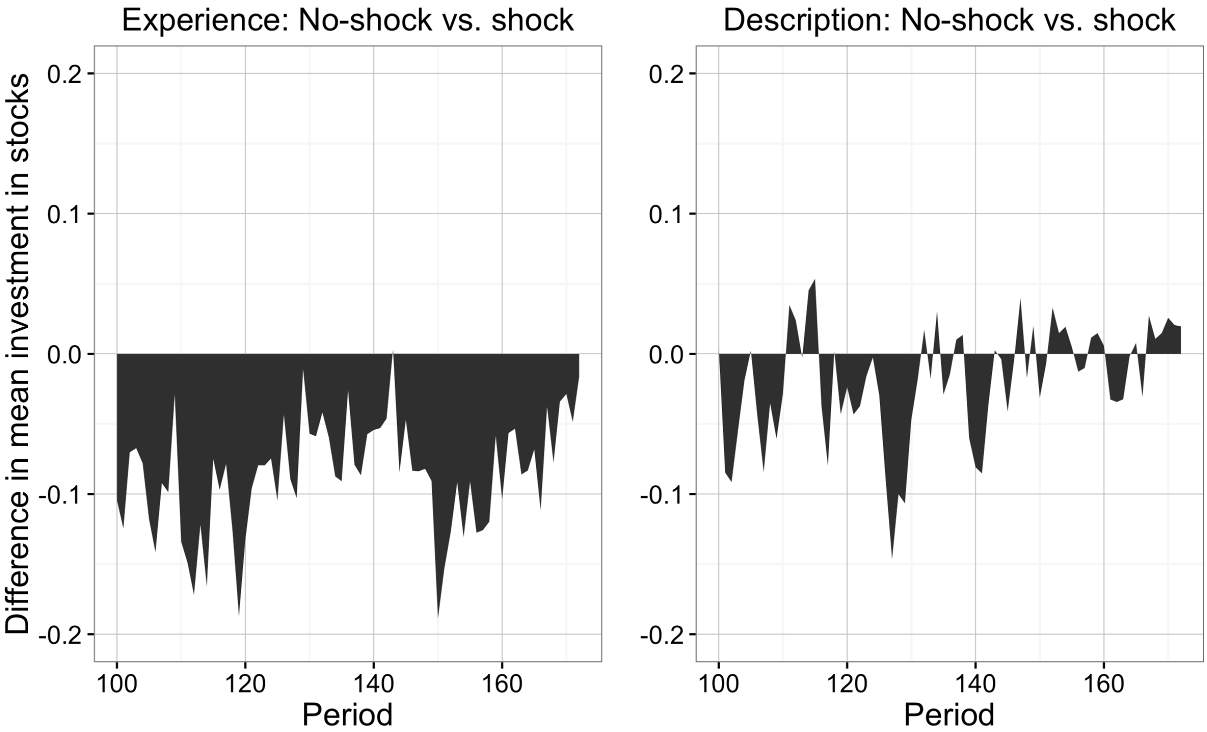


Figure 7. Difference in average financial risk taking (i.e., allocations to the index fund) between no-shock and shock experience and description conditions. Negative values indicate that investors in the no-shock conditions took, on average, less financial risk than investors in the shock conditions; positive values indicate the opposite.

Discussion of Experiments 1 and 2

In summary, Experiments 1 and 2 showed that experiencing a market shock changed risk taking in the expected direction: negative shocks decreased risk taking and positive shocks increased it. The experiments also revealed a description–experience gap in investment decisions. In both experiments, investors who experienced the market took less financial risk than those who learned about it from a graph. Interestingly, learning about market shocks from a graph had practically no effect.

Although the results of Experiments 1 and 2 are clear, they also raise questions. What underlies the observed effect of experiencing a shock on financial risk taking? The classic economic framework offers two potential explanations, namely, beliefs (expectations) and risk preferences. Does experiencing a crisis makes people pessimistic about the market? Or do they become more risk averse? Or both? Similarly, does learning about the market from description make people optimistic? Or does description makes them risk seeking? To address how beliefs and risk preferences affected investment behavior in our experiments, we modeled investment decisions using a classic economic framework that we modified to capture the observed regularities in behavior (e.g., recency).

Before we describe the modeling analysis, let us discuss another factor potentially influencing our results: the effect of wealth. Our experimental design compares the behavior of participants with different levels of wealth (e.g., participants who enter the market after the shock start with $100, whereas the endowments of those who experienced it already reflect the shock). The rationale for this decision was that experiences in general have consequences, and financial experiences in particular have consequences on wealth. Decoupling financial consequences from financial decisions would have allowed us to examine a rather hypothetical experience (i.e., a nonconsequential experience). As this is not the focus of our study, however, we deliberately did not equate the wealth of participants who learned from experience with that of those who learned from description. We acknowledge that wealth effects could potentially influence our results. To address this issue, we conducted a third experiment in which differences in wealth were eliminated—we return to this experiment shortly.

In sum, our results are potentially explained by differences in beliefs, risk preferences, and wealth. We address the impact of beliefs and risk preferences with a modeling analysis, and the effect of wealth experimentally.

A Model of Investment Decisions

We used Tobin's separation theorem (1958) to study the influence of beliefs and risk preferences. Specifically, we modelled participants' investment choices and examined how components of behavior assumed in that model drive the (1) description–experience gap and (2) the depression (and boom) baby effect. Tobin's model is an extension of Markowitz's (1952) mean-variance framework, and it is proposed as a normative model of capital allocation between a risky portfolio (e.g., IBEX-35) and a risk-free option. The model assumes that people trade off risk and return, and that this trade-off is mediated by risk aversion. Therefore, using Tobin's model helps us examine how our experimental manipulations affect participants' expectations of returns, their expectations of variance, and their risk aversion.

According to Tobin's model, the optimal allocation $y*$ between a risky and a safe investment option is

$$y^* = \frac{E(r_r)-r_s}{A\sigma_r^2} \quad , \tag{1}$$

where $E(r_r)$ is the expected return from the risky option, r_s is the return from the safe option, A is the level of risk aversion, and σ_r^2 is the variance of returns on the risky option. Therefore, the proportion invested in the risky option increases with the risk premium $E(r_r) - r_s$ and decreases with risk aversion and variance.

We modified Tobin's model in the following ways:

Expected returns. Memory constraints may lead to diverse estimates of $E(r_r)$. We modeled the expectation for period $t + 1$ as a weighted-average of the expectation for the current period and the current realized return (Hertwig, Barron, Weber, & Erev, 2006):

$$E(r_r)_{t+1} = (1-\omega) \cdot E(r_r)_t + \omega \cdot {r_r}_t \tag{2}$$

$$\omega = \left(\frac{1}{t}\right)^{[(1-\delta)d+\delta c]}, \tag{3}$$

where $\delta = 1$ indicates periods when the participant experienced the outcome of the investment and $\delta = 0$ indicates periods without investment. Parameters *c* and *d* modulate how stock returns are weighted. If $c = 1$, all experienced returns are weighted equally; if $c < 1$, recent experiences receive more weight than earlier ones (recency); and if $c > 1$, recent experiences receive less weight than earlier ones (primacy). Similarly, *d* modulates how described stock returns are weighted, with $d < 1$ indicating recency, $d > 1$ indicating primacy, and $d = 1$ indicating averaging. We assume that participants estimate expected returns based on all observed or experienced data. We acknowledge the possibility that participants may have had prior beliefs about stock markets in general, but we do not incorporate those possible beliefs in this analysis.

Variance. Memory constraints may also affect the estimation of variance. Therefore, we calculated standard deviation as differences from the expected returns $E(r_r)$, rather than as differences from the mean. At each period t,

$$\sigma_r^2 = \frac{\sum_{i=1}^{n}\left(r_r - E(r_r)\right)^2}{n-1}\,. \qquad [4]$$

We also assumed that all observed or experienced data is used to estimate σ_r^2.

Risk aversion. We estimated the level of risk aversion A for each individual. We allowed *A* to vary for different levels of wealth:

$$A_t = a + b \cdot B_t\,, \qquad [5]$$

where a is the baseline risk aversion and b is the change in risk aversion in response to the current portfolio balance B_t. For simplicity, we assume this relationship to be linear.

Allocation. Because Tobin's allocation is not constrained to the [0, 1] interval, we set $y^* > 1$ to 1, and $y^* < 0$ to 0.

For each participant, we computed the squared deviation between y^* and the observed proportion *R* in each investment period. We did so by systematically varying *a*, *b*, *c*, and *d*. For each set of parameters, we computed the mean of the squared deviations across periods

(MSD). We then selected the "*abcd*" set that minimized the MSD of each participant. There was only one participant for whom more than one set minimized the MSD; we therefore dropped that participant from the analysis (participant coded "sd80" in the bottom row of Figure A5). For all periods *t,* we predicted the allocation of each individual in period $t + 1$.

