Market Shocks and Professionals' Investment Behavior – Evidence from the COVID-19 Crash

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Abstract

We investigate how the experience of extreme events, such as the COVID-19 market crash, influence risk-taking behavior. To isolate changes in risk taking from other factors, we ran controlled experiments with finance professionals in December 2019 and March 2020. We observe that their investments in the experiment were 12 percent lower in March 2020 than in December 2019, although their price expectations had not changed, and although they considered the experimental asset less risky during the crash than before. Thus, lower investments are driven by higher risk aversion, not by changes in beliefs.

JEL: C91, G01, G11, G41
Keywords: Experimental finance, Countercyclical risk aversion, Finance professionals, Reinforcement learning, COVID-19

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1 Introduction

How are risk taking and beliefs about an asset's riskiness affected by extreme "shocks" like the COVID-19 pandemic? In this paper, we show evidence from controlled investment experiments conducted with finance professionals in December 2019 and March 2020. We find that their investments in the experiment were 12 percent lower during the stock market crash than before. With our experimental approach, we are able to control various confounding factors that are active during real-world economic crises and stock market crashes. In particular, we show that professionals' decreasing risk taking is accompanied by unchanged price expectations and remarkably, by lower beliefs about the riskiness of the experimental asset in March 2020 than in December 2019. Thus, we conclude that the drop in investments is not driven by beliefs, but by elevated levels of risk aversion.

Shocks and other extreme events can have a profound and long-lasting influence on our behavior and decisions (e.g., Hertwig et al., 2004). In a financial context, Malmendier and Nagel (2011) show that individuals who have experienced low stock market returns throughout their lives exhibit a lower willingness to take financial risk, are less likely to participate in the stock market, and are more pessimistic about future stock returns.[1] However, one major problem of identifying the impact of extreme events on economic preferences and beliefs with empirical data is the multitude of unobservable variables that are active during crises. Identification problems, such as changes in asset price expectations, drops in wealth levels, and simply inertia in a household's asset allocation, render causal inference difficult (e.g., Brunnermeier and Nagel, 2008; Calvet and Sodini, 2014).

As a related concept, countercyclical risk aversion postulates that investors are less risk averse during boom periods compared to bust periods (e.g., Campbell and Cochrane, 1999; Barberis et al., 2001). Cohn et al. (2015) show experimental evidence of countercyclical risk aversion, as financial professionals who were primed with a financial bust scenario were more fearful and risk averse than those primed with a boom scenario. Whereas Newell and Page (2017) also find evidence for countercyclical risk aversion in experimental asset markets with students, König-Kersting and Trautmann (2018) and Alempaki et al. (2019) show that countercyclical risk aversion does not necessarily hold for subjects outside the finance industry.

As a first main contribution of this paper, we merge both approaches: that is, (i) the investigation of a naturally occurring shock such as the COVID-19 stock market crash and (ii) the method of running controlled experiments with finance professionals to reduce identification problems.[2] Hence, our first research question asks, how does risk-taking behavior and the perception of risk

[1] Guiso et al. (2004, 2008) find that the cultural and political environment in which individuals grow up can affect their preferences and beliefs, such as trust in financial institutions and stock market participation.

[2] See also recent studies by Angrisani et al. (2020), Bu et al. (2020), and Giglio et al. (2020), who investigate the COVID-19 stock market crash and its impact on various measures of risk taking with survey or experimental data.

change during a stock market crash like the one that occurred during the COVID-19 pandemic? Our design allows us to isolate risk taking by distinguishing it from beliefs about asset risk (risk perception) and from beliefs about price expectations.

In particular, we utilize the stock market crash in March 2020 as a naturally occurring event to examine behavioral changes in experimental investment decisions in two waves: one during a comparatively calm and "bullish" stock market period in December 2019 (WAVE 1) and one during the volatile "bear" market of March 2020 (WAVE 2). We conducted our framed field experiment (Harrison and List, 2004) online with 315 financial professionals from our proprietary subject pool (www.before.world) and with 498 management and economics students from the University of Innsbruck. The professionals are based in Europe and work predominantly as portfolio and investment managers, financial advisors, and traders. 202 professionals (282 students) participated in WAVE 1 in December 2019, and 113 professionals (216 students) participated in WAVE 2 between March 16 and March 31.

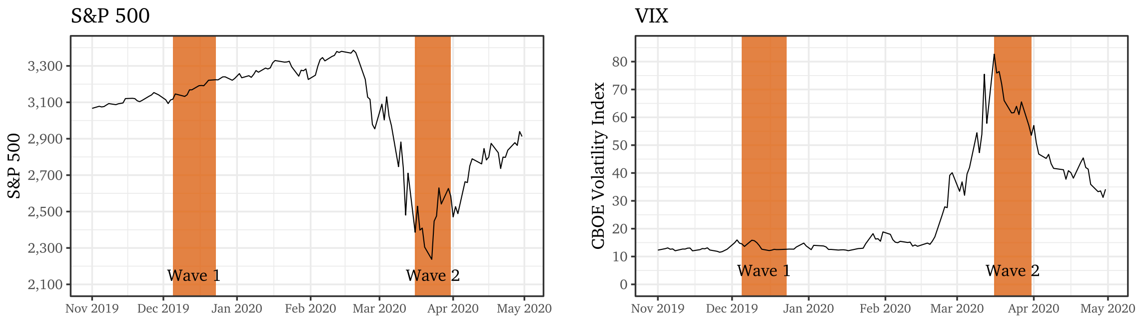


Figure 1: Time series of the S&P 500 stock index (left panel) and the CBOE Volatility Index (VIX, right panel) from November 2019 to May 2020 and the data collection periods. WAVE 1 of the experiment was conducted from December 5 to December 23, 2019; data for WAVE 2 were collected between March 16 and March 31, 2020.

Figure 1 outlines the timing of the two experimental waves. In the month leading up to the data collection in WAVE 2, the CBOE Volatility Index (VIX, right panel) increases almost sixfold from 14.8 to 82.7 on March 16—the highest closing level recorded since the index's introduction in 1993—and it remains exceptionally high until the end of the wave. In the same time period, the U.S. S&P 500 stock index (left panel) loses 25.5 percent and markets in Europe crash by 36.1 percent (Euro Stoxx 50 stock index). During data collection in WAVE 1 in December 2019, however, the VIX remains within a very narrow range at low levels from only 12.1 to 16.0, and the S&P 500 increases by more than 3 percent.

In both waves of the experiment, subjects were exposed to the identical investment task in which we presented the unfolding of a price or return chart of a risky stock over time with returns based on historical data. Every 20 trading days (10 seconds in the experiment), subjects had to make a number of decisions: which percentage of their endowment to invest in the risky stock (incentivized), perception of the stock's risk, stock price/return forecasts, and satisfaction with the stock. In a 2×3 factorial treatment design, we varied the presentation format (returns or prices) and the "direction" of an *experimental shock* (mostly positive returns, mostly negative returns, or a neutral case). Importantly, the volatility shock in the experiment was implemented between days 40 and 60, with maximum net price up- or downswings of up to 25 percent.

By utilizing the pandemic-induced stock market crash in March 2020, we are able to "import" professionals' behavior and emotions as potential drivers of investments in the experiment. Moreover, with the additional introduction of volatility shocks of the experimental stock within each wave, we can investigate behavioral differences in the reaction to "real-world" shocks (across waves) and to "experimental" shocks (within each wave).

We report, first, substantial changes in risk-taking behavior between both waves of the experiment. In particular, we show that professionals' investments in the same risky asset were 12 percent (or 9 percentage points, down from 77 to 68 percent of their endowment) lower in March 2020 than in December 2019. Importantly, we do not find differences in beliefs about future price and return expectations of the risky stock between the two waves. Thus, we infer that the drop in investments is not driven by beliefs, but by elevated levels of risk aversion, pointing at a similar finding as Cohn et al. (2015) for countercyclical risk aversion. This general finding is accompanied by the behavior of non-professionals (i.e., students), as they do not show any difference in investment behavior during the crash compared to the calm period. As students were less exposed to the stock market (in terms of investments and attention to the stock market developments), they did not experience the extreme volatility cluster in the stock market to the same extent as the professionals did.

Second, we find that professionals' beliefs about the riskiness of the asset (i.e., risk perception) has changed substantially across both waves, as they consider the experimental asset to be less risky in March 2020 than in December 2019. This can be explained by the neuroscientific concept of adaptive normalization (Payzan-LeNestour et al., 2020). Compared to the COVID-19-induced crash, the asset's volatility in the experiment appears to be relatively moderate in March 2020. In contrast, in December 2019, the very same volatility of the asset appears to be large compared to the experiences of a years-long bull phase in real-world markets. Similar to Sitkin and Pablo's (1992) argument, this indicates that decision makers take less risk, because they have perceived the potentially negative consequences of doing so. Again, students showed no differences in perception of the riskiness of the stock between December 2019 and March 2020. Note that risk perception in this study is distinct from risk attitudes. Risk perception is elicited by asking subjects about their perceived riskiness of a particular stock and thus, relies on individual judgments (i.e., beliefs). Therefore, these subjective judgments can be influenced by individuals' reference assets (e.g., the riskiness of real-world assets) and experiences from the past, rendering lower levels of risk perception in March 2020 plausible.

As a further contribution of this paper, we ask the research question whether a *volatility shock in the experiment* can affect investment behavior such as risk taking and a stock's risk perception. We answer this question irrespective of the timing (i.e., December 2019 or March 2020) of the experiment. In each wave, we apply the same 2×3 factorial treatment design with the "presentation format" (i.e., PRICES or RETURNS displayed in the charts) and the direction of the "experimental shock" of the stock (i.e., DOWN, STRAIGHT, or UP) serving as treatment variables. This design allows us to control for the role of framing effects in the display of stock price dynamics (e.g., Glaser et al., 2007, 2019) and for behavioral reactions to different types of shocks *within* an experimental setting.

As a third major finding, we show that finance professionals and students exhibit qualitatively similar reactions to volatility shocks in the experiment, but also show some marked differences: (i) Finance professionals' investment propensity is negatively associated with the direction (down, straight, or up) of the shock. Students, in comparison, show lower investment levels in general, and change their investment behavior following the experimental shocks to a lower degree. (ii) Finance professionals perceive all experimental shocks (down, straight, or up) to increase risk perception similarly. Students differ, as they do not perceive upwardly trending shocks to increase the riskiness of the stock. (iii) Finance professionals' and students' investment satisfaction levels are positively correlated with the direction of the experimental shock, and the shifts in satisfaction are short-term.

With this distinction between measuring behavioral reaction to a real stock market crash and a volatility shock within the experiment, we believe we point at an important methodological lesson. We find evidence that the effect of extreme real-world events – in this case the combination of a global pandemic which set off a stock market crash and an economic crisis – with all consequences like fear and uncertainty about the future can work differently from "laboratory-induced" crashes that do trigger comparable fundamental changes in behavior. That is, in laboratory shocks, professionals invest more (less) after a downward (upward) shock, pointing at a pattern related to the disposition effect. Following a massive real-world shock like the COVID-19 pandemic, however, professionals invest less throughout the experiment than before potentially due to a general shift in risk attitudes.

With this study, we contribute to different research strands. First, we add to the literature on reinforcement learning. Generally speaking, this literature shows that choices can depend on the decisions or payoffs experienced in the same actions in the past, even if some circumstances of the decision problem have changed (Camerer and Hua Ho, 1999). More specifically, Cogley and Sargent (2008), for instance, argue that the Great Depression created a long-lasting shift toward pessimistic beliefs. Translating the idea of reinforcement learning to stock market experiences, Greenwood and Nagel (2009) show that young mutual fund managers were more strongly invested in tech stocks at the bursting of the dot-com bubble at the beginning of 2000 than older managers. Graham and Narasimhan (2005) find that those who experienced the Great Depression as managers were more conservative with leverage in their capital structure decisions. Guiso et al. (2018) find that risk aversion increased substantially during the financial crisis in 2008, which led to reduced portfolio holdings in risky assets among private investors. We contribute by running a framed field experiment allowing us to control for potentially confounding factors (e.g., changes in wealth levels and stock price expectations) that render identification with empirical data difficult.

Second, we add to the literature on countercyclical risk aversion which is a major ingredient of asset pricing models, explaining countercyclical risk premia for stocks (e.g., Campbell and Cochrane, 1999; Barberis et al., 2001). Elevated levels of risk aversion during a bust imply that individuals demand a higher risk premium. Increased risk aversion could deepen crises even more, as lower investment levels reduce demand for assets, which could further dampen stock prices, in turn increasing risk aversion even more. Conversely, booming stock prices could be fueled by lower levels of risk aversion and higher investment levels, thus amplifying upward pressure on stock prices. Taken together, these patterns could be responsible for excess volatility in financial markets. Extending the findings of Cohn et al. (2015), König-Kersting and Trautmann (2018), and Alempaki et al. (2019), we contribute with an experimental test of changes in risk taking in a setting triggered by a real-world stock market crash rather than by priming in the experiment.

Finally, we add to studies on risk perception.[3] In a related study, Payzan-LeNestour et al. (2016) explore "variance after-effects". The authors report that perceived volatility is smaller after exposure to high volatility and vice versa. Consequently, they propose variance as constituting an independent cognitive property distinct from sensory effects, which can distort risk perception. Similarly, Payzan-LeNestour et al. (2020) find that people systematically underestimate risk after prolonged exposure to high risk, as they get accustomed to high volatility. We contribute by showing that the experience of real-world crashes can systematically reduce the level of risk perception among financial professionals. Thus, we are able to separate crash-induced changes in risk taking (risk preferences) from changes in beliefs about the asset's riskiness (risk perception) in a controlled manner.