Modeling Results

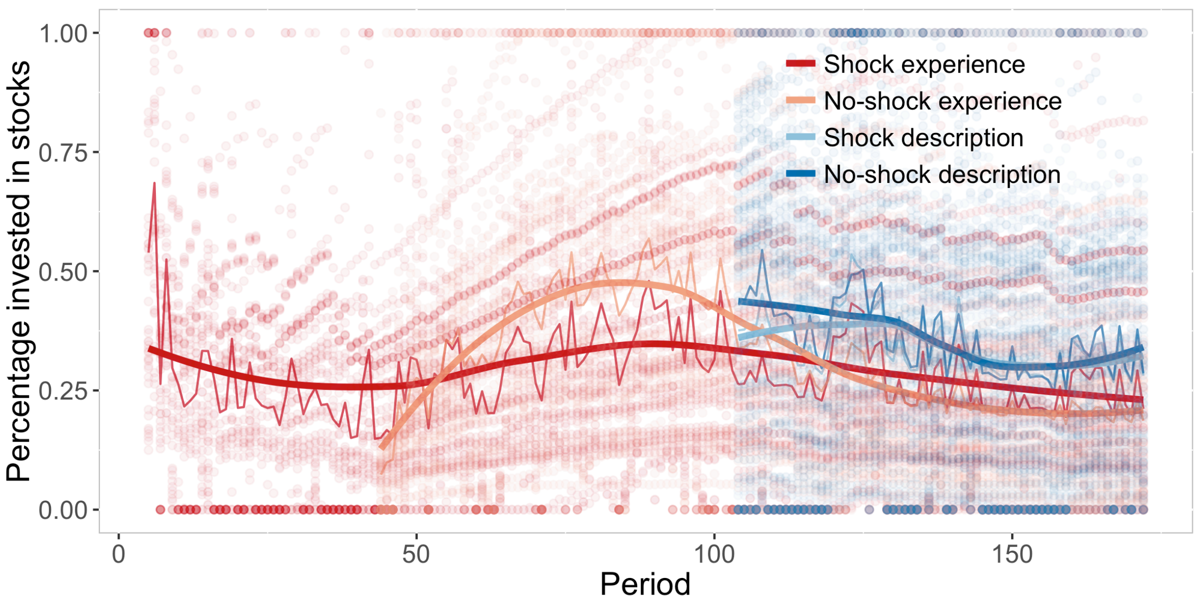
The points in Figure 8 show the predictions of the model for each participant in each period in Experiment 1. The thin line shows the mean allocation to the risky option for each condition; and the thicker line indicates the smoothed mean. Contrasting Figures 1 and 8 reveals that the model captures the aggregate patterns of behavior: more risk taking in the description than in the experience conditions; and less risk taking for participants who experienced the negative shock than for those who did not. The predictions for each individual are shown in Figure A4 in the Appendix. The overall fit of the model allows us to confidently interpret its three main components: risk aversion, expected returns, and variance.

What explains the description–experience gap? Figure 9 (left panel) shows that estimated expected returns differed only slightly across conditions. Similarly, within each of the shock and no-shock conditions, variance was almost identical across experience and description conditions (right panel). The description–experience gap is captured by differences in risk aversion, with participants learning about a negative shock from experience being more risk averse than participants learning from description (middle panel). This pattern translates into less financial risk taking in experience than description. However, we cannot rule out that the differences in risk aversion may be caused by differences in wealth at the beginning of the evaluation window.[4] We return to this issue in Experiment 3.

---

[4] We explored the distribution of parameters that reflect the starting level of risk aversion (*a*) and its response to wealth (*b*), but *a* and *b* were negatively correlated, suggesting that a low starting level of risk aversion (*a*) can be compensated by an increasing response to portfolio

What explains the depression baby effect? Zooming into the two experience conditions in Figure 8, we can now examine the driver of the depression baby effect. Ceteris paribus, higher risk aversion in the no-shock condition should result in lower risk taking. In contrast, the predicted pattern is the opposite (Figure 8), that is, more risk taking in the no-shock than in the shock condition. Therefore, we can exclude risk aversion as a factor driving the depression baby effect. With expectations of returns being similar (Figure 9, left panel), the depression baby effect seems largely explained by differences in expectations of variance (Figure 9, middle panel). That is, participants in the shock experience condition expected more variance than did participants in the no-shock condition. This higher expectation of variance—multiplied by risk aversion in the denominator of y^*—in the experience condition leads to lower predicted risk taking. Moreover, the decreasing difference in variance, coupled with the increasing difference in risk aversion, predicts the crossover in risk-taking around period 120. Although correctly predicted, the crossover occurs earlier in the model than in observed behavior (approximately period 155; see Figure 1)



balance (b), and a high a compensated by a low b. We therefore restrict the interpretation to A as the combination of the two parameters.

Figure 8. Predictions of the percentage invested in stocks by condition for Experiment 1. Dots indicate individuals' predicted allocations. The thin lines show the mean predictions; the thicker lines show the data smoothed by local polynomial regression fitting (Cleveland et al., 1992).

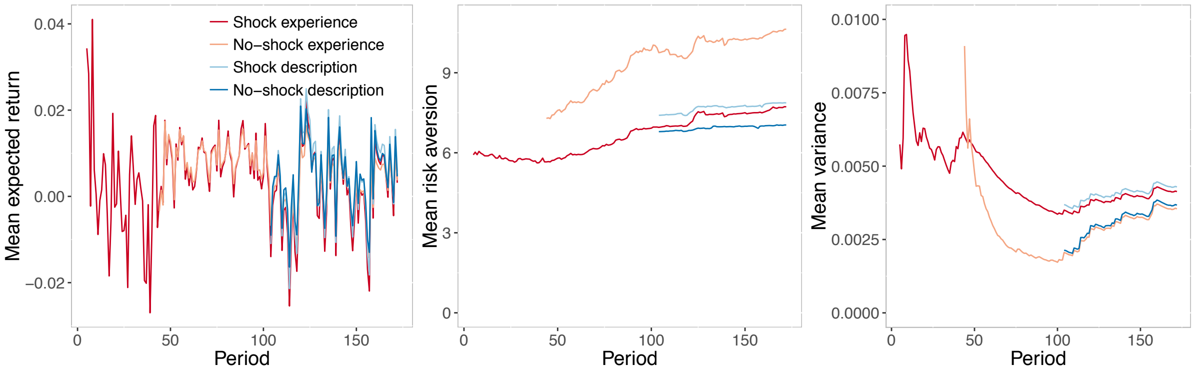


Figure 9. The three main components of the model across periods. The left panel shows the evolution of the mean expected return. The middle panel shows the evolution of mean risk aversion (A). The right panel shows the evolution of mean variance.

Modeling summary

We modeled individual investment trajectories using a variant of Tobin's (1958) separation theorem. The model incorporates three components that help us to unpack the description–experience gap and the depression baby effect. We found that the description–experience gap was almost entirely explained by differences in risk aversion, with participants who learned from experience being more risk averse. The depression baby effect, in contrast, was not explained by risk aversion but by differences in expectations. In particular, participants who experienced the shock expected a more volatile market than those who did not. This observation is consistent with the survey findings of Malmendier and Nagel (2011), whose data indicated that higher exposure to volatility is associated with lower risk taking (although not significantly so) and that the depression baby effect is explained partly by greater pessimism with respect to expected returns.

We also modeled investment behavior for Experiment 2. However, we found that although the model fitted the data well, analysis of error landscapes suggested that the parameters were unreliable. Because the market in this study was less attractive, many participants avoided risks throughout the investment periods, a behavior that—given the market conditions—could be captured by different sets of parameters. The modeling results for this dataset are therefore inconclusive, and we do not report them here.

This modeling analysis allowed us to examine the contribution of beliefs and risk preferences to investment behavior. Yet the effects of wealth remain to be explored. Experiment 3 was conducted explicitly to address this issue.

Experiment 3

We designed the final Experiment with the explicit goal of controlling for wealth effects. It was the identical to Experiment 1 in all respects except for the following: (1) We used the negative shock experience condition from Experiment 1 as a benchmark, and thus collected data from new participants in only three (rather than four) conditions: no-shock experience, no-shock description, and shock description. (2) In these conditions, each participant's initial wealth was *yoked* (i.e., matched) to the wealth of another participant from Experiment 1. For instance, the *initial* wealth of each participant in the no-shock experience condition (N = 50) was yoked to the wealth *in the corresponding period* of a participant in the negative shock experience condition in Experiment 1. To this end, we matched the number of participants in Experiment 3 to that in Experiment 1. By the same token, the wealth of participants in the shock description condition (N = 50) was yoked to that of the 50 participants in the shock experience condition in Experiment 1, and the wealth of participants in the no-shock description condition (N = 50) was yoked to that of the 50 participants in the no-shock experience condition in Experiment 1.

Participants' instructions read: "Your initial portfolio amounts to (a fictitious) €100 plus the amount gained or lost by another participant in a previous experiment."[5] In all other respects, including the compensation scheme, Experiment 3 was identical to Experiment 1.

Results

The results from Experiment 3 largely replicated those from Experiment 1 (Figure 10): (1) Participants who experienced the crisis took less financial risk than those who did not; (2) participants who experienced the market took less financial risk than those who learned about it from a graph; and (3) whether or not participants saw a graph of the crisis made no difference to their financial risk taking. Although the pattern of results in Experiment 3 is more moderate than that seen in Experiment 1 (compare Figures 2 and 10), wealth effects do not seem to drive the description–experience gap in financial risk taking, nor do they underlie the depression baby effect (Figure 10, lower panel).

Specifically, investors who had experienced the shock were generally less inclined to take financial risk (R_{se} = 22.4%) than were those who had not (no-shock experience) (R_{nse} = 27.5%), $R_{se–nse}$ = –5.1% [–11%, 1%]. Participants who learned from a graph took more financial risk (R_d = 30.2%) than did participants who experienced the market (R_e = 25%), $R_{d–e}$ = 5.3% [2%, 9%]. Finally, and also replicating the results of Experiment 1, there was no difference in risk taking between investors in the description condition who had learned about the shock from a graph (R_{sd} = 30.5%) and those who had not (R_{nsd} = 30%), $R_{sd–nsd}$ = 0.6% [–4%, 5%].