Our study has several potential limitations. First, we refrained from running the experiment with the same professionals and students in both waves. The major reason were learning effects between both waves, letting subjects potentially anticipate the experimental shocks from

[3]Recently, studies have investigated framing effects in risk perception and financial decision-making, analyzing the presentation of return charts vs. price charts: e.g., Weber et al. (2005), Diacon and Hasseldine (2007), Kaufmann et al. (2013), and Huber and Huber (2019). More generally, our study also relates to findings on the impact of display format (returns or prices) and the framing of the investment decision. In a series of experiments with students, general population samples, and professionals, Grosshans and Zeisberger (2018) and Schwaiger et al. (2019) demonstrate that the *sequence* of returns (i.e., the shape of the price path) has a systematic effect on investors' satisfaction. Participants prefer an initial downturn with a subsequent price increase (down-up stocks) to an initial surge with a subsequent price decrease (up-down stocks), given identical prices at the end.

the beginning in WAVE 2. Reassuringly, in Section 2.3, we show that the subjects' characteristics across waves do not differ. Second, the economic crisis and the stock market crash around the COVID-19 pandemic are unique, as they combine a global economic crisis (a stock market crash) with uncertainty about the development of a health crisis (i.e., the pandemic). It is common in major economic crises that several factors influence behavior simultaneously. For instance, the crisis could trigger a wealth decline and a lower expected path for future labor income. Classic background risk – uninsurable or uninsured risk – could have increased the risk of job loss. The unforeseeable development of the pandemic (in March 2020) could have induced additional fear among participants regarding health issues. However, we cannot and do not claim which particular factors might have contributed to changes in investment behavior and risk perception. In contrast, we utilize this extreme real-world event to investigate changes in risk aversion and risk perception in a controlled laboratory setting. This would be difficult with empirical or survey data, as, for instance, lower portfolio shares of risky assets could be attributed to increased risk aversion, lowered beliefs about the future outlook, lowered wealth levels due to losses or an unobservable combination of all three ingredients. In our experiments, we keep the decision environment identical across both waves, allowing us to control for beliefs and wealth effects in the experiment.

2 The Experiment

2.1 The Investment Task

In each treatment, we sequentially presented subjects with 100 daily returns of a risky stock, whose returns were based on historical data from the NASDAQ and DAX indices, respectively. Every 0.5 seconds, one of the 100 returns was realized and was added either to a return bar chart or a price line chart, depending on the treatment. Returns during non-shock periods were taken from calmer times from the same index as the respective shock. We modeled the volatility shock in the following way. The DOWN shock was either the NASDAQ crash from April to May 2000 or the DAX crash from September to October 2008. The UP shock contained the mirrored returns from the DOWN shock; STRAIGHT was a sample of returns from UP and DOWN returns, but selected in a way to arrive at a total period's return close to zero, while having the same standard deviation as in the other shock paths.[4]

Figure 2 shows the return distributions of the calm and turbulent periods for the three different experimental shock (treatment) conditions (DOWN, STRAIGHT, UP), respectively. Figure 3 depicts

[4]The standard deviation of returns was 0.93 percent in non-shock periods vs. 4.99 percent in the shock periods. The roughly five-fold increase in volatility is comparable to the one we saw in real stock markets in March 2020 compared to December 2019, i.e., the two waves of this experiment.

the representative sequence of action for the "DOWN" time series. In all time series, we modeled the pre-shock phase in periods 1 and 2, the shock in period 3, and the post-shock phase in periods 4 and 5.

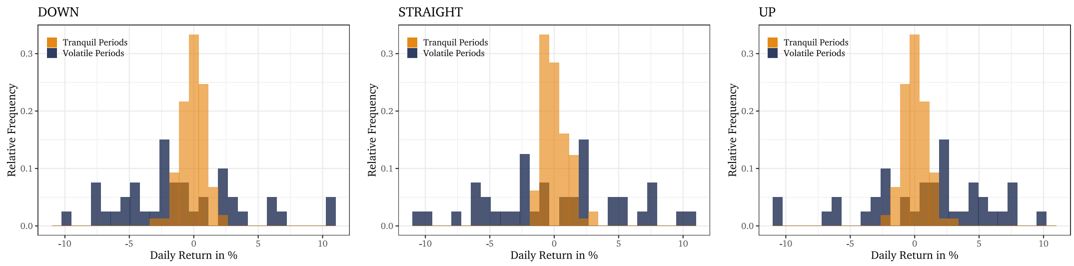


Figure 2: Histograms of daily returns of the time series used in the experiment for all three treatments. The returns from the volatile periods (blue) represent the shock period (period 3), and the returns from the calm (tranquil) periods (orange) were used in the periods preceding and following the shock.

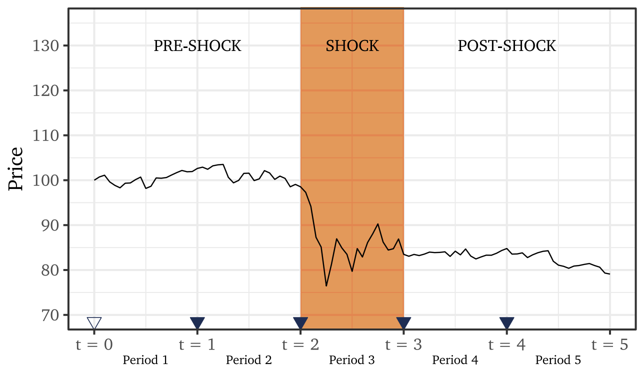


Figure 3: Sample sequence of action in one of the experimental time series used. The pre-shock period is the time up to $t = 2$, the shock period is implemented in period 3, and the post-shock phase runs from periods 4 to 5. At $t = 1$, $t = 2$, $t = 3$, and $t = 4$, subjects had to answer a number of questions in addition to deciding which percentage of their endowment to invest in the risky stock; at $t = 0$, subjects only decide which percentage of their endowment to invest.

Every 20 return draws (every 20 trading days, referred to as one trading month in the experiment), i.e., five times for each stock, the subjects had to make a number of decisions. This allows us to elicit the following variables (see also the experimental instructions in Online Appendix A for further details)[5]:

[5]In the experiment, we also asked questions about a subject's recommendation of the stock ("If you were an analyst, would your recommendation for the stock be SELL, HOLD, or BUY?": Likert scale ranging from "strong sell" (1) to "strong buy" (5)) and about a subject's optimistic and pessimistic forecast for the stock price (e.g., "What is your optimistic/pessimistic estimate for the price at the end of the next month? (only in 5% of cases the actual price will be above/below this price)") for price or return predictions. To keep the paper short and concise, we report results for the recommendations and for the difference between a subject's optimistic and pessimistic forecasts in the Online Appendix.

INVESTMENT: Percentage invested in the (risky) stock ("What percentage of your wealth do you want to invest in the risky stock in the next month?", from 0% to 100%).

RISK PERCEPTION: Perception of the stock's risk ("How risky do you perceive this stock on the basis of its past returns?", Likert scale ranging from "not risky at all" (1) to "very risky" (7)).

PRICE FORECAST ("What is your estimate of the most likely price at the end of next month?", only if prices are displayed).

RETURN FORECAST ("What is your estimate of the most likely monthly return in the next month?", only if returns are displayed).

SATISFACTION: Satisfaction with the stock ("Please state your satisfaction with the stock on a scale ranging from -3 to 3, where -3 indicates 'very unsatisfied' and 3 indicates 'very satisfied.' ").

2.2 Treatments

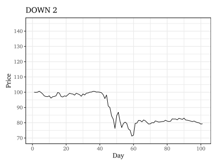
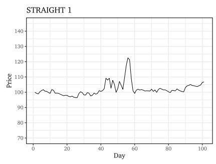
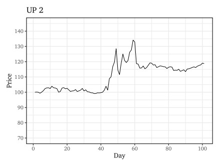
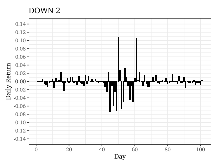
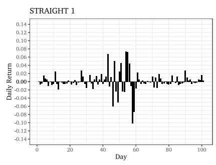
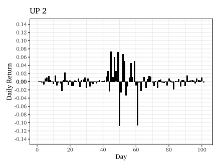
In a 2×3 design, we varied the "presentation format" (PRICES or RETURNS) and the "experimental shock" of the stock (DOWN, STRAIGHT, or UP). In a between-subjects design, subjects were randomly assigned to one of two presentation format conditions. That is, each subject was presented with each of the path types DOWN, STRAIGHT, and UP of the same presentation format in random order. We consider this treatment variable to be important, as a number of studies addressing framing effects find substantial behavioral differences in the presentation format of stock prices (e.g., Glaser et al., 2007, 2019). The authors report that return forecasts as opposed to price forecasts result in higher expectations, whereas displaying static historical returns instead of historical prices yields lower expectations. In addition, we motivate our second treatment variable—the underlying shock in the experiment (DOWN, STRAIGHT, or UP)—by the importance of learning more about individuals' reactions to extreme events within a laboratory environment.[6]

Summing up, each subject was presented with each of the path types DOWN, STRAIGHT, and UP of the same presentation format in random order. In each path (stock), 100 returns were revealed over time, each lasting for 0.5 seconds, with decisions to take every 20 return draws. Consequently, each subject made five decisions per stock and thus, 15 decisions overall. For an

[6]Regarding the experimental "shocks," we are particularly interested in shifts in volatility, which are common in financial markets: In contrast to early seminal models in finance assuming constant volatility (e.g. Merton, 1969; Black and Scholes, 1973), it is now widely acknowledged that volatility varies over time (see for example Andersen and Bollerslev, 1997; Alizadeh et al., 2002; Mandelbrot and Hudson, 2008) and that calm times are interrupted by (high-)volatility clusters. Crucially, financial (volatility) shocks have been shown to be related to uncertainty in the real economy, and they can cause and propagate recessions (e.g. Ludvigson et al., 2019). Importantly, we refer to total volatility in financial markets as simply *volatility* as a distinct concept from real economic (output) uncertainty (Ludvigson et al., 2019) and for simplicity, do not distinguish between a (stable) long-run component and a (fluctuating, mean-reverting) short-run component of volatility (e.g. Ding and Granger, 1996; Engle and Lee, 1998; Gallant et al., 1999; Alizadeh et al., 2002; Chernov et al., 2003; Adrian and Rosenberg, 2008; Chiu et al., 2018).

overview, see Table 1, and for details on each of the applied price and return paths, respectively, see Figures B1 and B2 in Appendix B.

Table 1: Between- and within-subjects treatment structure with a 2×3 factorial design. The treatment variable "presentation format" was implemented such that subjects were presented with charts composed of either PRICES or RETURNS. The treatment variable "experimental shock" (DOWN, STRAIGHT, or UP) was implemented within-subjects such that each subject experienced all three paths (either in the return or the price chart condition) but in a randomized order.

		Experimental shock (within-subjects)		
		DOWN	STRAIGHT	UP
Presentation format (between-subjects)	PRICES			
	RETURNS			

2.3 Experimental Procedure

In both waves of the experiment, subjects were exposed to the identical investment task in which we sequentially presented the same set of 100 daily prices or returns of the risky stock.[7]

In particular, we invited financial professionals from our proprietary subject pool of professionals (www.before.world), some of whom had already participated in lab-in-the-field or online experiments of different types (e.g. Kirchler et al., 2018; Schwaiger et al., 2019; Weitzel et al., 2019). In total, 315 financial professionals and 498 economics and business students from the Innsbruck EconLab at the University of Innsbruck completed the experiment. The professionals are based in Europe and work predominantly as portfolio and investment managers, traders, or financial advisors. 202 professionals (282 students) participated in WAVE 1 in December 2019; 113 pro-

[7]By designing our experiment and letting the asset distribution "develop" over time, we drew indirectly on literature on "learning from experience" (Hertwig et al., 2004). Comparing decisions from descriptions and decisions from experience, a number of studies identify a description-experience gap in risky choice (for an overview, see Hertwig and Erev, 2009). In the context of financial investment decisions, Kaufmann et al. (2013) introduce a "risk-tool," which forces experimental participants to interactively sample possible investment outcomes using simulations. The authors report that the combination of experience sampling and distribution display leads to more risk taking, more realistic expectations, and fewer biases such as overestimation of loss probabilities. Similarly, Bradbury et al. (2015) show that simulated experience (i.e., sampling a number of returns from a given distribution) improves investors' calibration regarding a stock's risk and their investment decisions compared to decisions purely based on description.

fessionals (216 students) participated in Wave 2 between March 16 and March 31 at the climax of the COVID-19 stock market crash.

Importantly, no subject participated in both waves. We consciously refrained from running the experiment with the same professionals and students in both waves. The first reason was that subjects could have remembered the experiment in which they participated three months previously, and therefore, they might have anticipated the experimental shocks from the beginning in Wave 2. This argument particularly applies to the professionals, as they rarely participate in experiments, increasing the likelihood they would remember parts of the experiment (i.e., especially the crashes). The second reason was potential attrition from the first to the second wave, leaving us with too small a sample among the professionals.

Therefore, we decided to recruit new subjects for Wave 2 from the same subjects pools (i.e., www.before.world and Innsbruck EconLab) used in Wave 1, and we are confident that the subjects' characteristics across waves do not differ. Table C1 in the Online Appendix outlines sociodemographic information of the experimental subjects across the waves. On average, professionals were 37.9 (39.2) years of age at the time of the experiment (SD = 8.5 (9.5)) in Wave 1 (Wave 2), the fraction of female participants among all professionals was around 15 percent across the waves, the fraction of professionals with a university degree was 86 percent and nearly 30 percent of professionals selected investment and portfolio management as their primary job function, followed by trading and financial advice. Notably, none of the differences in demographics between the two waves are statistically significant at the 5%-level, indicating no impact of the professionals' sample compositions on behavioral differences between the two waves. In line with the professionals, the student samples in both waves did not differ from each other either. For further details on the sample composition, see Table C1 in the Online Appendix. For further details on the (unlikely) impact of unobservable variables on our major findings, see our application of Oster's (2019) approach outlined in Section 3.1.

After the main experiment, we elicited subjects' self-reported general and financial risk tolerance with survey questions from the German Socio-Economic Panel (GSOEP; see Dohmen et al., 2011), their cognitive reflection abilities using two (not well-known) cognitive reflection test (CRT) questions from Toplak et al. (2014), and a number of demographics (age, gender, education, profession). Table C1 in the Online Appendix shows that professionals answered, on average, 1.3 CRT questions correctly, which is 0.3 correct answers more than the students' average ($p < 0.005$, Mann-Whitney U-test, $N = 813$). Moreover, professionals' self-reported general (7.5 across the two waves) and financial risk tolerance levels (7.7) were markedly higher than those reported by students (general: 6.6; financial: 5.5; $p < 0.005$ for both, Mann-Whitney U-tests, $N = 813$).