[5] The original instructions were in German; they were given both in the instruction manual (on-screen and printed) and immediately before the investment periods began.

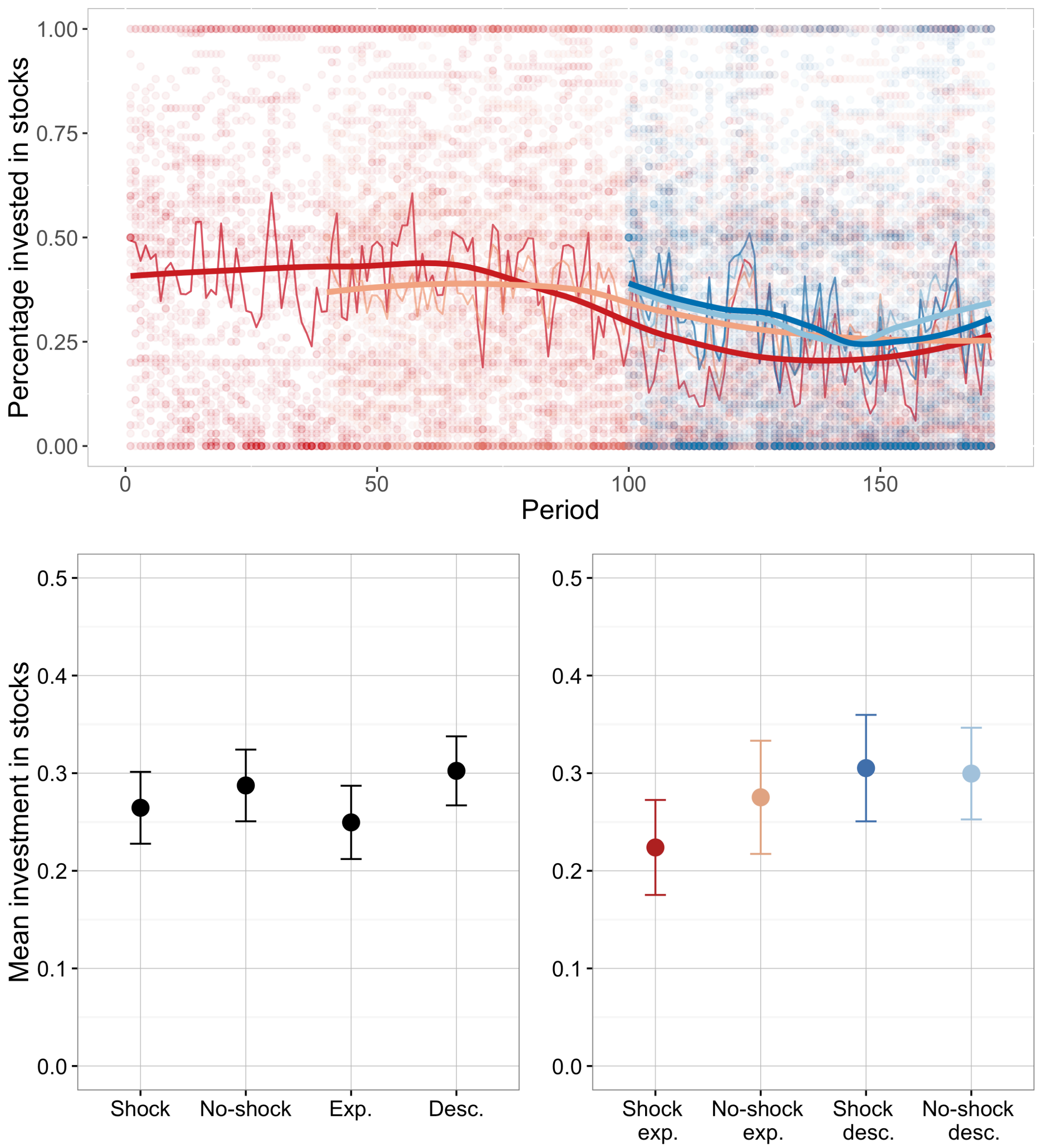


Figure 10. Upper panel. Percentage invested in stocks by condition. Dots indicate individuals' allocations. The thin lines show the mean percentage; the thicker lines show the data smoothed by local polynomial regression fitting (Cleveland et al., 1992). The red line indicates the shock experience condition from Experiment 1, and is displayed to serve as a benchmark. *Lower panel*. Investment in stocks by condition. Error bars indicate the 95% confidence interval. Means and confidence intervals were calculated by averaging risk taking for each individual across periods and computing the mean across individuals (i.e., means and CIs reflect independent observations).

General Discussion

Bringing together research on the depression baby hypothesis (Malmendier & Nagel, 2011) and the description–experience gap (Hertwig & Erev, 2009), we showed that experimental investors who learned about the market through direct experience took less financial risk than those who learned about it from a graphical display. We found this pattern consistently in three experiments. In two of them, we used symmetrically opposite markets: one characterized by an initial crisis and one by an initial boom (Figures 2 and 5). In the third experiment, we repeated Experiment 1 with control for wealth effects (by a yoking intervention) and the pattern of results was replicated. These findings provide a first indication that the description–experience gap, commonly studied in research relying on monetary gambles (Hertwig, in press; Erev & Roth, 2014), is likely to generalize to nonstationary environments such as stock markets. Furthermore, our results are in line with the survey findings of Malmendier and Nagel (2011), and show that the experience of a stock market crash on risk taking can be replicated experimentally, extending the findings by Guerrero et al. (2012). We observed both a depression and a boom effect, with the latter being larger. Furthermore, we found that symbolic descriptions (e.g., graphs) of distant stock market turbulence seem to lack the power of experience to substantially alter financial risk taking. Finally, investors in both description and experience conditions and for both market events (crisis and boom) proved reactive to recent experience. Specifically, the investment behavior of the large majority of investors covaried positively with local changes in stock prices. This observation is consistent with the findings of other studies that also observed strong recency effects in investments (Kroll et al., 1988), a behavior that is not predicted by standard portfolio choice theories.

Finally, we modified a standard model of capital allocation between a risky and a risk-free asset (Tobin, 1958) to disentangle the description–experience gap and the impact of the shock. The description–experience gap was captured by differences in risk aversion, with participants learning from experience being more risk averse than participants learning from description—a pattern consistent with myopic loss aversion. In contrast, the depression baby effect was fully captured by differences in expectations of variance: those who had experienced a shock expected higher variance and therefore took less risk.

Practical Implications

Investors who were educated about the history of the market through graphical representations seemed unreactive to the distant history of stock prices. Whether they learnt about a pronounced initial downturn or upturn or saw no such information made no difference to their investment behavior (see Figures 1 and 5). In the experience conditions, in contrast, investors reacted to the shocks: In Experiment 1, investors who experienced a negative shock took less financial risk than those who did not in 82% of the periods of the evaluation window (Figure 3); the latter invested, on average, 20% more of their resources in stocks. In Experiment 2, investors who experienced a boom took, relative to those who did not, more risk in nearly all periods (Figure 7, left) and invested 54% more of their resources in stocks.

These findings, in conjunction with other recent evidence showing that public understanding of financial risk is poor when learned from descriptive sources (Bateman, Stevens, & Lai, 2015; Walther, 2015), suggest that learning from experience has far-reaching practical implications—for instance, in the context of financial advice giving and of gauging investors' risk attitudes, as required by bodies such as the European Union (Council Directive 2004/39/EC on markets in financial instruments, [2004] OJ L 145/1). Much progress is now being achieved in improving financial risk communication by allowing investors to simulate investment experience: simulations improve risk perception, increase risk taking, and reduce regret (Bradbury et al., 2014, 2016; Kaufmann et al., 2011). Similarly, Lusardi et al. (2015) showed that (described) simulations accompanied by narratives improve risk perception.

Our results differ from these approaches in that our participants were exposed to consequential experiences. We showed that financial risk taking is highly sensitive to the idiosyncrasies of past experience. An understanding of how consequential and non-consequential experiences affect risk taking will therefore be necessary to further improve the communication of financial risks.

Exploring Simple Investment Strategies

Although the economic model of capital allocation provides plausible explanations of the effects we observed, it is important to bear in mind that the resulting explanations are conditioned on the theoretical constructs assumed in that model. The modified Tobin (1958) model we used is arguably implausible as a process model, because the information processes it assumes are beyond human's bounded cognitive capacity (Simon, 1956, 1957). What are the alternatives? Specifically, is there any indication that participants may have employed simpler investment strategies? Such strategies have been found to perform well against complex investment models (DeMiguel, Garlappi, & Uppal, 2009; Jacobs, Müller, & Weber, 2014; Tu & Zhou, 2011). For example, people may divide their funds equally among options (i.e., the 1/*N* heuristic; Benartzi & Thaler, 2001), follow "momentum" strategies chasing winning stocks (Grinblatt, Titman, & Wermers, 1995), or even employ "contrarian" strategies, betting that losers will improve (Gregory, Harris, & Michou, 2001).

To explore the possibility that people rely on simple investment strategies, we defined several such strategies and examined their prevalence in Experiments 1 and 2 (definitions of each strategy are provided in the Appendix, as is a description of the classification procedure; see Table A1). As reported in Table A2 in the Appendix, a substantial proportion of participants (52%) were identified as using momentum strategies, that is, increasing the proportion invested in stocks after a price rise and decreasing it after a drop (61% in Experiment 1 and 40% in Experiment 2). Two types of momentum strategies were predominant: participants who tracked the stock price while taking low risk (27% and 20% in Experiments 1 and 2, respectively), and participants who did so while diversifying across the two options (27% and 17%). A minority of participants seemed to be unreactive to changes in the stock price, with 2% and 5%, respectively, using naïve diversification (roughly a 50/50 split), and 4% and 11%, respectively, using constant safe strategies. The classifications of all participants, together with their individual investment decisions, are presented in Figure A4.

Our classification also suggests that the investment strategies appear not to depend on the mode of learning; yet, the mode of learning can shape the parameters within a class of strategies. For instance, in both experiments, a large proportion of participants who learned from experience and description relied on momentum strategies—but more participants employed a momentum *safe* strategy (with a lower level of risk) in the experience condition than in the description condition (Figure A4). Relatedly, as Figure A4 shows, there was no clear difference in the frequency of strategy use between the two initial market events (crisis versus boom). Again, however, the distinction resides in the *levels* of risk taking following a shock, as reflected in the participants' propensity to adopt riskier or safer strategies. In Experiment 1, more participants adopted safe strategies (constant-target strategy and momentum strategy) in the shock than in the no-shock condition. Analogously, in Experiment 2, more participants adopted safe strategies (constant-target strategy and momentum strategy) in the no-shock than in the shock condition.

Limitations

One limitation of our studies is that we do not know to what extent our results will generalize to behavior in the real stock market, where investors have myriad investment options, can invest substantially larger amounts of money, and where investment periods may span years. The issue of generalizability also pertains to the use of historical data. We used real-market returns in our studies—following Guerrero et al.'s (2012) approach—to render the experimental investment task similar to real world investing in the stock market—at least in terms of the return distribution—and to be able to endow all experimental investors with the same experience of a macroeconomic shock. Of course, one limitation is that the observed behavior may be contingent on one historical return distribution and not generalize to others. Yet, the finding that experimental investors take less risk, that is, allocate less of their investments into stocks (relative to a risk-free option) has now been replicated in two different historical return distributions, the Dow Jones Industrial Average returns from the periods surrounding the Crash of 1929 (Guerrero et al., 2012) and the Spanish stock index returns in the period of July 1999 to September 2013 employed in our studies.

Nevertheless, we highlight that the extent to which the various key results—the effects of bust (Study 1) and boom (Study 2) experiences on risk taking and the differential effects of learning about the market from personal experience—need to be replicated in other return distributions. To this end, one possibility is to employ a "model" of the market. Indeed, other studies of investment behavior have used simulated markets drawing returns from a model of the market (i.e., an underlying return distribution, as in Bradbury et al., 2015; Kaufmann et al., 2013). Here we decided against this approach for the following reason. We focused on financial risk taking after experiencing a shock (bust or boom), not after experiencing a market in equilibrium. Creating a model of a shock is not as straightforward as producing a risky investment option based on the mean of past returns and an assumed distribution (as done by for example, Kaufmann et al., 2013). A model of a shock requires assumptions regarding mean return before, during, and after the shock, the variance of returns during those three periods, and the speed at which the change occurs, among others. Therefore, modeling a shock involves making a number of assumptions that may limit, rather than help generalizability.

Another possible limitation of our experimental design is that our investors did not know the investment time horizon (i.e., the number of periods during which they were asked to make investment decisions). In this sense, our design was that of an infinitely repeated game rather than a finitely repeated game. This design may be representative for some investors who invest without a clear horizon in mind, but may not be for others who decide *a priori* when to stop investing. Yet, let us point out that although our investors were asked to make an unknown series of investments, they were free to never invest in the stock market (i.e., by only choosing the risk-free option), thus avoiding the volatility of the market altogether. Future experimental studies may explore the role of finite versus infinite time horizon.

To conclude, our experimental approach offers new results and answers but also asks new questions. One key question is to what extent results will generalize to the behavior of real investors. In this sense, our results represent an experimental existence proof that descriptions and experiences of the stock market can produce divergent behavior in situations where classic financial and economic theories indicate that they would be identical. Existence proofs within an experimental micro-world, no matter how interesting they are, do not ascertain external validity. Yet, they can impel new lines of inquiry.

Twenty-First Century Depression Babies

Against the background of our findings and their limitations, one may speculate on how investors will respond to the macroeconomic shock of 2008 and the ensuing Great Recession in Europe and the U.S. The response will likely depend on whether investors experienced the stock market crash personally or learnt about it through description (e.g., graphs, as in Figures A1–A3). Both the survey findings of Malmendier and Nagel (2011) and our experimental results suggest that the former are likely to invest less in the stock market and to take less financial risk than the latter. Building on these experimental demonstrations of “depression babies” and “boom babies,” future research can begin to explore the generalizability of our findings to real markets, and to identify and experimentally manipulate the *qualia* of experience that cause people to learn differently from experience than from descriptive sources.

References

Apergis, N. (2015). Financial portfolio choice: Do business cycle regimes matter? Panel evidence from international household surveys. *Journal of International Financial Markets, Institutions & Money, 34*, 14–27. http://dx.doi.org/10.1016/j.intfin.2014.10.007

Bateman, H. Stevens, R. & Lai, A. (2015). Risk Information and Retirement Investment Choice Mistakes Under Prospect Theory. *Journal of Behavioral Finance, 16*, 279–296, http://dx.doi.org/10.1080/15427560.2015.1095749

Benartzi, S., & Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics, 110*, 73–92. http://dx.doi.org/10.2307/2118511

Benartzi, S., & Thaler, R. H. (2001). Naive diversification strategies in defined contribution saving plans. *American Economic Review*, *91*, 79–98. http://dx.doi.org/10.1257/aer.91.1.79

Bradbury, M. A., Hens, T., & Zeisberger, S. (2014). Improving investment decisions with simulated experience. *Review of Finance*, *19,* 1019–1052. http://dx.doi.org/10.1093/rof/rfu021

Bradbury, M. A., Hens, T., & Zeisberger, S. (2016) How risk simulations improve long-term investment decisions. Retrieved from Social Science Research Netwok website: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2603780

Cleveland, W. S., Grosse, E., & Shyu, M.-J. (*1992*). *A package of C and Fortran routines for fitting local regression models.* Available from http://www.stat.purdue.edu/~wsc/papers.html

Cumming, G. (2012). *Understanding the new statistics: Effect sizes, confidence intervals, and meta-analysis.* New York, NY: Routledge. http://dx.doi.org/10.4324/9780203807002

DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies*, *22*, 1915–1953. http://dx.doi.org/10.1093/rfs/hhm075

Erev, I., & Roth, A. E. (2014). Maximization, learning, and economic behavior. *Proceedings of the National Academy of Sciences, 111*, 10818–10825. http://dx.doi.org/10.1073/pnas.1402846111

Financial Crisis Inquiry Commission. (2011). *Final report of the National Commission on the causes of the financial and economic crisis in the United States.* Retrieved from http://www.gpo.gov/fdsys/pkg/GPO-FCIC/pdf/GPO-FCIC.pdf

Funk, S., Rapoport, A., & Jones, L. V. (1979). Investing capital on safe and risky alternatives: An experimental study. *Journal of Experimental Psychology: General, 108*, 415–440. http://dx.doi.org/10.1037//0096-3445.108.4.415

Gordon, M. J., Paradis, G. E., & Rorke, C. H. (1972). Experimental evidence on alternative portfolio decision rules. *American Economic Review, 62*, 107–118.

Gregory, A., Harris, R. D., & Michou, M. (2001). An analysis of contrarian investment strategies in the UK. *Journal of Business Finance & Accounting*, *28*, 1192–1228. http://dx.doi.org/10.1111/1468-5957.00412

Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review, 85*, 1088–1105.

Guerrero, F., Stone, G. R., & Sundali, J. A. (2012). Fear in asset allocation during and after stock market crashes: An experiment in behavioral finance. *The Journal of Behavioral Finance & Economics, 2*, 50–81.

Hertwig, R. (2016). Decisions from experience. In G. Keren & G. Wu (Eds.), *The Wiley Blackwell handbook of judgment and decision making* (Vol. 1, pp. 240–267). Chichester, United Kingdom: Wiley Blackwell.

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science, 15,* 534–539. http://dx.doi.org/10.1111/j.0956-7976.2004.00715.x

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2006). The role of information sampling in risky choice. In K. Fiedler & P. Juslin (Eds.), *Information sampling and adaptive cognition* (pp. 71–91). New York, NY: Cambridge University Press.

Hertwig, R., & Erev, I. (2009). The description–experience gap in risky choice. *Trends in Cognitive Sciences, 13*, 517–523. http://dx.doi.org/10.1016/j.tics.2009.09.004

Jacobs, H., Müller, S., & Weber, M. (2014). How should individual investors diversify? An empirical evaluation of alternative asset allocation policies. *Journal of Financial Markets*, *19*, 62–85. http://dx.doi.org/10.1016/j.finmar.2013.07.004

Kaufmann, C., Weber, M., & Haisley, E. (2013). The role of experience sampling and graphical displays on one's investment risk appetite. *Management Science, 59*, 323–340. http://dx.doi.org/10.1287/mnsc.1120.1607

Kroll, Y., Levy, H., & Rapoport, A. (1988). Experimental tests of the mean-variance model for portfolio selection. *Organizational Behavior and Human Decision Processes, 42*, 388–410. http://dx.doi.org/10.1016/0749-5978(88)90007-6

Lusardi, A., Samek, A., Kapteyn, A., Glinert, L., Hung, A., & Heinberg, A. (2014). Visual tools and narratives: new ways to improve financial literacy. *Journal of Pension Economics and Finance*, 1–27. http://dx.doi.org/10.1017/S1474747215000323

Malmendier, U., & Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics, 126*, 373–416. http://dx.doi.org/10.1093/qje/qjq004

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7,* 77–91. http://dx.doi.org/10.1111/j.1540-6261.1952.tb01525.x

Merton, R. C. (1969). Lifetime portfolio selection under uncertainty: The continuous-time case. *The Review of Economics and Statistics, 5*1, 247–257. http://dx.doi.org/10.2307/1926560

Palan, S. (2013). A review of bubbles and crashes in experimental asset markets. *Journal of Economic Surveys, 27,* 570–88. http://dx.doi.org/10.1111/joes.12023

Rapoport, A. (1984). Effects of wealth on portfolios under various investment conditions. *Acta Psychologica, 55*, 31–51. http://dx.doi.org/10.1016/0001-6918(84)90058-1

Schmandt-Besserat, D. (1996). *How writing came about.* Austin, TX: University of Texas Press.