At the end of the experiment, we randomly selected one of the five months (investment decisions) from one of the three paths for payment. A subject's percentage return from the randomly selected month times three was added to an endowment of EUR 20. Student subjects' endowment was

EUR 5.[8] Financial professionals earned, on average, EUR 20.27 with a standard deviation of EUR 3.87 (5.45 and 0.82 for students, respectively) and minimum and maximum payments of EUR 8 and EUR 32 (2 and 8 for students, respectively). The median duration of the experiment was 20.4 minutes for professionals and 19.4 minutes for students.[9]

3 Results

3.1 Behavioral Differences Between December 2019 and March 2020

Figure 4 and Table 2 show the main results of this study. We plot the mean values of the percentage invested (first line), risk perception (second line), return or price forecasts (third and fourth lines, respectively), and finally, satisfaction levels for the periods before the experimental shock ("pre-shock") and the periods after the experimental shock ("post-shock") in the experiments of WAVE 1 (blue bars) and WAVE 2 (orange bars). The data of the professionals are shown in the left columns and those of student subjects are displayed in the right columns. In Table 2, we report summary statistics for both waves and both subject pools. In the column "Diff.," we show the effects sizes for differences between waves and the associated test statistics for double-sided t-tests.

Result 1: Finance professionals show less risk-taking behavior in WAVE 2 of the experiment. In contrast, students do not exhibit changes in risk taking.

Support: As outlined in Table 2, we find a drop in investment levels of 9 percentage points (from 77 to 68 percent of their endowment, $p < 0.005$ following Benjamin et al., 2018) from December 2019 to March 2020, although the investment task was identical.[10] Moreover, we show that the return and price forecasts in the experiment are indifferent between the two waves (see lines 3 and 4 in Table 2). With this finding, we can infer that differences in investment levels are not driven by price or return beliefs, but by changes in risk attitudes.

In Table 3, we go one step further and run ordinary least squares (OLS) regressions for the percentage invested (Investment). Notably, results are robust to different regression models and

[8]For instance, if a subject invested 70% of her wealth in the risky stock in the randomly selected month and the stock's return in this month was 15%, then the return from this month would have been 70% × 15% = 10.5%. The subjects' payment from the experiment would have been EUR 20 × (1 + 10.5% × 3) = EUR 26.30.

[9]This hourly wage of approximately EUR 60 for professionals is comparable to, for instance, Haigh and List (2005), Kirchler et al. (2018), and Weitzel et al. (2019), who report hourly payments of USD 96 (equivalent to EUR 73 at the time of their experiment), EUR 72, and EUR 65 for their professionals, respectively.

[10]With a sample size of 315 financial professionals (498 students) and a significance level of $\alpha = 0.05$, the two-sided t-tests reported in Table 2 allow us to detect a small- to medium-sized effect of $d = 0.33$ ($d = 0.25$) with 80% power. The least squares regressions presented in tables 3 and 4 suffice to detect effect sizes f^2 between 0.02 (without covariates, full professionals sample) and 0.09 (with covariates, only prices/only returns) with 80% power (minimum detectable effect sizes for students are even smaller due to the larger sample size).

specifications.[11] We run separate regressions for each subject pool, and we add control variables like answers to the questions on general and financial risk taking from the GSOEP, CRT score, age, and gender next to a dummy variable depicting observations from the second wave (dummy WAVE 2). We find a statistically significant drop of 8.9 percentage points (6.9 percentage when adding control variables; $p < 0.005$ and $p < 0.05$, respectively) in the fraction invested in the risky asset from WAVE 1 to WAVE 2.

Investment propensity is further driven by self-reported risk tolerance in financial matters and by CRT scores. In other words, those who report they were willing to take higher risks in financial markets are those who invest more in the experiment compared to their peers. Notably, we do not find statistically significant differences in self-reported survey measures of risk tolerance in general and financial matters across the waves for each subject pool (see Table C1 in the Online Appendix). Thus, one can conservatively infer that the COVID-19 crash primarily influenced professionals' incentivized investment behavior as reported in the experiment rather than a general and abstract propensity to take risks.

Turning to the CRT scores, we show that the subjects with higher cognitive abilities are those with higher investment levels in the experiment. As we find no statistically significant differences between professionals' characteristics in WAVE 1 and WAVE 2, we expect selection on *observables* not to influence the results (see Table C1 in the Online Appendix for the non-statistically significant differences in subject characteristics across the waves). In addition, sensitivity analyses following Oster (2019) show that it is unlikely that the estimated effect between the waves is driven by *unobservable* variables.[12]

Importantly, student subjects do not show any differences in investment behavior before and during the stock market crash. Reassuringly, their general investment behavior across the two waves of the experiment is strongly driven by their self-reported levels of general and financial risk tolerance. This finding is also shown in the professional sample and supported by previous studies by, for instance, Kirchler et al. (2019). The absence of behavioral differences across the waves in the student sample further accompanies the explanation of professionals' changes in risk-taking behavior that is driven by the experience of the stock market crash in March 2020. Students potentially did not experience the extreme crash in the stock market as severely as professionals did.

[11]See Table C3 for the analogous Tobit models in which the outcome variable, INVESTMENT, is censored to lie between 0 and 100 percent, and Table C5 for interaction effects between the subject pool and the experimental wave.

[12]We apply the approach suggested by Oster (2019) and examine coefficient movements with respect to movements in R^2 to rule out potential omitted variable biases. Assuming that the inclusion of omitted variables can lead to a maximum attainable R^2 of 0.34 ($= 1.3R^2$ from Model (6) in Table 3, and related investment tasks, such as Ehm et al., 2014, Cohn et al., 2017, and Kirchler et al., 2018 report R^2s between 0.08 and 0.26), we compute a relative degree of selection on observed and unobserved controls of $\delta = 7.71$. Thus, a selection on unobservables would have to be 7.71 times as strong as selection on observables for the significant difference in INVESTMENT between WAVE 1 and WAVE 2 to vanish.

This claim is backed up by survey questions asked in the experiment.[13] Only roughly one third of students in the experiment indicated they had invested in financial products at least once during the preceding five years. In addition, more than two thirds of students reported they consulted financial news only once a week or less often.

Table 2: Summary statistics and differences between WAVE 1 (December 2019) and WAVE 2 (March 2020) for the INVESTMENT (percentage invested, from 0% to 100%), RISK PERCEPTION (Likert scale from 1 to 7), RETURN FORECAST (open question), PRICE FORECAST (open question), and SATISFACTION (Likert scale from –3 to 3) for financial professionals and student subjects. Columns WAVE 1 and WAVE 2 show mean values for each variable with standard deviations in parentheses. The Diff. columns outline the respective differences between WAVE 1 and WAVE 2 for each subject pool; t-statistics for differences between waves are provided in parentheses (double-sided t-test). The stars * and ** indicate the 5% and the 0.5% significance levels, respectively.

	Financial Professionals			Students		
Variable	WAVE 1	WAVE 2	Diff.	WAVE 1	WAVE 2	Diff.
INVESTMENT	76.94	68.02	−8.92**	57.47	55.99	−1.49
	(26.17)	(31.96)	(−2.99)	(29.61)	(30.31)	(−0.66)
RISK PERCEPTION	4.89	4.55	−0.34**	4.80	4.73	−0.07
	(1.36)	(1.29)	(−3.29)	(1.40)	(1.43)	(−1.01)
RETURN FORECAST	1.63	1.62	−0.01	3.53	3.52	−0.01
	(9.09)	(13.01)	(−0.08)	(15.95)	(20.65)	(−1.00)
PRICE FORECAST	100.75	100.78	0.03	102.69	102.82	0.14
	(12.76)	(15.35)	(0.11)	(18.55)	(22.74)	(1.00)
SATISFACTION	−0.12	−0.06	0.06	−0.53	−0.48	0.05
	(1.66)	(1.53)	(0.74)	(1.71)	(1.67)	(1.18)
Observations	202	113		282	216	

Result 2: Finance professionals' perception of the riskiness of the experimental asset drops markedly during the COVID-19 stock market crash. In contrast, students do not exhibit changes in risk perception across the waves.

Support: We show evidence of professionals' decrease in risk perception of the experimental asset as a reaction to the stock market crash (see Table 2). In particular, we find a statistically significant decrease in the perception of the riskiness of the asset (drop from 4.89 to 4.55, $p < 0.005$) from December 2019 to March 2020. In Table 4, we run OLS regressions and control for general and financial risk taking from the GSOEP, CRT score, age, and gender next to a dummy variable

[13]We asked students "Have you invested in financial products (e.g., stocks, funds, etc.) in the last 5 years?" ("Yes" or "No") and "How many times have you informed yourself about financial news in the last month?" ("Daily", "Several times a week", "Once a week", "Less than once a week", or "Never").

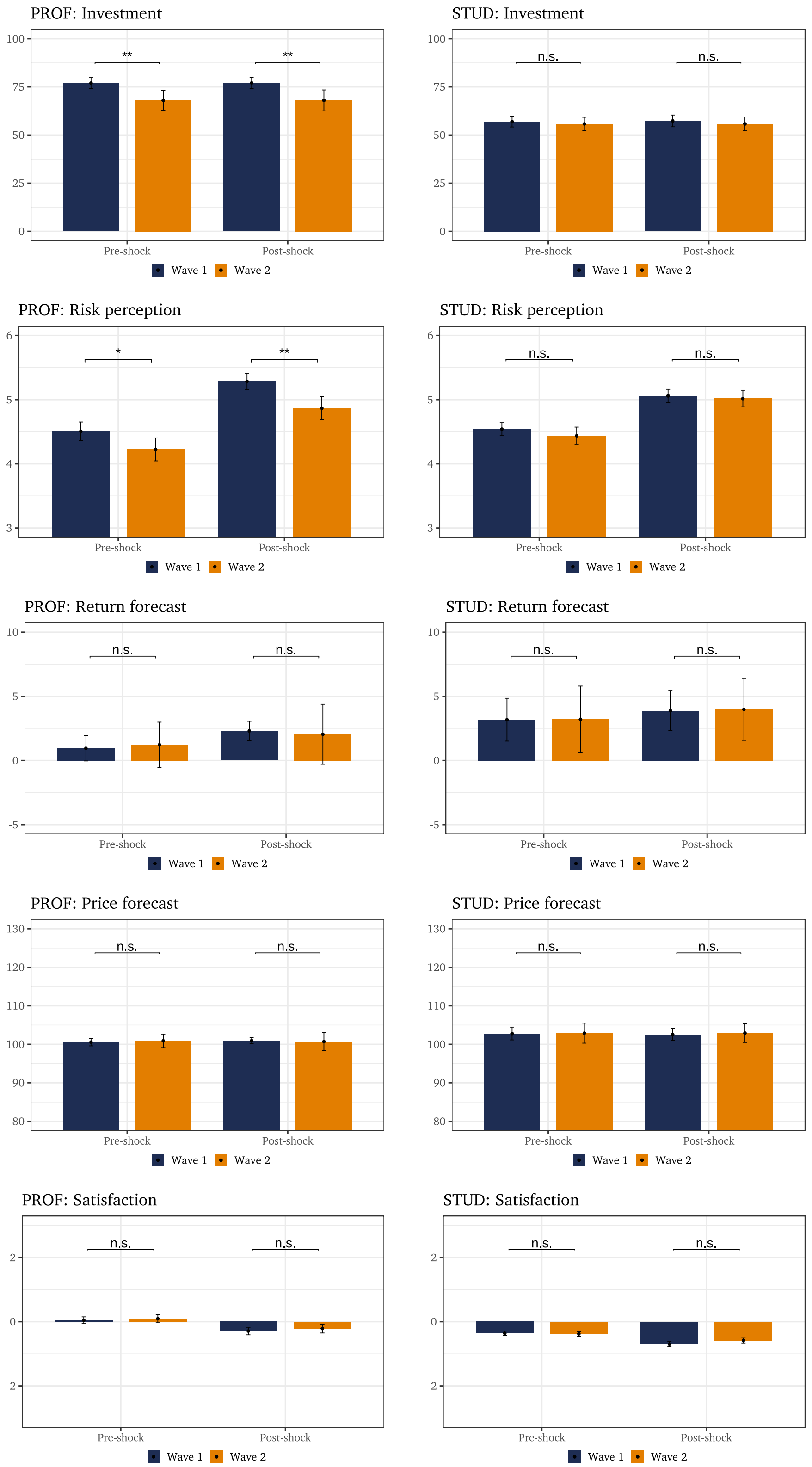


Figure 4: Descriptive overview for INVESTMENT, RISK PERCEPTION, RETURN FORECAST, PRICE FORECAST, and SATISFACTION for WAVE 1 (December 2019) and WAVE 2 (March 2020) for financial professionals (PROF) and student subjects (STUD). Columns WAVE 1 (blue bars) and WAVE 2 (orange bars) show the mean values for each variable. "Pre-shock" ("Post-shock") indicates the periods before (after) the experimental shock. The whiskers indicate the 95% confidence intervals. * and ** indicate the 5% and the 0.5% significance levels, respectively.

Table 3: INVESTMENT: Ordinary least squares regression analyses for each subject pool (financial professionals and students) and each presentation format (RETURNS or PRICES) for both waves. WAVE 2 is a dummy variable taking the value 1 for observations from the second wave (March 2020), zero otherwise. Models 4–6 and 10–12 are run with control variables, such as a subject's self-reported risk tolerance in general and financial matters following the German SOEP questions, CRT score, age, and gender. The stars * and ** indicate the 5% and the 0.5% significance levels, respectively.