Smith, V. L., Suchanek, G. L., & Williams, A. W. (1988). Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica,* 56, 1119–1151. http://dx.doi.org/10.2307/1911361

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review, 63*, 129–138. http://dx.doi.org/10.1037/h0042769

Simon, H. A. (1957). *Models of man.* New York, NY: John Wiley & Sons. http://dx.doi.org/10.1037/h0042769

Thaler, R. H., Tversky, A., Kahneman, D., & Schwartz, A. (1997). The effect of myopia and loss aversion on risk taking: An experimental test. *Quarterly Journal of Economics, 112*, 647–661. http://dx.doi.org/10.1162/003355397555226

Tobin, J. (1958). Liquidity preference as behavior towards risk. *The Review of Economic Studies*, 25, 65–86. http://dx.doi.org/10.2307/2296205

Tu, J., & Zhou, G. (2011). Markowitz meets Talmud: A combination of sophisticated and naive diversification strategies. *Journal of Financial Economics*, *99*, 204–215. http://dx.doi.org/10.1016/j.jfineco.2010.08.013

Walther, T. (2015). Key investor documents and their consequences on investor behavior. *Journal of Business Economics, 85*, 129–156. http://dx.doi.org/10.1007/s11573-014-0724-6

Weber, M., Weber, E. U., & Nosić, A. (2013). Who takes risks when and why: Determinants of changes in investor risk taking. *Review of Finance, 17*, 847–883. http://dx.doi.org/10.1093/rof/rfs024

Appendix

Screenshots of the Investment Task

Figure A1. Screenshot of the investment task (in German), including the graph showing the price of the Spanish stock index fund, IBEX-35 (lower left), and the table showing the portfolio (lower right), distinguishing between the return on stocks and cash in each period.

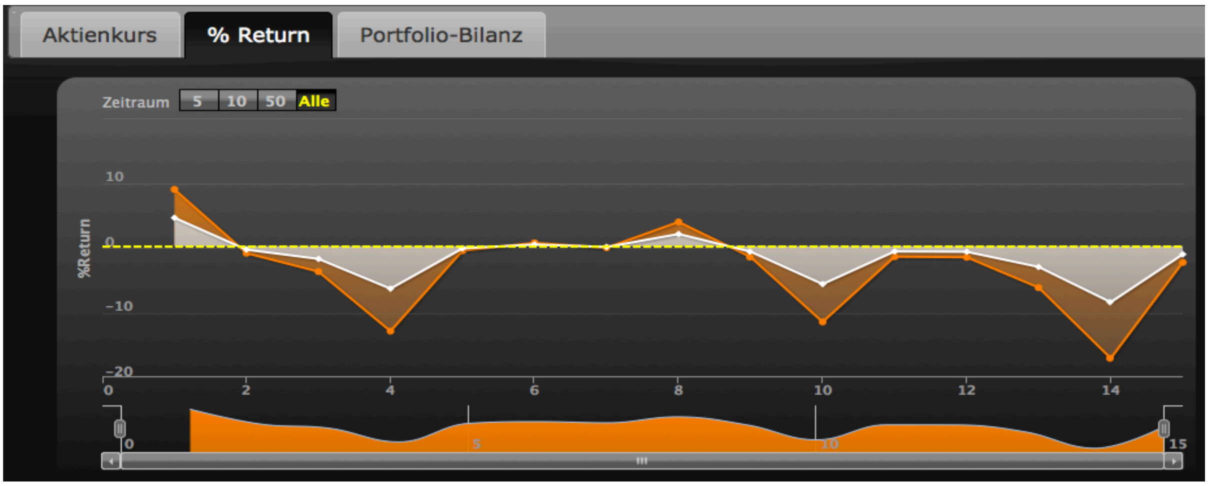


Figure A2. Screenshot of the graph showing the percentage return on each of the two investment options

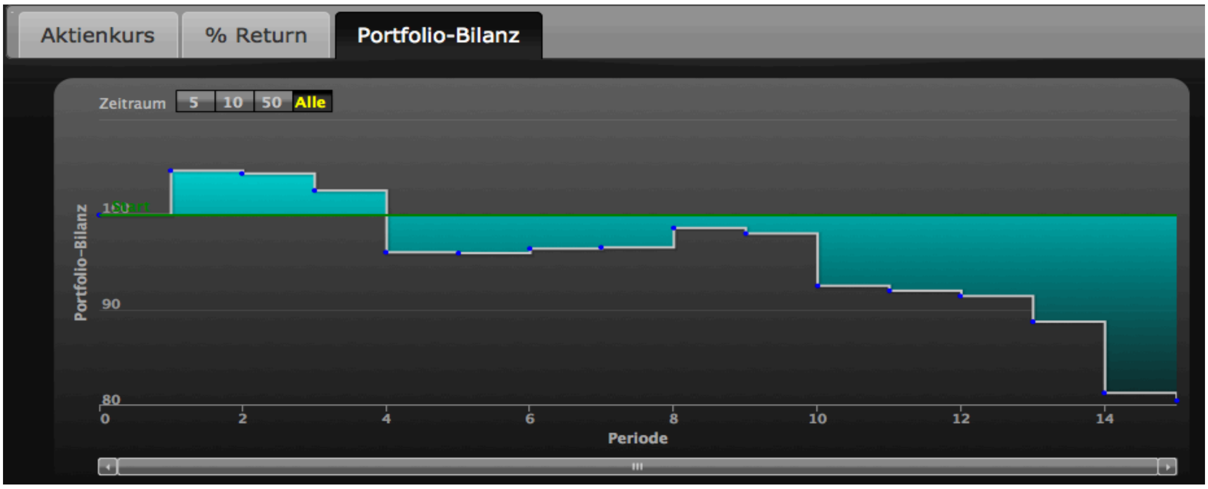


Figure A3. Screenshot of the graph showing an individual's portfolio comprised of the accumulated gains and losses across periods.

Simple Investment Strategies: Classification

In taking advantage of existing models of heuristics, we highlight that our analysis is somewhat different from previous ones: For instance, we analyze a period-by-period application of the investment strategies rather than a single application over a longer horizon. Similarly, our analysis of the 1/*N* rule applies to a situation of *N* = 2, whereas in other analyses, *N* is typically larger than 2 (e.g., DeMiguel et al., 2009).

Strategies Unreactive to Fluctuations in Stock Price

Naïve diversification (1/N heuristic). Investors using the naïve diversification strategy divide their budget evenly among the *N* options available (Benartzi & Thaler, 2001). This strategy does not depend on the attractiveness of the options, so it is not susceptible to the fluctuations of the market. In Experiments 1 and 2, naïve diversification would mean consistently investing 50% of the budget in stocks.

Constant-target strategy. Investors using the constant-target strategy select a target level of risk taking in the first investment period (in terms of a specific proportion invested in the index fund) and maintain this target until the end. We distinguish between two types of the constant-target strategy, depending on the level of risk taken: **constant risky** and **constant safe**.

Nondiversification strategy. Investors using this strategy put all of their eggs in one basket—in our experiments, either the "risk" basket (100% index fund) or the "safe" basket (100% cash deposit).

Strategies Reactive to Fluctuations in Stock Price

Momentum strategies. Investors recruiting momentum strategies adjust their allocations as a function of market changes. Specifically, they increase allocations in the options that increased in price in the $t - 1$ period (Grinblatt et al., 1995). In our experiments, momentum strategies imply increasing the investment in stocks after an increase in stock price.

We distinguish four types of momentum strategies. Using **momentum nondiversified** strategies means moving the total budget into stocks following a rise in prices and moving the total budget out of stocks following a drop. **Momentum diversified** strategies are more moderate, and follow stock fluctuations in a proportional manner. **Momentum risky** and **momentum safe** strategies respond to changes in stock prices, but adopting different levels of risk: momentum risky entails high risk and momentum safe entails low risk.[6]

Contrarian strategies. Investors following contrarian strategies reduce their allocations to stocks in period *t* after a price increase in period *t* – 1, and increase their allocation to stocks after a price drop (Gregory et al., 2001).

Strategy Classification

To classify participants on the basis of these simple investment strategies, we calculated the following indicators for each sequence of investments during the evaluation window: (a) mean proportion invested in stocks, (b) standard deviation of the proportion invested in stocks, (c) slope of the best-fitting linear model of the investment trend, (d) correlation between the change in stock price in period *t* and the change in stock investment in period *t* + 1. We then used these four criteria to classify each investor. Table A1 describes how we defined the strategies according to the four criteria.

[6] Our momentum strategies consider only responses to the immediately previous period (monthly trends). This conceptualization differs from the more common approach in finance that considers longer momentums.

Table A1

Definition of Investment Strategies According to Four Criteria

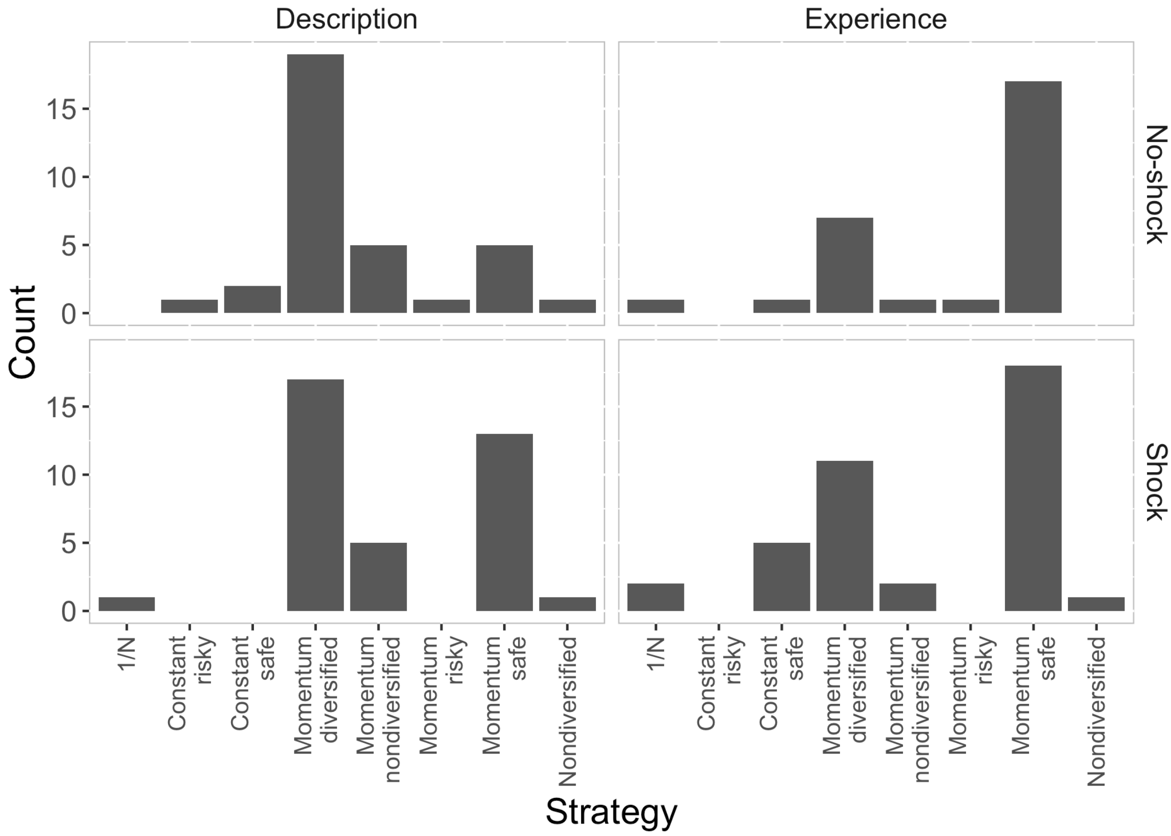
	Mean	SD	Trend	Correlation
Strategies *unreactive* to stock price fluctuations				
Naïve diversification (1/*N*)	[.4, .6]	< .1	[.1, –.1]	ns
Constant risky	> .8	< .1	[.1, –.1]	ns
Constant safe	< .2	< .1	[.1, –.1]	ns
Nondiversified		> .4		ns
Strategies *reactive* to stock price fluctuations				
Momentum				
Nondiversified		> .4		s (+)
Diversified	[.2, .8]	< .4		s (+)
Risky	> .8			s (+)
Safe	< .2			s (+)
Contrarian				s (–)

Note. ns denotes nonsignificant correlations (with $N = 73$, $r < .31$). s (+) denotes significant positive correlations, and s (–) denotes significant negative correlations.

Table A2

Number of Participants Classified to Each Investment Strategy

	Experiment 1		Experiment 2	
Strategies *unreactive* to stock price fluctuations	**16**	***8%***	**31**	***19%***
Naïve diversification (1/*N*)	4	*2%*	8	*5%*
Constant risky	1	*1%*	0	*0%*
Constant safe	8	*4%*	17	*11%*
Nondiversified	3	*2%*	6	*4%*
Strategies *reactive* to stock price fluctuations	**122**	***61%***	**64**	***40%***
Momentum	122	*61%*	64	*40%*
Nondiversified	13	*7%*	3	*2%*
Diversified	54	*27%*	28	*17%*
Risky	2	*1%*	0	*0%*
Safe	53	*27%*	33	*20%*
Contrarian	0	*0%*	0	*0%*
Unclassified	**62**	***31%***	**66**	***41%***
N	200		161	


Description
Experience
No-shock
Shock
Count
15
10
5
0
1/N
Constant risky
Constant safe
Momentum diversified
Momentum nondiversified
Momentum risky
Momentum safe
Nondiversified
Strategy

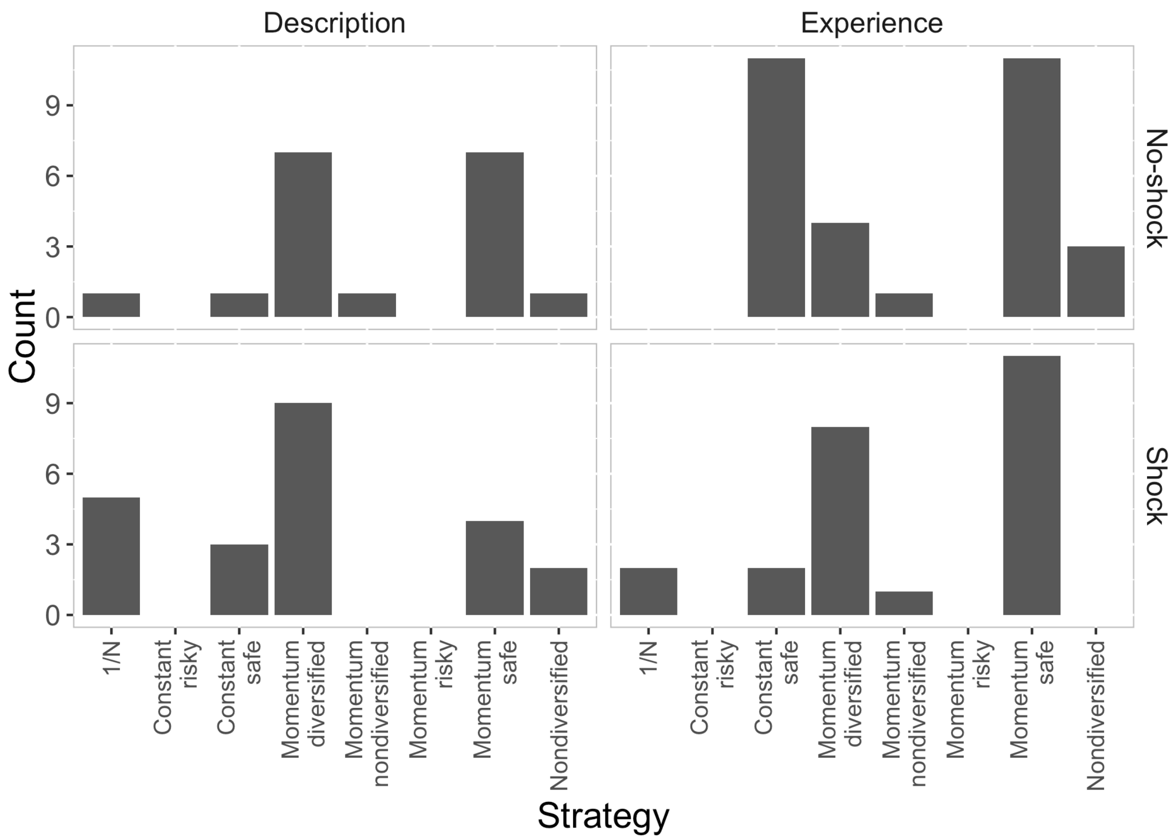

Description
Experience
No-shock
Shock
Count
9
6
3
0
1/N
Constant risky
Constant safe
Momentum diversified
Momentum nondiversified
Momentum risky
Momentum safe
Nondiversified
Strategy

Figure A4. Classification of participants according to their investment strategy by mode and length of learning and the criteria listed in Table A1. The top panel shows results for Experiment 1; the bottom panel shows results for Experiment 2.