	Dependent variable: INVESTMENT											
	Financial Professionals						Students					
	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WAVE 2	−12.191**	−5.231	−8.925**	−8.152*	−5.637	−6.866*	−1.497	−1.389	−1.486	−1.919	−0.841	−1.247
	(4.044)	(4.187)	(2.969)	(3.586)	(3.542)	(2.548)	(3.089)	(3.221)	(2.240)	(2.731)	(2.840)	(1.997)
General risk tolerance				2.353	0.162	1.151				2.695**	2.324**	2.469**
				(1.239)	(0.994)	(0.786)				(0.700)	(0.797)	(0.547)
Financial risk tolerance				3.168*	3.682**	3.549**				1.450	2.832**	2.190**
				(1.240)	(1.182)	(0.804)				(0.804)	(0.778)	(0.567)
CRT score				5.937*	7.268**	6.675**				1.598	−2.036	−0.299
				(2.162)	(2.394)	(1.618)				(1.680)	(1.677)	(1.191)
Age				−0.212	−0.311	−0.223				0.784	0.526	0.602
				(0.174)	(0.227)	(0.138)				(0.457)	(0.454)	(0.319)
Female				−0.652	−6.419	−3.247				−4.291	−3.175	−4.008
				(5.573)	(4.565)	(3.457)				(3.148)	(3.183)	(2.230)
Constant	74.265**	79.520**	76.945**	31.378**	52.952**	40.302**	56.164**	58.626**	57.473**	12.900	18.807	17.341*
	(2.044)	(1.920)	(1.413)	(10.973)	(13.857)	(8.545)	(1.996)	(2.001)	(1.418)	(12.797)	(11.361)	(8.476)
S.e.	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust
Observations	157	158	315	157	158	315	237	261	498	237	261	498
R^2	0.062	0.012	0.033	0.300	0.244	0.261	0.001	0.001	0.001	0.215	0.235	0.218
Adjusted R^2	0.056	0.006	0.030	0.272	0.214	0.247	-0.003	-0.003	-0.001	0.195	0.217	0.209

Table 4: RISK PERCEPTION: Ordinary least squares regression analyses for each subject pool (financial professionals and students) and each presentation format (RETURNS or PRICES) for both waves. WAVE 2 is a dummy variable taking the value 1 for observations from the second wave (March 2020), zero otherwise. Models 4–6 and 10–12 are run with control variables, such as a subject's self-reported risk tolerance in general and financial matters following the German SOEP questions, CRT score, age, and gender. The stars * and ** indicate the 5% and the 0.5% significance levels, respectively.

	Dependent variable: RISK PERCEPTION											
	Financial Professionals						Students					
	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WAVE 2	−0.311*	−0.376*	−0.350**	−0.288*	−0.332*	−0.325**	−0.144	−0.008	−0.079	−0.144	0.026	−0.066
	(0.141)	(0.155)	(0.106)	(0.146)	(0.146)	(0.106)	(0.100)	(0.115)	(0.078)	(0.100)	(0.111)	(0.077)
General risk tolerance				0.010	0.075	0.051				0.008	0.013	0.015
				(0.056)	(0.053)	(0.042)				(0.028)	(0.031)	(0.022)
Financial risk tolerance				0.047	−0.112*	−0.027				0.023	0.020	0.022
				(0.049)	(0.048)	(0.037)				(0.030)	(0.030)	(0.022)
CRT score				0.121	0.281*	0.202**				0.007	0.144*	0.074
				(0.085)	(0.103)	(0.068)				(0.061)	(0.066)	(0.046)
Age				0.016*	−0.002	0.010				−0.0004	−0.027	−0.015
				(0.007)	(0.009)	(0.006)				(0.021)	(0.018)	(0.015)
Female				−0.220	−0.134	−0.156				−0.065	−0.034	−0.045
				(0.154)	(0.224)	(0.140)				(0.095)	(0.118)	(0.077)
Constant	4.738**	5.041**	4.892**	3.564**	5.022**	4.067**	4.667**	4.912**	4.797**	4.521**	5.190**	4.861**
	(0.085)	(0.094)	(0.064)	(0.452)	(0.535)	(0.352)	(0.066)	(0.063)	(0.046)	(0.503)	(0.444)	(0.356)
S.e.	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust
Observations	157	158	315	157	158	315	237	261	498	237	261	498
R^2	0.030	0.035	0.033	0.105	0.099	0.073	0.009	0.00002	0.002	0.022	0.035	0.022
Adjusted R^2	0.024	0.029	0.030	0.069	0.063	0.055	0.005	-0.004	0.0001	-0.004	0.012	0.010

depicting observations from the second wave (WAVE 2).[14] We find that the significance levels remain unchanged when we add control variables. Risk perception seems to be partly driven by CRT scores with high-CRT professionals perceiving the asset to be riskier than others. Again, sensitivity analyses following Oster (2019, see above) show that it is unlikely that the estimated effect between the waves is driven by unobservable variable selection.[15]

Again, student subjects do not show any differences in risk perception before and during the stock market crash. Interestingly, CRT scores are not systematically correlated with risk perception in the experiment, pointing to another difference to the professional sample.

Summing up the findings from both subject pools, we conclude that professionals consider the asset to be less risky before than during the onset of the pandemic and the associated stock market crash. This result can be explained by professionals' real-world experience of different magnitudes of volatility. Compared to the COVID-19 stock market crash, the experimental asset's volatility in the experiment obviously appears to be comparatively moderate in March 2020. In contrast, in December 2019, the asset's volatility appears to be more extreme compared to the experiences of professionals in the market, following a years-long calm bull phase. Again, students exhibit no differences in risk perception between December 2019 and March 2020.

Result 3: Finance professionals' price and return forecasts and their satisfaction levels with the asset do not differ between the two experimental waves. Again, students' behavior does not differ across waves.

Support: As shown in Figure 4 and in Table 2, we observe no statistically significant differences in professionals' beliefs about the future development of the risky asset. This is interesting, as professionals experienced a downturn of 30 to 40 percent in the real-world stock markets, which could potentially lead to more pessimistic expectations in general. However, we find that beliefs are unaffected by the stock market crash in March 2020 and show, in tandem with the findings for investment levels (Result 1), that the crash likely has a more general impact on professionals' risk-taking behavior.

Moreover, we show that the satisfaction levels of student subjects did not change over time. This leaves us with the finding that student behavior did not change at all between the two waves.

[14]Results are robust to different regression models and specifications; see Table C4 for the analogous ordered logistic models catering to the ordinal nature of the outcome variable, RISK PERCEPTION, and Table C6 for interaction effects between the subject pool and the experimental wave.

[15]Assuming a maximum attainable R^2 of 0.10 ($= 1.3R^2$ from Model (6) in Table 4, and related risk perception elicitations, such as Holzmeister et al., 2020, for example, report an R^2 of 0.05), we compute $\delta = 9.58$. Thus, selection on unobservables would have to be 9.58 times as strong as selection on observables for the significant difference in RISK PERCEPTION between the waves to disappear.

3.2 Behavioral Patterns Within Waves

Figure 5 and Tables C9 and C10 in the Online Appendix show details for WAVE 1 and WAVE 2 and present the major results within both waves. In Figure 5, we plot fitted values from regressions with period dummies for $t \in \{2, 3, 4\}$ for each major variable (i.e., percentage invested and risk perception) for the presentation formats RETURNS (triangles) and PRICES (dots), the experimental shocks DOWN (blue), STRAIGHT (orange), and UP (red), and the respective interaction terms. The experimental shock always occurred during period 3. However, we use $t \in \{2, 3, 4\}$ in the regressions and figures to refer to the end of the respective period where subjects entered their decisions (see Figure 3). Figures B3 and B4 in the Online Appendix show details of the other variables, like price and return forecasts, satisfaction levels, and recommendations for both waves.[16]

In both tables, we run ordinary least squares regression analyses for each subject pool and for both presentation formats (RETURNS or PRICES) separately, and we measure differences in the dependent variables before and after the experimental shock. We treat the sample of finance professionals as the primary analysis and consider the student sample to be of secondary importance.

Result 4a: Finance professionals' investment levels are negatively associated with the direction of the experimental shock. Students, in comparison, show lower investment levels in general, and change their investment behavior following the experimental shocks to a lower degree.

Support: We show that professionals' fraction invested in the stock increases (decreases) statistically significantly after a negative (positive) experimental shock in both presentation formats. In particular, professionals invest approximately 5 and 10 percentage points more in the stock following a downward shock compared to the investment levels following a straight shock in WAVE 1 and WAVE 2, respectively (see the first and third rows in Figure 5 and columns 1 and 2 of Tables C9 and C10, $p < 0.005$). Importantly, we show no substantial differences in post-shock reactions between the presentation formats (see Tables C11 and C12 in the Online Appendix). If at all, the reaction to the volatility shocks in the investment game appears to be larger in WAVE 2 than in WAVE 1.

Students, in contrast, do not change their investment behavior following a downward shock, but reduce their invested fraction statistically significantly following an upward shock in both presentation formats by 3.2 to 4.5 percentage points compared to the levels in the condition STRAIGHT (see Figure 5). However, this finding is significant only for WAVE 1.

Result 4a points at a behavioral pattern that appears to be in line with the disposition effect (Odean, 1998), indicating that investors have a stronger preference for realizing winning rather than losing stocks. At first sight, however, Result 4a might contradict Result 1, as we observe

[16] The corresponding regression models with coefficient estimates and standard errors are provided in tables C7 and C8 in the Online Appendix. See also figures **??** to **??** in the Supplementary Data and Analyses that present more detailed time trends for all variables.

a statistically significant drop in investments following the stock market crash in March 2020 in WAVE 2, but we do not observe this drop following the experimental shock in the investment game. However, we believe that this pattern points at a very important methodological lesson. The real-world shock is an “incidental” shock and is unrelated to the experimental task. The experimental shock, however, is directly related to the task and therefore, triggers different dynamics. Thus, we conclude that extreme events in real-world stock markets with all associated consequences, such as fear and uncertainty about the future, might work differently from “laboratory-induced” shocks that cannot trigger comparable long-lasting changes in attitudes and behavior.

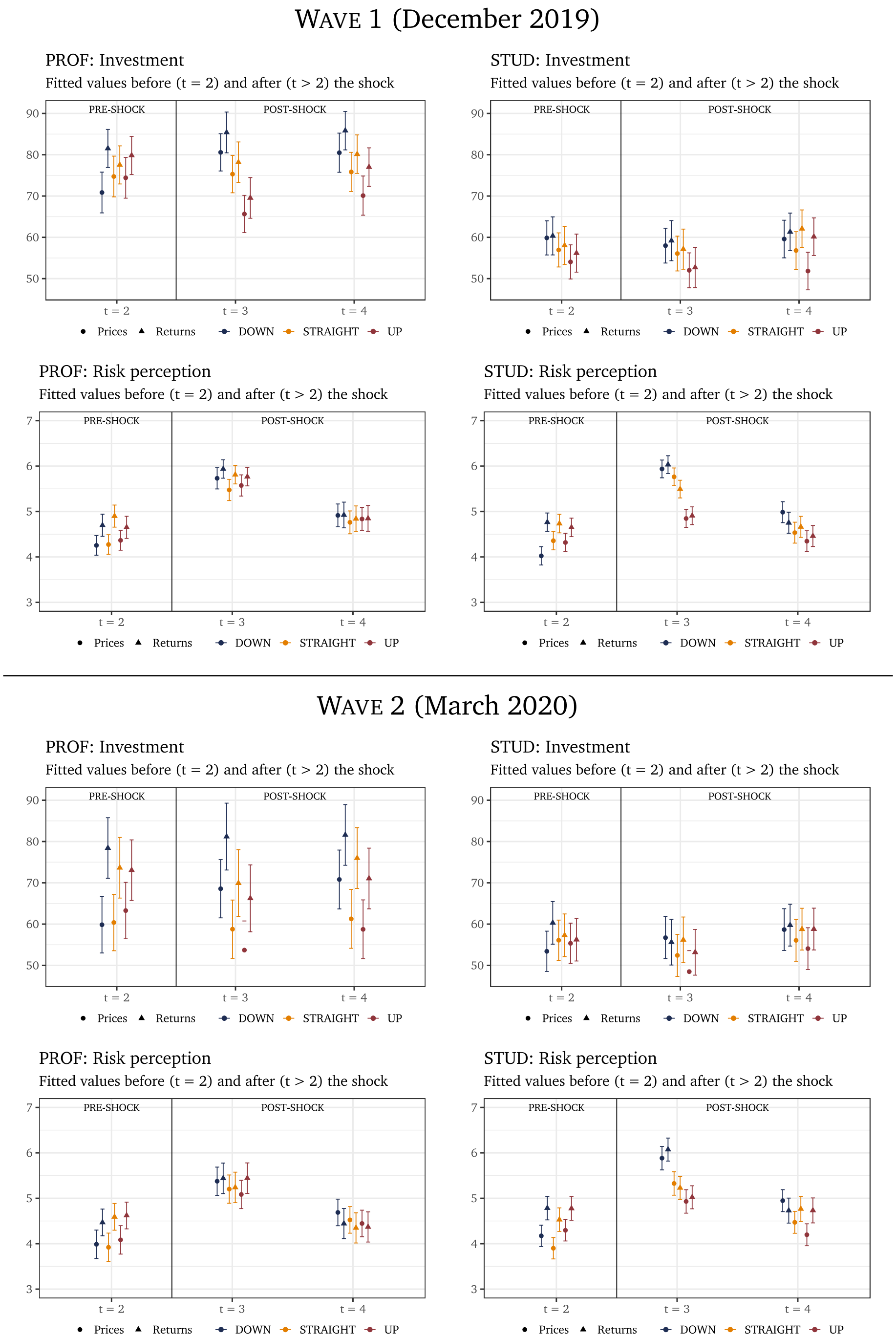


Figure 5: Fitted values of the major outcome variables (INVESTMENT and RISK PERCEPTION) before ($t = 2$; PRE-SHOCK), and after the experimental shock ($t > 2$; POST-SHOCK) for both presentation formats RETURNS (triangles) and PRICES (dots) and the shock types DOWN (blue), STRAIGHT (orange), and UP (red). Results for the professionals (PROF) are shown in the left column, those of the students (STUD) in the right column. Findings of the first wave (**WAVE** 1) are shown in the first two lines, and findings of the second wave (**WAVE** 2) are presented in the final two lines. Return forecasts are converted into price forecasts for better comparability. The whiskers indicate the 95% confidence intervals.

Result 4b: Finance professionals perceive all volatility shocks in the experiment (i.e., DOWN, STRAIGHT, or UP) to increase risk similarly, independent of the presentation format. Students show partly similar patterns, but they do not perceive an upward price or return shock to increase the riskiness of the stock.

Support: We report that all interaction terms of the post-shock phase among finance professionals are not statistically significant, pointing at no difference in risk perception between different directions of the experimental shock. Compared to pre-shock levels of risk perception, the experimental shocks increase risk perception by approximately one point on the 7-point Likert scale ($p < 0.005$, see the second and fourth rows in Figure 5 and columns 5 and 6 in Tables C9 and C10 in the Online Appendix). This finding is in contrast to Holzmeister et al. (2020), who report that professionals' and lay-people's risk perception of stocks does not vary with the stocks' volatility (i.e., standard deviation of returns). One can speculate, but the potential differences between Holzmeister et al.'s study and this study could be driven by the display mode in the experiment: Holzmeister et al. (2020) show histograms of returns, while we present evolving price and return charts over time.

We also report that professionals' reactions to shocks of different types hold similarly for price and return charts (see the interaction term POST_SHOCK × RETURNS, testing for differences after the shock between the presentation formats in Tables C13 and C14 in the Online Appendix).

However, students show different levels of risk perception of the stock in the case of downward shocks. Columns 7 and 8 in Tables C9 and C10 in the Online Appendix indicate a statistically significantly lower (higher) risk perception of an upward (downward) shock in both presentation formats and in both waves compared to straight shocks ($p < 0.005$ for prices, $p < 0.05$ for returns).

As for Result 4a, this pattern demonstrates an important methodological lesson as well. Result 4b might seem to contradict Result 2, i.e., reduced risk perception of the experimental asset in WAVE 2, but it did not. The experimental shocks during the experiment were likely judged against the periods before the shock, and thus, the stock was perceived to be riskier (Result 4b). In contrast, the entire stock's volatility across all periods was perceived as less risky in WAVE 2 than in WAVE 1, likely because the professionals' reference assets from the real world were more risky in March 2020 than in December 2019 (Result 2).

Result 4c: Finance professionals' price forecasts are in the direction of the experimental shock and do not systematically differ between the presentation formats. Students exhibit similar patterns, but show more extreme predictions when returns are presented.

Support: We find that finance professionals exhibit significantly higher (lower) price forecasts after an upward (a downward) experimental shock compared to price shocks without clear directional movement of type STRAIGHT. In particular, the professionals' price predictions following an upward shock are 15.3 higher than in the treatment with straight volatility shocks and 13.9 lower in the case of downward shocks in WAVE 1 ($p < 0.005$; findings for WAVE 2 are qualitatively identical). Note that prices change by $+16.0$ with an upward shock and -17.6 with a downward shock. Thus, predicted prices adapt well to changes in realized prices, but they under-react mildly in the downward case. The expectation in (and hope for) a mean reversion of prices may be the most important factor, also leading to increasing investments after a negative shock (and decreasing investments after a positive shock); see Figures B3 and B4 and column 9 of Tables C9 and C10 in the Online Appendix. We show in Tables **??** and **??** in the Supplementary Data and Analyses that professionals' reactions to shocks of different types do not differ between the presentation formats.

Students, however, exhibit differences in forecasts between presentation formats. Although the forecast patterns following up and downward shocks are qualitatively similar to what we observe with the professionals, students show more extreme behavior in the presentation format RETURNS. Return predictions (transformed into prices for better comparability) after straight and upward shocks are statistically significantly higher than in the presentation format PRICES ($p < 0.005$, see Tables **??** and **??** in the Supplementary Data and Analyses).

Result 4d: Finance professionals' investment satisfaction is positively correlated with the direction of the experimental shock, but drops to pre-shock levels in the final period. Students show qualitatively similar behavior.

Support: We report that professionals' satisfaction levels drop statistically significantly after a downward shock (even after a shock of the category STRAIGHT) and increase statistically significantly after an upward shock in both waves (see Figures B3 and B4 and columns 13 and 14 in Tables C9 and C10 in the Online Appendix). For instance, compared to the pre-shock treatment phase, satisfaction levels drop by approximately 1.2 points (on the 7-point Likert scale) following a downward shock and increase by close to 1 point after an upward shock in WAVE 1 ($p < 0.005$). Moreover, we show that satisfaction shifts are short-term, as satisfaction approximately reaches pre-shock levels at $t = 4$ again. These findings hold qualitatively for both presentation formats and for the student sample (see Tables **??** and **??** in the Supplementary Data and Analyses).

4 Conclusion

In this paper, we investigated how the experience of the onset of the COVID-19 pandemic and the associated stock market crash influence financial professionals' risk-taking behavior. To isolate changes in risk taking from various other factors that are active during real-world stock market crashes, we ran investment experiments before and during the climax of the crash. The experiments were conducted with 315 internationally operating financial professionals and 498 student subjects.

First, we reported that professionals' investments in the risky experimental stock dropped by 9 percentage points (or 12 percent, respectively) from December 2019 to the end of March 2020. Importantly, we did not find differences in beliefs about future price and return expectations across the two waves. This finding implies that the drop in investments was not driven by beliefs, but by elevated levels of risk aversion. This finding was further supported by the behavior of non-professionals (i.e., students). They obviously did not experience the extreme volatility cluster in the stock market to the same extent as professionals did, and therefore, the students' financial risk-taking behavior did not change.

Second, we found a potential impact of the stock market crash on professionals' risk perception, as they consider the experimental asset to be less risky in March 2020 than in December 2019. Compared to the volatility cluster in real-world markets in March 2020, the asset's volatility in the experiment appeared to be relatively moderate. In contrast, in December 2019, the experimental asset's volatility appeared to be more extreme with respect to the experiences of a years-long bull phase in real-world markets. Students exhibited no differences in risk perception between December 2019 and March 2020.

These findings emphasize the importance of the concepts of reinforcement learning and counter-cyclical risk aversion for investors' risk-taking behavior and their perception of risk. We believe that the investigation of these amplification mechanisms following booms and busts (i.e., busts increase risk aversion, which could increase downside pressure of prices further and thus, potentially contributing to an even more severe crisis and dampen price recovery) are important avenues for future research. The combination of controlled experiments with industry professionals and private investors and naturally occurring events such as real-world booms or crashes appear to be fruitful avenues for future work.

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Online Appendix to
'Market Shocks and Professionals' Investment Behavior—Evidence from the COVID-19 crash'

A Instructions of the Experiment

Dear participant,

Thank you very much for accepting our invitation to take part in this short online experiment. It takes approximately 15 minutes. The experiment has real monetary incentives and the payoff will vary depending on your decisions.

All data will be anonymous and no individual results will be disclosed publicly or to other participants of the experiment.

Please do not use your mobile phone or tablet — visibility is much better on a computer screen.
The experiment is open for the upcoming 4 weeks. If the maximum number of participants has been reached before this deadline, we will close the experiment.

Thank you very much for your contribution to science and good luck in the experiment!

——————— (new page) ———————

The Experiment

The following experiment consists of three parts. In each of the three parts, you will make investment decisions in a financial market. In each part, you have to decide in each of five months/rounds, which percentage of your wealth you want to invest in the risky stock shown in this part. The wealth not invested is held in cash.

The risky stocks' returns in all parts are based on a distribution of returns from actual historical data of large stock indices from the last 20 years. During this time, the stock indices' development was characterized by fluctuations. The distribution of daily returns for the risky stocks corresponds to earning an average daily return of 0.03% (that corresponds to an average yearly return of 6.44%) with a standard deviation of daily returns of 2.36%.
Here are some examples on the likelihood of various price fluctuations:

- In 50 out of 100 cases, the daily return is between -0.60% and 0.73%.
- In 90 out of 100 cases, the daily return is between -2.77% and 2.77%.
- In 95 out of 100 cases, the daily return is between -6.06% and 6.32%.

——————— (new page) ———————

Procedure

Each of the three parts consists of five months. At the start of each month you can invest between 0% and 100% of your wealth in the respective risky stock. If you invest less than 100% of your wealth in the risky stock, the amount not invested in the risky stock is held in cash.

Each month consists of 20 trading days and therefore contains 20 daily returns. Every 0.5 seconds, one daily return from the distribution described above is realized and displayed on the screen.

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Payment

At the end of the experiment, one of the five months from one of the three parts will be randomly selected to determine your payment. Your percentage return from this randomly selected month times three is then added to an endowment of EUR 20.

Example: If you invest 70% of your wealth in the risky stock in the randomly selected month and the stock's return in this month is 15%, then your return from this month will be $70\% \times 15\% = 10.5\%$. Your payment from this experiment is then EUR $20 \times (1 + 10.5\% \times 3) =$ EUR 26.30.

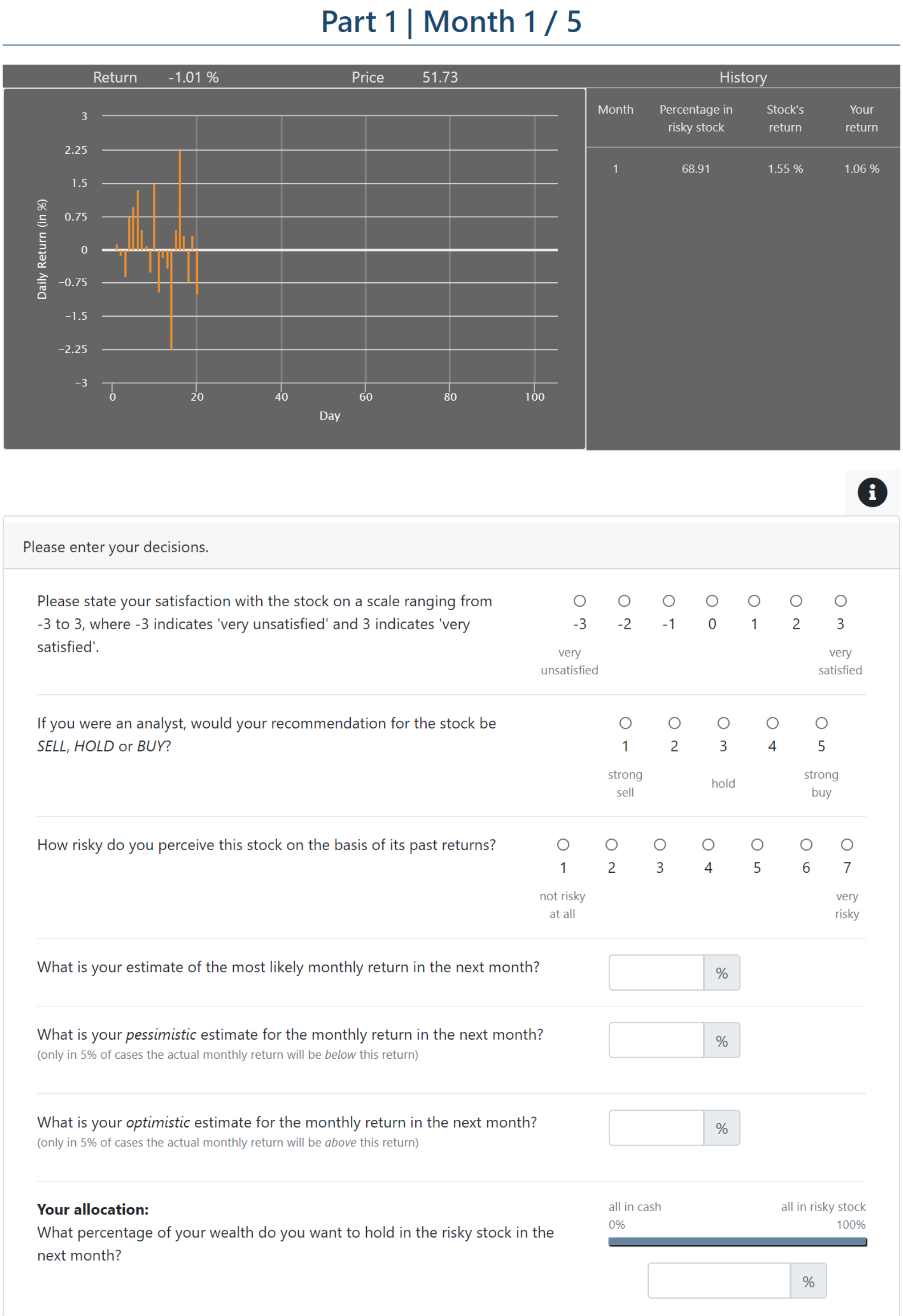

Figure A1: Screenshot of the decision screen with a RETURN chart.