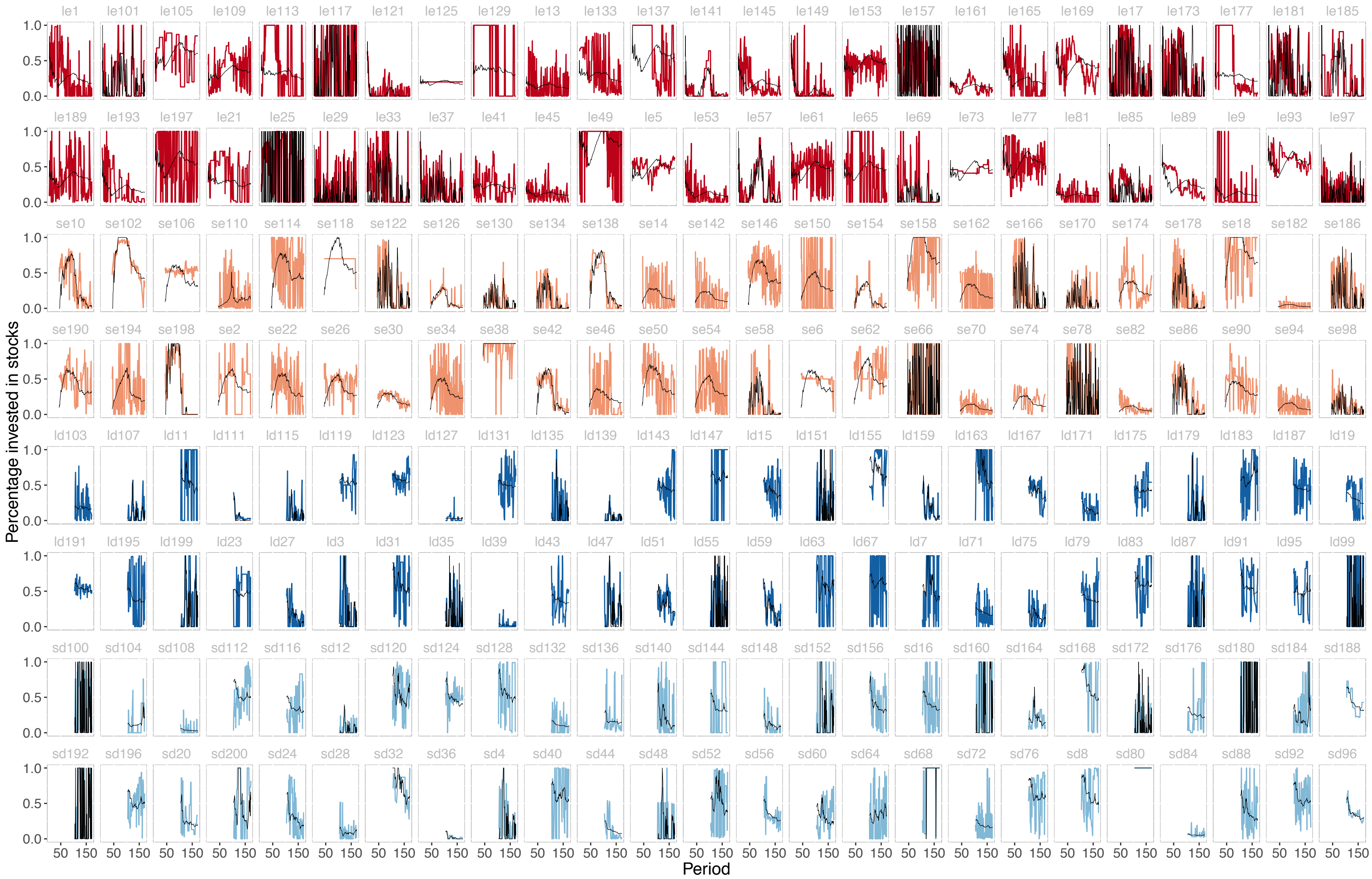

Percentage invested in stocks
Period

Figure A5. Experiment 1. Proportion invested in stocks for each individual in each trial. The colors of the curves correspond to the four conditions, with the shock experience condition at the top (in red), followed by the no-shock experience condition (in orange), the shock description condition (in blue), and the no-shock description condition (in light blue). The subtitle of each graph is the participant ID. The black line indicates the predictions of the model.

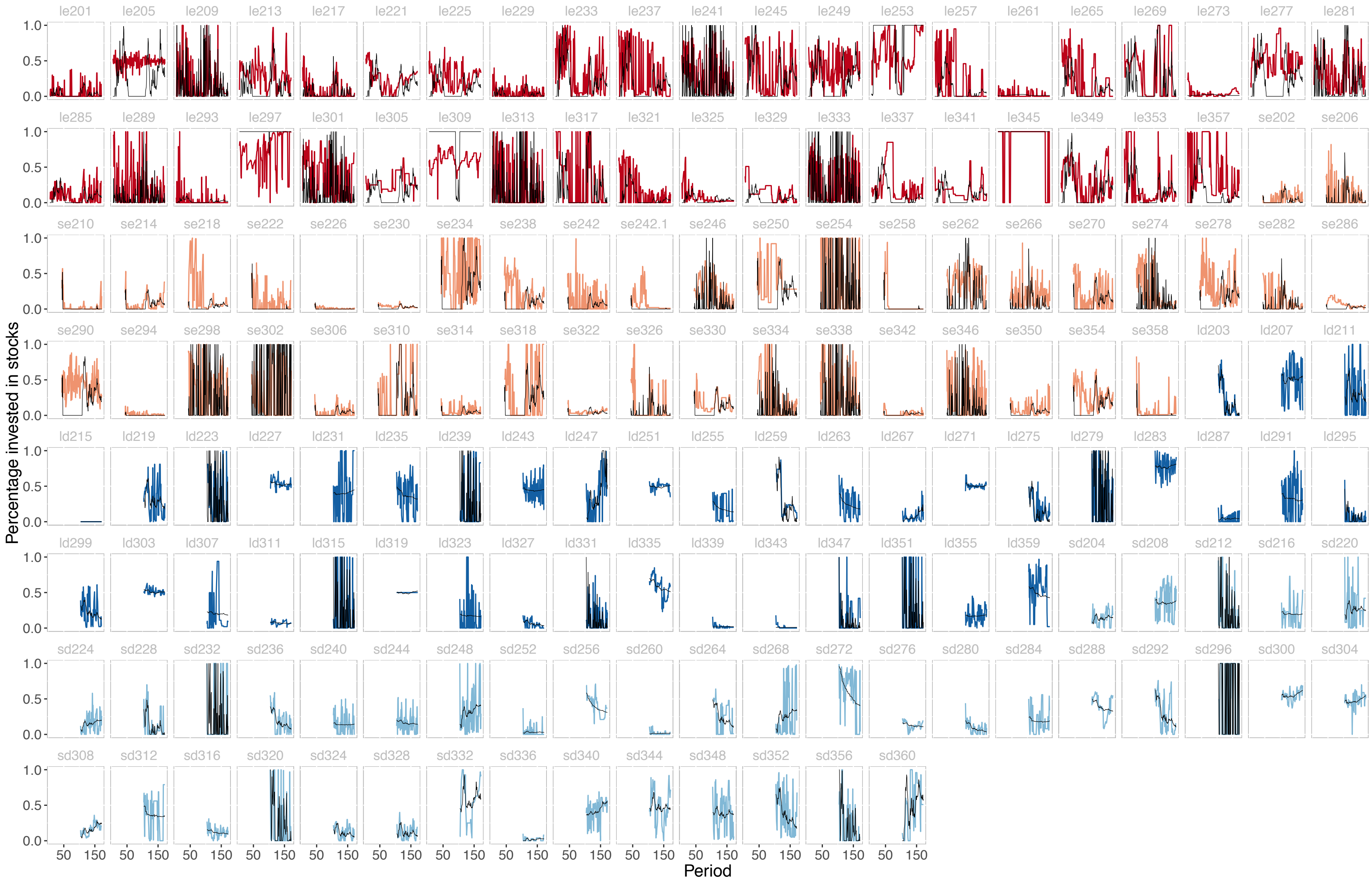

le201 le205 le209 le213 le217 le221 le225 le229 le233 le237 le241 le245 le249 le253 le257 le261 le265 le269 le273 le277 le281
le285 le289 le293 le297 le301 le305 le309 le313 le317 le321 le325 le329 le333 le337 le341 le345 le349 le353 le357 se202 se206
se210 se214 se218 se222 se226 se230 se234 se238 se242 se242.1 se246 se250 se254 se258 se262 se266 se270 se274 se278 se282 se286
se290 se294 se298 se302 se306 se310 se314 se318 se322 se326 se330 se334 se338 se342 se346 se350 se354 se358 ld203 ld207 ld211
ld215 ld219 ld223 ld227 ld231 ld235 ld239 ld243 ld247 ld251 ld255 ld259 ld263 ld267 ld271 ld275 ld279 ld283 ld287 ld291 ld295
ld299 ld303 ld307 ld311 ld315 ld319 ld323 ld327 ld331 ld335 ld339 ld343 ld347 ld351 ld355 ld359 sd204 sd208 sd212 sd216 sd220
sd224 sd228 sd232 sd236 sd240 sd244 sd248 sd252 sd256 sd260 sd264 sd268 sd272 sd276 sd280 sd284 sd288 sd292 sd296 sd300 sd304
sd308 sd312 sd316 sd320 sd324 sd328 sd332 sd336 sd340 sd344 sd348 sd352 sd356 sd360
Percentage invested in stocks
0.0
0.5
1.0
50
150
Period

Figure A6. Experiment 2. Proportion invested in stocks for each individual in each trial. The colors of the curves correspond to the four conditions, with the shock experience condition at the top (in red), followed by the no-shock experience condition (in orange), the shock description condition (in blue), and the no-shock description condition (in light blue). The subtitle of each graph is the participant ID. The black line indicates the predictions of the model.