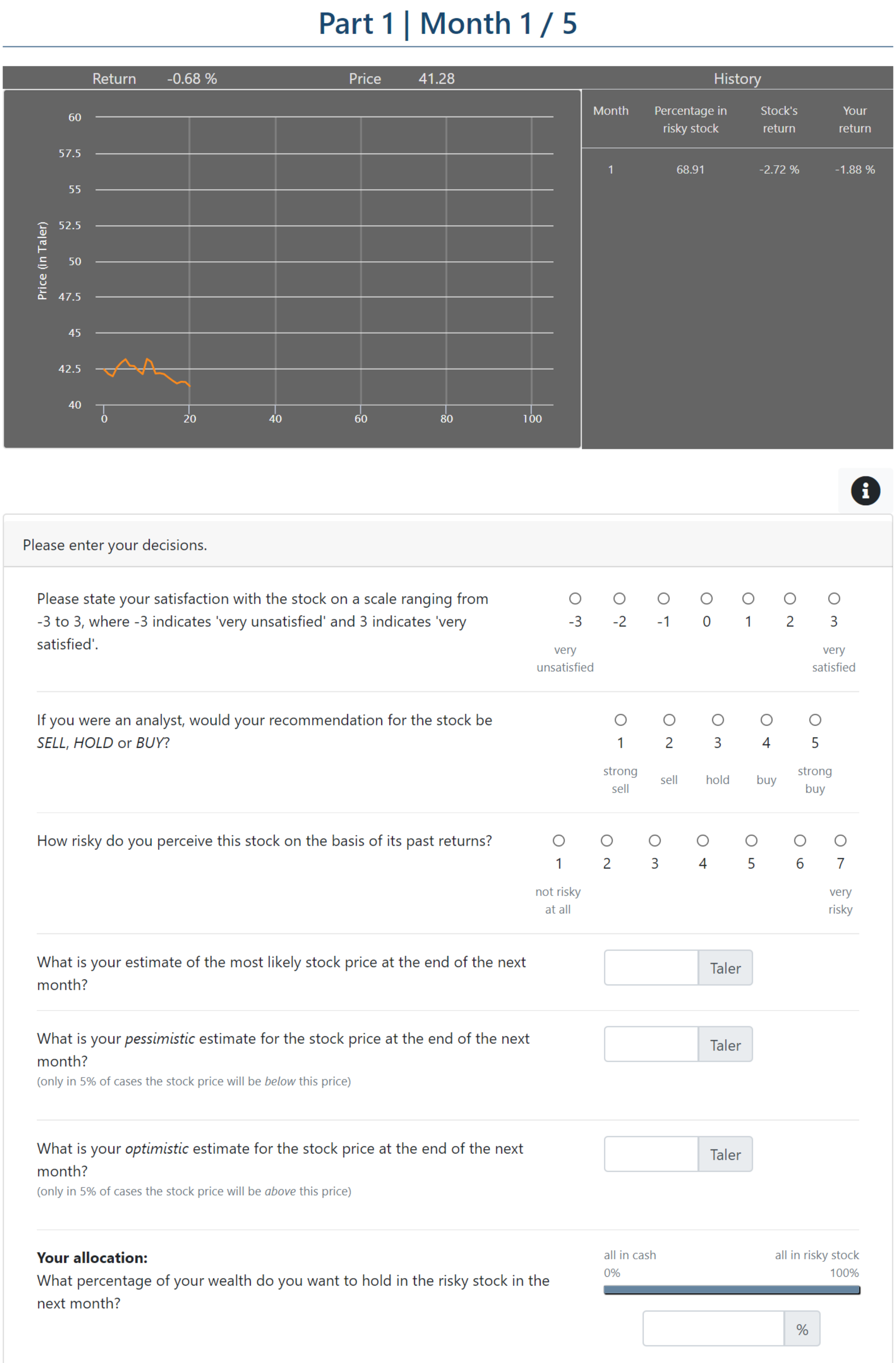

Figure A2: Screenshot of the decision screen with a PRICE chart.

B Additional Figures

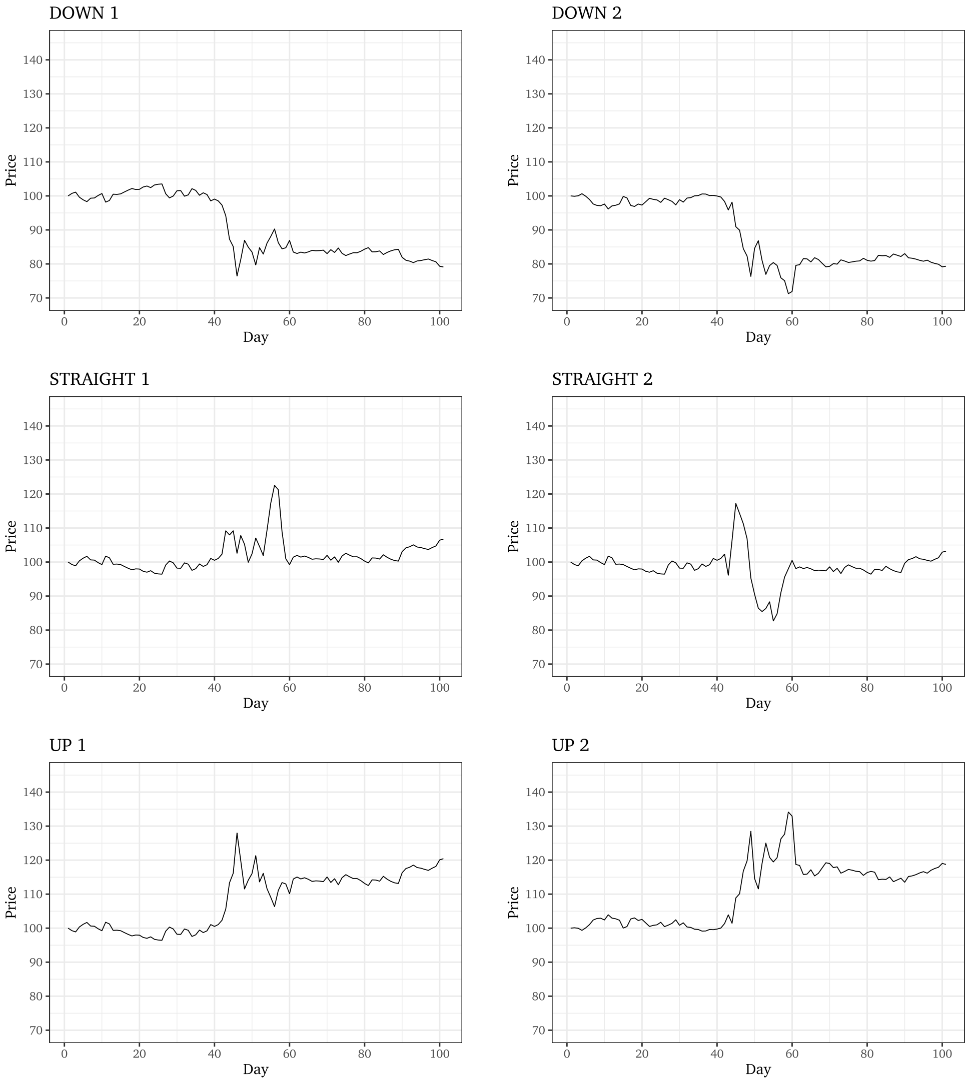

Figure B1: Price Charts: Overview over the six price paths run in the experiment. The shocks are modelled in period three. Each subject is presented with each of the path-types DOWN, STRAIGHT, and UP in random order in such a way that a subject either sees DOWN 1 and UP 2 or vice versa.

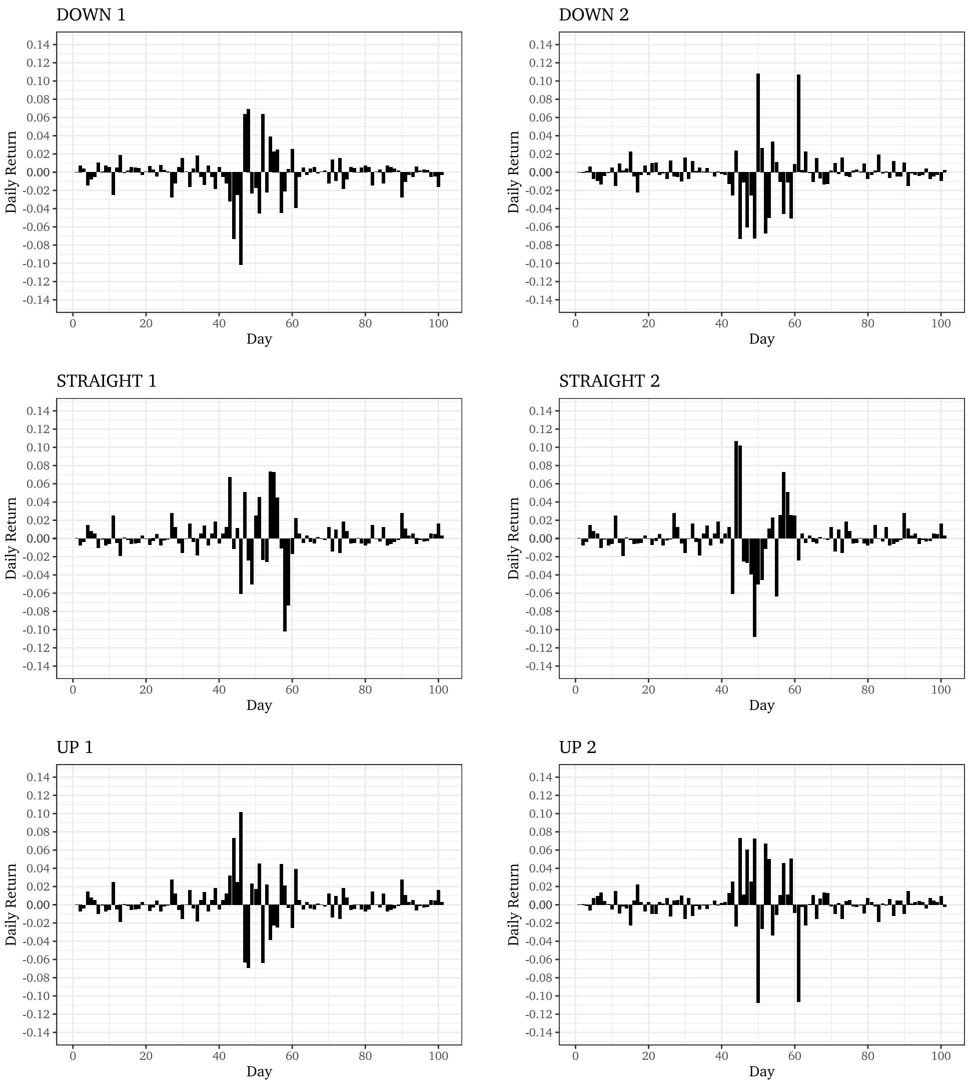

Figure B2: Return Charts: Overview over the six return paths run in the experiment. The shocks are modelled in period three. Each subject is presented with each of the path-types DOWN, STRAIGHT, and UP in random order in such a way that a subject either sees DOWN 1 and UP 2 or vice versa.

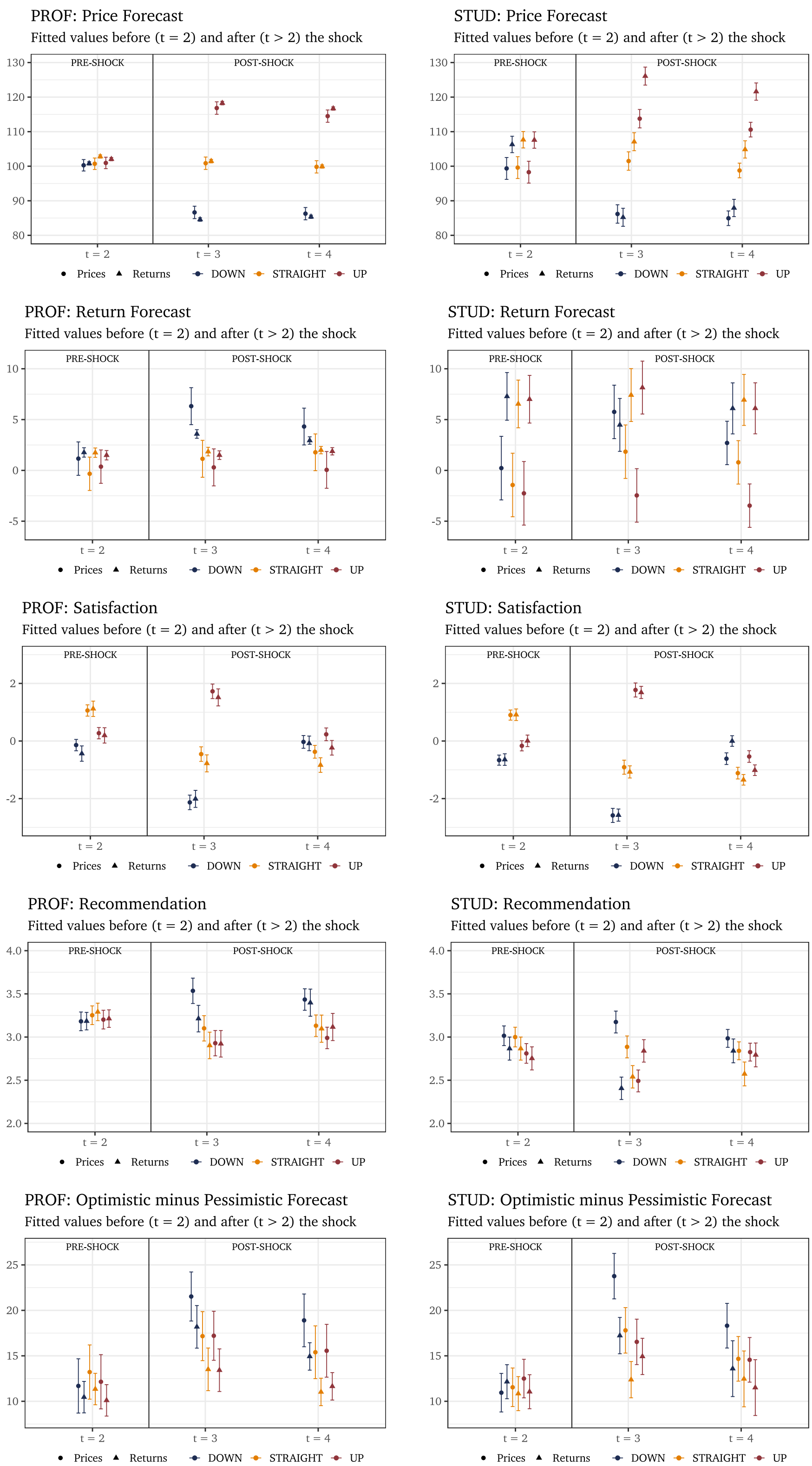

Figure B3: **Wave** 1 (December 2019): Fitted values of the additional variables (PRICE FORECAST or RETURN FORECAST, SATISFACTION, RECOMMENDATION, and the difference between 95$^{\text{th}}$ and 5$^{\text{th}}$ quantile forecasts (optimistic minus pessimistic forecast)) before ($t = 2$; PRE_SHOCK), and after the shock ($t > 2$; POST_SHOCK) for both presentation formats RETURNS (triangles) and PRICES (dots) and the shock types DOWN (blue), STRAIGHT (orange), and UP (red). Results for the professionals (PROF) are shown in the left column, those of the students (STUD) in the right column. Return forecasts are converted into price forecasts for better comparability. The whiskers indicate the 95% confidence intervals.

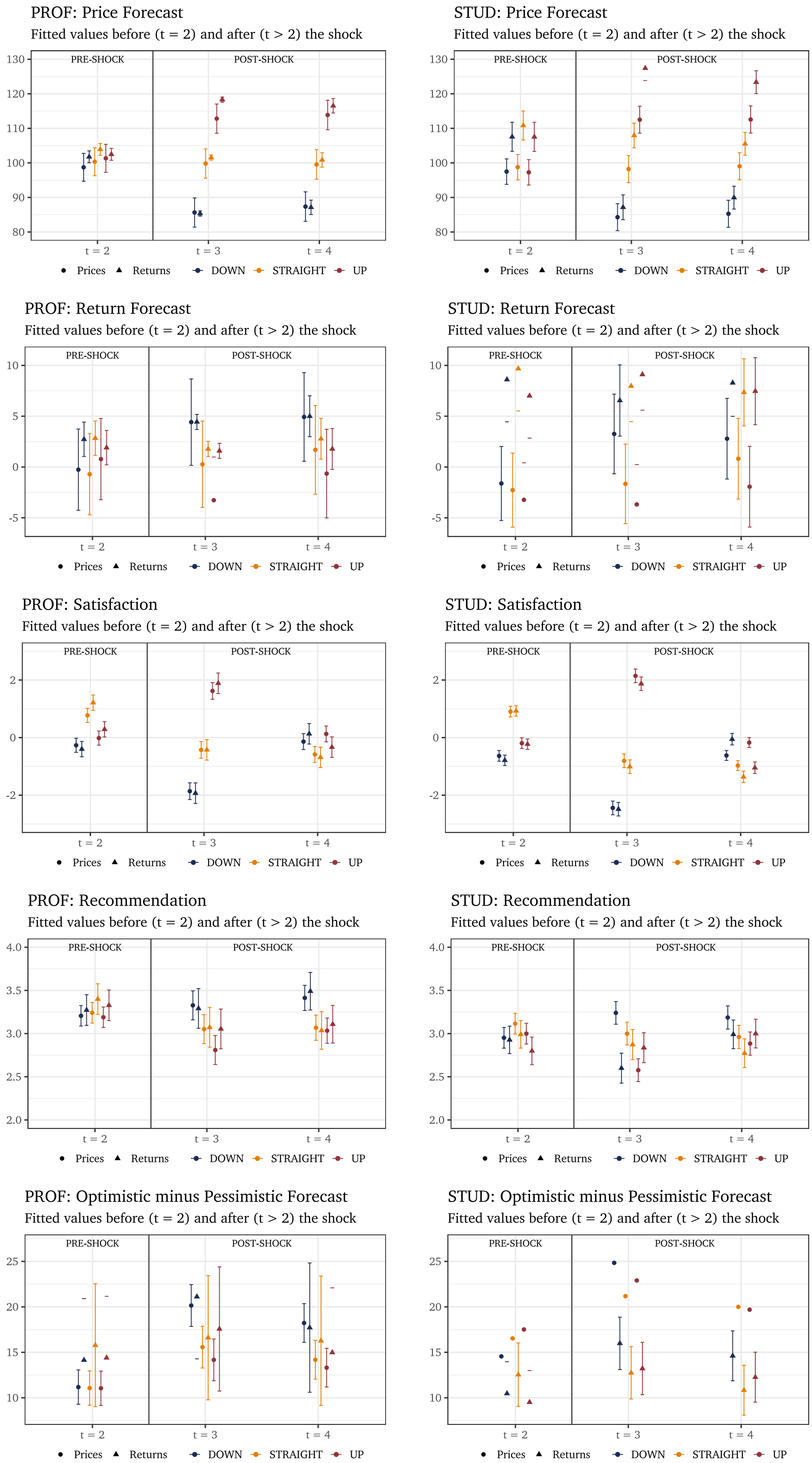

Figure B4: **Wave 2** (March 2020): Fitted values of the major outcome variables (PRICE FORECAST or RETURN FORECAST, SATISFACTION, RECOMMENDATION, and the difference between 95^{th} and 5^{th} quantile forecasts (optimistic minus pessimistic forecast)) before ($t = 2$; PRE_SHOCK), and after the shock ($t > 2$; POST_SHOCK) for both presentation formats RETURNS (triangles) and PRICES (dots) DOWN (blue), STRAIGHT (orange), and UP (red). Results for the professionals (PROF) are shown in the left column, those of the students (STUD) in the right column. Return forecasts are converted into price forecasts for better comparability. The whiskers indicate the 95% confidence intervals.

C Additional Tables

Table C1: Demographic statistics of financial professionals (left column) and student subjects (right column). 'Risk tolerance (general)' measures subjects' risk taking by using the general risk question from the German Socio-Economic Panel on a Likert-scale from 0 ('not willing to take risk') to 10 ('very willing to take risk')—(GSOEP; see Dohmen et al., 2011); 'Risk tolerance (financial)' measures subjects' risk taking in financial matters taken from GSOEP as well; 'CRT2' measures how many out of two cognitive reflection test (CRT) questions from Toplak et al. (2014) were answered correctly (Question 1: 'If John can drink one barrel of water in 6 days, and Mary can drink one barrel of water in 12 days, how long would it take them to drink one barrel of water together?'; Question 2: 'Jerry received both the 15th highest and the 15th lowest mark in the class. How many students are in the class?'); 'Investment in financial products' indicates the fraction of subjects that have invested in financial products during the past five years. Values in column 't' indicate the respective test statistics from t-tests between Wave 1 (December 2019) and Wave 2 (March 2020); none of the differences between Wave 1 and Wave 2 are statistically significant at the 5% level.

	Financial Professionals					Students				
	Wave 1		Wave 2			Wave 1		Wave 2		
Variable	Mean	(s.d.)	Mean	(s.d.)	t	Mean	(s.d.)	Mean	(s.d.)	t
Age	37.90	(8.49)	39.23	(9.49)	1.24	22.70	(3.06)	23.19	(3.34)	1.70
Female	0.13		0.18		1.08	0.46		0.49		0.57
Risk tolerance (general)	7.60	(2.03)	7.35	(2.20)	1.01	6.69	(2.42)	6.59	(2.34)	0.47
Risk tolerance (financial)	7.77	(2.06)	7.61	(2.17)	0.65	5.54	(2.44)	5.45	(2.51)	0.38
CRT2	1.38	(0.75)	1.27	(0.71)	1.30	1.06	(0.80)	1.06	(0.86)	0.06
Investment in fin. prod.						0.33		0.33	0.00	
Highest lev. of education:										
Compulsory school	0.00		0.01			0.01		0.01		
Apprenticeship	0.00		0.03			0.00		0.00		
Technical college	0.01		0.00			0.02		0.02		
High school	0.07		0.16			0.55		0.46		
University	0.90		0.78			0.40		0.47		
Prefer not to say	0.01		0.03			0.01		0.04		
Job function:										
Chief-Level Executive	0.02		0.01							
Consultant	0.09		0.14							
Financial Advisor	0.12		0.08							
Fund Manager	0.06		0.04							
Investment Management	0.10		0.12							
Portfolio Manager	0.19		0.15							
Research Analyst	0.05		0.06							
Trader	0.10		0.14							
Other	0.26		0.26							
	$N = 202$		$N = 113$			$N = 282$		$N = 216$		

Table C2: Summary statistics and differences between WAVE 1 (December 2019) and WAVE 2 (March 2020) for INVESTMENT (percentage invested; from 0 to 100%), RISK PERCEPTION (Likert-scale from 1 to 7), RETURN FORECAST (open question), PRICE FORECAST (open question), and SATISFACTION (Likert-scale from -3 to 3) for financial professionals and student subjects. The data is separated for the presentation format, i.e., RETURNS and PRICES. Columns WAVE 1 and WAVE 2 show mean values for each variable with standard deviations in parentheses. The Diff. columns show the respective differences between WAVE 1 and WAVE 2 for each subject pool; t-statistics for differences between waves are provided in parentheses (double-sided t-test). The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

		Financial Professionals			Students		
Variable		WAVE 1	WAVE 2	Diff.	WAVE 1	WAVE 2	Diff.
INVESTMENT	RETURNS	79.52 (25.74)	74.29 (31.94)	5.23 (1.24)	58.63 (30.23)	57.24 (31.06)	1.39 (0.43)
	PRICES	74.27 (26.36)	62.07 (30.85)	12.19** (2.99)	56.16 (28.84)	54.67 (29.46)	1.50 (0.48)
RISK PERCEPTION	RETURNS	5.04 (1.40)	4.68 (1.29)	0.36* (2.41)	4.91 (1.37)	4.91 (1.44)	0.00 (0.07)
	PRICES	4.74 (1.30)	4.43 (1.28)	0.31* (2.19)	4.67 (1.42)	4.53 (1.39)	0.14 (1.44)
RETURN FORECAST	RETURNS	1.97 (2.72)	2.59 (5.99)	−0.61 (−1.02)	6.70 (15.80)	7.96 (19.05)	−1.26 (−0.96)
	PRICES	1.26 (12.67)	0.70 (17.16)	0.56 (0.18)	−0.08 (15.35)	−1.18 (21.23)	1.11 (−1.00)
PRICE FORECAST	RETURNS	101.18 (9.90)	101.77 (10.76)	−0.59 (−0.99)	105.98 (19.25)	107.35 (22.07)	−1.38 (−1.00)
	PRICES	100.31 (15.16)	99.85 (18.65)	0.47 (0.14)	98.94 (16.96)	98.02 (22.47)	0.92 (−1.00)
SATISFACTION	RETURNS	−0.19 (1.78)	−0.05 (1.66)	−0.15 (−1.11)	−0.56 (1.71)	−0.54 (1.69)	−0.01 (−0.21)
	PRICES	−0.05 (1.53)	−0.07 (1.40)	0.03 (0.24)	−0.50 (1.71)	−0.40 (1.65)	−0.10 (−1.53)
Observations	RETURNS	103	55		150	111	
	PRICES	99	58		132	105	
	Total	202	113		282	216	

Table C3: INVESTMENT: Tobit regression analyses for each subject pool (financial professionals and students) and each presentation format (RETURNS or PRICES) for both waves. The dependent variable, INVESTMENT, is censored between 0 and 100 percent. WAVE 2 is a dummy variable taking the value 1 for observations from the second wave (March 2020), zero otherwise. Models 4-6 and 10-12 are run with control variables such as a subject's self-reported risk tolerance in general and financial matters following the German-SOEP questions, CRT score, age, and gender. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	Dependent variable: INVESTMENT											
	Financial Professionals						Students					
	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WAVE 2	−13.105**	−5.769	−9.783**	−8.620*	−6.525	−7.543*	−1.502	−1.045	−1.333	−1.952	−0.517	−1.122
	(4.508)	(5.174)	(3.477)	(3.978)	(4.388)	(2.971)	(3.202)	(3.469)	(2.368)	(2.826)	(3.058)	(2.108)
General risk tolerance				2.242	0.030	1.027				2.791**	2.351*	2.534**
				(1.560)	(1.249)	(0.985)				(0.726)	(0.882)	(0.590)
Financial risk tolerance				3.797*	4.111*	4.169**				1.419	3.105**	2.311**
				(1.520)	(1.483)	(0.999)				(0.836)	(0.854)	(0.605)
CRT score				6.550*	9.878**	8.164**				1.601	−1.976	−0.245
				(2.428)	(2.918)	(1.866)				(1.732)	(1.787)	(1.250)
Age				−0.214	−0.290	−0.209				0.796	0.592	0.627
				(0.191)	(0.268)	(0.158)				(0.465)	(0.477)	(0.330)
Female				−0.813	−6.890	−3.271				−4.651	−3.274	−4.224
				(5.837)	(5.819)	(4.008)				(3.241)	(3.369)	(2.324)
Constant	76.376**	83.346**	79.920**	28.513*	49.969**	36.636**	56.531**	59.340**	58.012**	12.680	16.304	16.230
	(2.431)	(2.559)	(1.780)	(12.053)	(16.578)	(9.778)	(2.073)	(2.132)	(1.492)	(13.109)	(11.962)	(8.795)
S.e.	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust
Observations	157	158	315	157	158	315	237	261	498	237	261	498
Log Likelihood	-657.665	-613.999	-1,277.236	-635.751	-595.581	-1,238.560	-1,063.082	-1,166.009	-2,231.255	-1,035.125	-1,131.781	-2,171.444

Table C4: RISK PERCEPTION: Ordered logistic regression analyses for each subject pool (financial professionals and students) and each presentation format (RETURNS or PRICES) for both waves. WAVE 2 is a dummy variable taking the value 1 for observations from the second wave (March 2020), zero otherwise. Models 4-6 and 10-12 are run with control variables such as a subject's self-reported risk tolerance in general and financial matters following the German-SOEP questions, CRT score, age, and gender. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	Dependent variable: RISK PERCEPTION											
	Financial Professionals						Students					
	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WAVE 2	−0.653*	−0.666*	−0.663**	−0.569	−0.597*	−0.612**	−0.250	0.085	−0.095	−0.242	0.133	−0.069
	(0.289)	(0.292)	(0.205)	(0.300)	(0.295)	(0.208)	(0.227)	(0.219)	(0.157)	(0.229)	(0.220)	(0.159)
General risk tolerance				0.107	0.118	0.120				0.024	−0.021	0.010
				(0.104)	(0.087)	(0.067)				(0.066)	(0.060)	(0.045)
Financial risk tolerance				0.059	−0.180*	−0.049				0.052	0.055	0.055
				(0.095)	(0.089)	(0.065)				(0.067)	(0.060)	(0.045)
CRT score				0.258	0.534*	0.377*				0.019	0.329*	0.172
				(0.192)	(0.202)	(0.136)				(0.144)	(0.134)	(0.098)
Age				0.028	−0.010	0.015				−0.012	−0.050	−0.033
				(0.016)	(0.017)	(0.011)				(0.038)	(0.037)	(0.026)
Female				−0.474	−0.369	−0.375				−0.107	−0.089	−0.092
				(0.415)	(0.387)	(0.277)				(0.240)	(0.237)	(0.167)
S.e.	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust
Observations	157	158	315	157	158	315	237	261	498	237	261	498