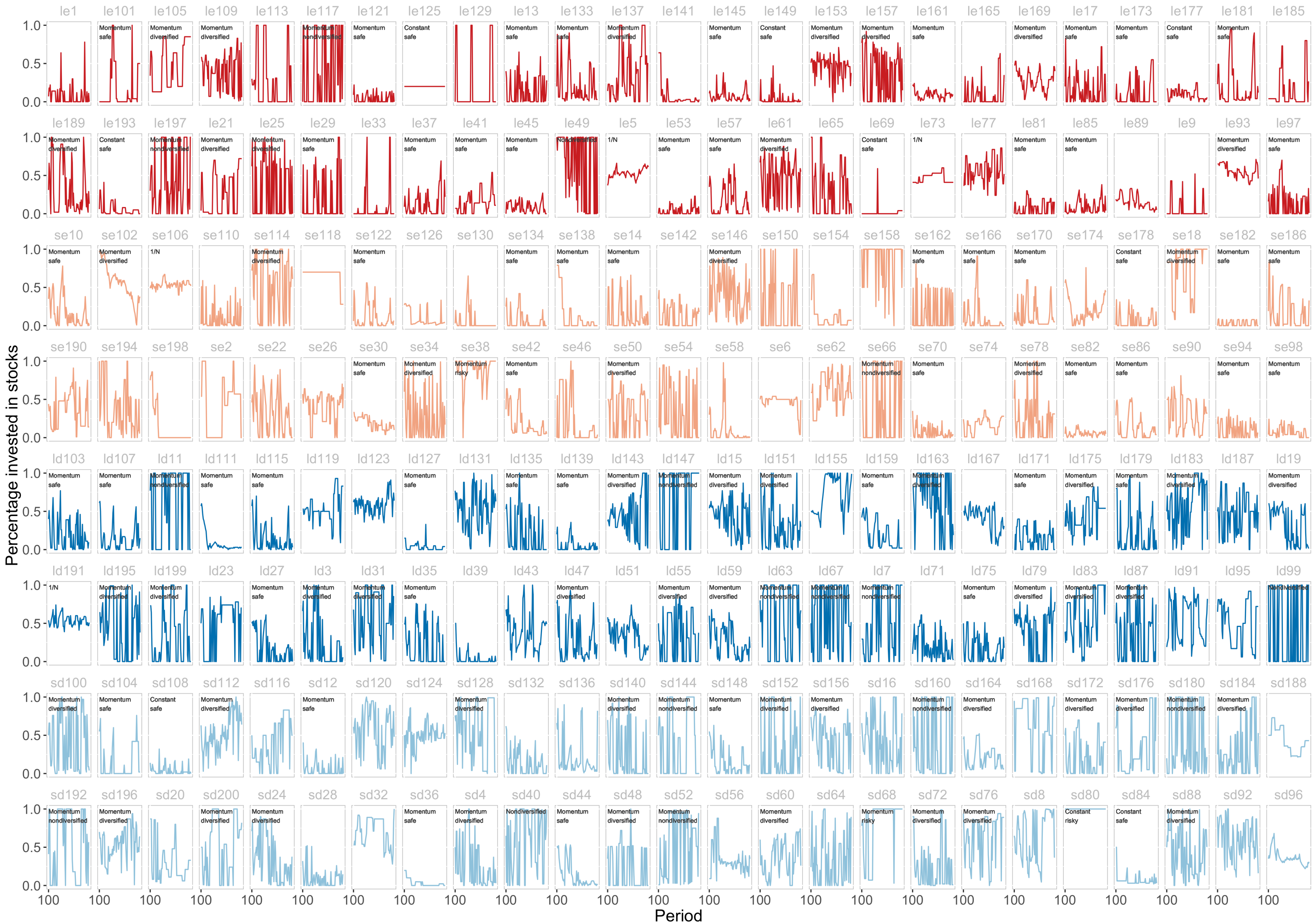

Percentage invested in stocks
Period
le1 le101 le105 le109 le113 le117 le121 le125 le129 le13 le133 le137 le141 le145 le149 le153 le157 le161 le165 le169 le17 le173 le177 le181 le185
le189 le193 le197 le21 le25 le29 le33 le37 le41 le45 le49 le5 le53 le57 le61 le65 le69 le73 le77 le81 le85 le89 le9 le93 le97
se10 se102 se106 se110 se114 se118 se122 se126 se130 se134 se138 se14 se142 se146 se150 se154 se158 se162 se166 se170 se174 se178 se18 se182 se186
se190 se194 se198 se2 se22 se26 se30 se34 se38 se42 se46 se50 se54 se58 se6 se62 se66 se70 se74 se78 se82 se86 se90 se94 se98
ld103 ld107 ld11 ld111 ld115 ld119 ld123 ld127 ld131 ld135 ld139 ld143 ld147 ld15 ld151 ld155 ld159 ld163 ld167 ld171 ld175 ld179 ld183 ld187 ld19
ld191 ld195 ld199 ld23 ld27 ld3 ld31 ld35 ld39 ld43 ld47 ld51 ld55 ld59 ld63 ld67 ld7 ld71 ld75 ld79 ld83 ld87 ld91 ld95 ld99
sd100 sd104 sd108 sd112 sd116 sd12 sd120 sd124 sd128 sd132 sd136 sd140 sd144 sd148 sd152 sd156 sd16 sd160 sd164 sd168 sd172 sd176 sd180 sd184 sd188
sd192 sd196 sd20 sd200 sd24 sd28 sd32 sd36 sd4 sd40 sd44 sd48 sd52 sd56 sd60 sd64 sd68 sd72 sd76 sd8 sd80 sd84 sd88 sd92 sd96

Figure A7. Experiment 1. Proportion invested in stocks for each individual in each trial. The colors of the curves correspond to the four conditions, with the shock experience condition at the top (in red), followed by the no-shock experience condition (in orange), the shock description condition (in blue), and the no-shock description condition (in light blue). The subtitle of each graph is the participant ID. Each graph also indicates the classification of each participant's strategy. Graphs without a classification represent unclassified participants.

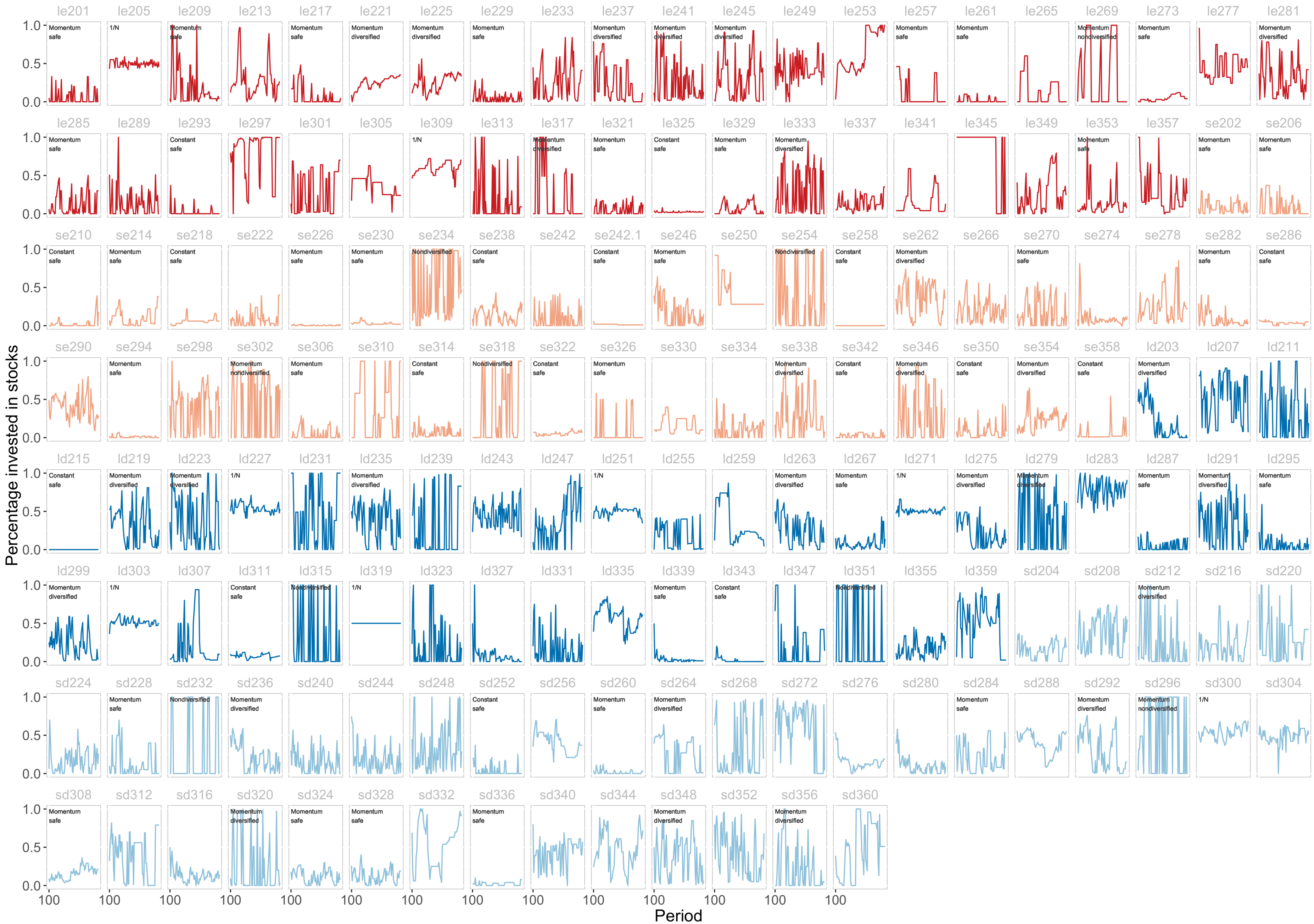

Percentage invested in stocks
Period

Figure A8. Experiment 2. Proportion invested in stocks for each individual in each trial. The colors of the curves correspond to the four conditions, with the shock experience condition at the top (in red), followed by the no-shock experience condition (in orange), the shock description condition (in blue), and the no-shock description condition (in light blue). The subtitle of each graph is the participant ID. Each graph also indicates the classification of each participant's strategy. Graphs without a classification represent unclassified participants.