Table C5: INVESTMENT: Ordinary least squares regression analyses for each presentation format (RETURNS or PRICES) for both waves. WAVE 2 is a dummy variable taking the value 1 for observations from the second wave (March 2020), zero otherwise. PROF is a dummy variable taking the value 1 for finance professionals and zero otherwise. Models 4-6 are run with control variables such as a subject's self-reported risk tolerance in general and financial matters following the German-SOEP questions, CRT score, age, and gender. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	Dependent variable: INVESTMENT					
	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
WAVE 2	−1.497	−1.389	−1.486	−1.711	−0.275	−0.897
	(2.240)	(3.221)	(2.240)	(2.777)	(2.860)	(2.011)
PROF	18.101**	20.895**	19.471**	8.740*	14.284**	11.181**
	(2.002)	(2.773)	(2.002)	(3.550)	(4.255)	(2.716)
WAVE 2 × PROF	−10.694**	−3.842	−7.439*	−7.707	−5.017	−6.492*
	(3.719)	(5.283)	(3.719)	(4.532)	(4.678)	(3.284)
General risk tolerance				2.614**	1.453*	1.976**
				(0.628)	(0.638)	(0.458)
Financial risk tolerance				2.137**	3.286**	2.783**
				(0.660)	(0.626)	(0.453)
CRT score				3.511*	1.350	2.511*
				(1.354)	(1.345)	(0.959)
Age				−0.052	−0.182	−0.108
				(0.167)	(0.200)	(0.128)
Female				−3.778	−3.035	−3.367
				(2.679)	(2.593)	(1.854)
Constant	56.164**	58.626**	57.473**	26.606**	34.426**	30.209**
	(1.418)	(2.001)	(1.418)	(6.469)	(7.078)	(4.733)
S.e.	robust	robust	robust	robust	robust	robust
Observations	394	419	813	394	419	813
R^2	0.104	0.136	0.116	0.294	0.312	0.296
Adjusted R^2	0.097	0.129	0.112	0.280	0.299	0.289

Table C6: RISK PERCEPTION: Ordinary least squares regression analyses for each presentation format (RETURNS or PRICES) for both waves. WAVE 2 is a dummy variable taking the value 1 for observations from the second wave (March 2020), zero otherwise. PROF is a dummy variable taking the value 1 for finance professionals and zero otherwise. Models 4-6 are run with control variables such as a subject's self-reported risk tolerance in general and financial matters following the German-SOEP questions, CRT score, age, and gender. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	Dependent variable: RISK PERCEPTION					
	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
WAVE 2	−0.144	−0.008	−0.079	−0.153	0.016	−0.076
	(0.078)	(0.115)	(0.078)	(0.100)	(0.113)	(0.077)
PROF	0.070	0.129	0.095	−0.236	0.166	−0.074
	(0.079)	(0.113)	(0.079)	(0.151)	(0.170)	(0.116)
WAVE 2 × PROF	−0.167	−0.368	−0.271*	−0.158	−0.378*	−0.259*
	(0.131)	(0.193)	(0.131)	(0.173)	(0.188)	(0.131)
General risk tolerance				0.004	0.027	0.022
				(0.027)	(0.029)	(0.020)
Financial risk tolerance				0.035	−0.016	0.009
				(0.026)	(0.027)	(0.019)
CRT score				0.048	0.159**	0.102*
				(0.049)	(0.054)	(0.037)
Age				0.013	−0.006	0.005
				(0.007)	(0.008)	(0.005)
Female				−0.075	−0.091	−0.064
				(0.083)	(0.101)	(0.067)
Constant	4.667**	4.912**	4.797**	4.139**	4.829**	4.408**
	(0.046)	(0.063)	(0.046)	(0.236)	(0.263)	(0.179)
S.e.	robust	robust	robust	robust	robust	robust
Observations	394	419	813	394	419	813
R^2	0.019	0.015	0.015	0.050	0.042	0.034
Adjusted R^2	0.011	0.008	0.012	0.031	0.023	0.025

Table C7: Ordinary least squares regression analyses for each subject pool (financial professionals and students) and each presentation format (RETURNS or PRICES) with standard errors clustered at the subject-level for **WAVE** 1. t indicates time period and UP and DOWN stand for the direction of the shock in the respective treatment. $t = 2$ and the STRAIGHT path act as the reference categories. All specifications are run with control variables such as a subject's risk tolerance, CRT score, age, and gender. The analogous estimates without control variables are provided in tables **??** through **??** in the Supplementary Data and Analyses. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	INVESTMENT				RISK PERCEPTION				PRICE FORECAST				SATISFACTION			
	Fin. Prof.		Students		Fin. Prof.		Students		Fin. Prof.		Students		Fin. Prof.		Students	
	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$t = 1$	−0.324	2.947	−4.259*	0.006	−0.046	−0.162	0.218*	0.322**	−3.576**	−3.904**	−2.293	−3.373**	−1.970**	−2.042**	−2.359**	−2.397**
	(2.084)	(2.268)	(1.623)	(1.925)	(0.082)	(0.093)	(0.095)	(0.107)	(0.815)	(0.271)	(1.389)	(0.704)	(0.138)	(0.197)	(0.135)	(0.133)
$t = 3$	0.575	0.630	−0.876	−0.901	1.201**	0.916**	1.407**	0.760**	0.151	−1.339**	1.901	−0.567	−1.515**	−1.896**	−1.811**	−1.987**
	(2.114)	(1.637)	(1.300)	(1.968)	(0.120)	(0.116)	(0.114)	(0.101)	(0.488)	(0.352)	(1.277)	(0.647)	(0.133)	(0.190)	(0.147)	(0.124)
$t = 4$	1.104	2.601	−0.140	4.046*	0.487**	−0.056	0.178	−0.073	−0.897	−2.887**	−0.831	−2.806**	−1.434**	−1.955**	−2.017**	−2.260**
	(2.557)	(2.041)	(1.734)	(2.015)	(0.106)	(0.144)	(0.128)	(0.131)	(0.579)	(0.288)	(1.242)	(0.738)	(0.122)	(0.181)	(0.138)	(0.129)
$t = 1 \times$ DOWN	−1.990	−1.147	3.205	−0.585	−0.111	−0.113	−0.528**	−0.396**	2.455**	3.442**	2.210	3.524**	1.081**	1.261**	1.252**	1.037**
	(2.705)	(2.010)	(2.104)	(2.247)	(0.113)	(0.123)	(0.126)	(0.113)	(0.732)	(0.270)	(1.440)	(0.890)	(0.155)	(0.204)	(0.157)	(0.145)
$t = 2 \times$ DOWN	−3.877	3.985*	2.913	2.311	−0.019	−0.203	−0.333*	0.029	−0.444	−1.999**	−0.241	−1.361	−1.202**	−1.556**	−1.565**	−1.558**
	(2.886)	(2.001)	(1.842)	(2.299)	(0.110)	(0.144)	(0.145)	(0.116)	(1.314)	(0.218)	(1.523)	(0.813)	(0.152)	(0.211)	(0.161)	(0.151)
$t = 3 \times$ DOWN	5.273**	7.229*	1.919	2.066	0.257*	0.121	0.174	0.540**	−14.235**	−16.892**	−15.321**	−21.874**	−1.677**	−1.233**	−1.674**	−1.500**
	(1.840)	(2.590)	(2.507)	(2.432)	(0.127)	(0.108)	(0.121)	(0.120)	(1.533)	(0.506)	(1.393)	(0.910)	(0.146)	(0.154)	(0.134)	(0.133)
$t = 4 \times$ DOWN	4.659*	5.694*	2.781	−0.764	0.155	0.081	0.450**	0.089	−13.548**	−14.552**	−13.829**	−16.938**	0.342*	0.753**	0.502**	1.347**
	(2.232)	(2.215)	(2.110)	(1.885)	(0.134)	(0.130)	(0.119)	(0.108)	(1.535)	(0.386)	(1.125)	(0.722)	(0.137)	(0.164)	(0.132)	(0.115)
$t = 1 \times$ UP	1.757	0.670	2.959	0.087	0.159	0.022	−0.267*	−0.259*	3.031	1.935**	0.203	1.031	0.960**	0.716**	1.003**	0.825**
	(2.371)	(1.860)	(2.346)	(1.873)	(0.104)	(0.115)	(0.133)	(0.114)	(2.159)	(0.283)	(1.360)	(0.707)	(0.158)	(0.170)	(0.169)	(0.134)
$t = 2 \times$ UP	−0.315	2.296	−2.900	−1.857	0.093	−0.247*	−0.038	−0.085	0.234	−0.757**	−1.319	−0.076	−0.788**	−0.925**	−1.068**	−0.907**
	(2.274)	(2.543)	(2.525)	(2.292)	(0.115)	(0.125)	(0.124)	(0.117)	(0.503)	(0.256)	(1.305)	(0.541)	(0.140)	(0.172)	(0.165)	(0.144)
$t = 3 \times$ UP	−9.656**	−8.624*	−4.054	−4.434*	0.101	−0.048	−0.917**	−0.588**	15.969**	16.796**	12.259**	18.987**	2.181**	2.291**	2.682**	2.761**
	(2.749)	(3.164)	(2.262)	(2.255)	(0.116)	(0.113)	(0.138)	(0.125)	(1.246)	(0.432)	(1.574)	(0.831)	(0.165)	(0.220)	(0.198)	(0.158)
$t = 4 \times$ UP	−5.732*	−3.124	−4.973*	−1.926	0.076	0.005	−0.189	−0.201	14.681**	16.774**	11.825**	16.746**	0.606**	0.601**	0.578**	0.333**
	(2.692)	(2.564)	(2.354)	(1.821)	(0.102)	(0.133)	(0.127)	(0.125)	(0.682)	(0.320)	(1.289)	(0.722)	(0.132)	(0.139)	(0.128)	(0.108)
Constant	35.968*	61.851**	11.364	42.416*	2.717**	4.470**	4.080**	4.032**	101.138**	100.684**	94.194**	121.188**	0.320	1.645**	0.260	0.652
	(15.529)	(16.582)	(14.122)	(18.402)	(0.577)	(0.644)	(0.692)	(0.567)	(3.447)	(0.999)	(8.283)	(9.897)	(0.532)	(0.519)	(0.396)	(0.477)
Observations	1,188	1,236	1,584	1,800	1,172	1,220	1,560	1,776	1,188	1,236	1,584	1,800	1,186	1,227	1,580	1,794
R^2	0.185	0.131	0.176	0.156	0.223	0.157	0.179	0.102	0.349	0.917	0.242	0.360	0.361	0.270	0.384	0.394
Adjusted R^2	0.174	0.119	0.167	0.148	0.213	0.146	0.171	0.094	0.340	0.916	0.234	0.354	0.353	0.261	0.377	0.389

Table C8: Ordinary least squares regression analyses for each subject pool (financial professionals and students) and each presentation format (RETURNS or PRICES) with standard errors clustered at the subject-level for **WAVE** 2. t indicates time period and UP and DOWN stand for the direction of the shock in the respective treatment. $t = 2$ and the STRAIGHT path act as the reference categories. All specifications are run without or with control variables such as a subject's risk tolerance, CRT score, age, and gender. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	INVESTMENT				RISK PERCEPTION				PRICE FORECAST				SATISFACTION			
	Fin. Prof.		Students		Fin. Prof.		Students		Fin. Prof.		Students		Fin. Prof.		Students	
	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$t = 1$	2.520	2.149	−3.268	−0.869	0.022	−0.152	0.247*	0.191	−3.011**	−4.698**	−2.331	−6.276**	−1.304**	−1.947**	−2.263**	−2.386**
	(2.898)	(3.430)	(1.932)	(2.122)	(0.093)	(0.140)	(0.122)	(0.101)	(0.918)	(0.809)	(1.294)	(1.014)	(0.177)	(0.212)	(0.145)	(0.132)
$t = 3$	−1.612	−3.724	−3.671*	−1.109	1.282**	0.648**	1.426**	0.700**	−0.517	−2.366*	−0.550	−2.896**	−1.199**	−1.639**	−1.709**	−1.936**
	(2.439)	(3.400)	(1.592)	(2.140)	(0.174)	(0.178)	(0.142)	(0.114)	(0.714)	(0.892)	(0.748)	(0.947)	(0.179)	(0.226)	(0.161)	(0.147)
$t = 4$	0.885	2.343	−0.028	1.478	0.609**	−0.243	0.569**	0.236	−0.791	−3.058**	0.266	−5.320**	−1.358**	−1.902**	−1.875**	−2.291**
	(3.010)	(3.022)	(2.007)	(2.301)	(0.159)	(0.182)	(0.131)	(0.133)	(1.006)	(0.408)	(0.890)	(1.072)	(0.178)	(0.200)	(0.132)	(0.137)
$t = 1 \times$ DOWN	−3.566	−3.994	2.910	−0.834	−0.007	−0.146	−0.100	−0.095	2.409*	3.599**	1.094	4.498**	0.876**	1.107**	1.159**	1.114**
	(2.479)	(3.221)	(2.316)	(2.379)	(0.147)	(0.153)	(0.144)	(0.146)	(0.930)	(0.574)	(1.920)	(1.203)	(0.189)	(0.256)	(0.164)	(0.169)
$t = 2 \times$ DOWN	−0.543	4.790	−2.682	3.010	0.067	−0.123	0.273	0.255	−1.620*	−2.160*	−1.278	−3.281*	−1.039**	−1.615**	−1.538**	−1.716**
	(3.488)	(3.363)	(2.168)	(2.365)	(0.144)	(0.155)	(0.164)	(0.135)	(0.792)	(0.932)	(1.017)	(1.462)	(0.174)	(0.257)	(0.167)	(0.182)
$t = 3 \times$ DOWN	9.793**	11.278**	4.289	−0.555	0.173	0.199	0.557**	0.844**	−14.170**	−16.199**	−13.913**	−20.791**	−1.434**	−1.506**	−1.637**	−1.478**
	(2.655)	(3.580)	(2.634)	(2.428)	(0.120)	(0.150)	(0.150)	(0.125)	(1.383)	(0.949)	(1.510)	(1.182)	(0.182)	(0.218)	(0.152)	(0.146)
$t = 4 \times$ DOWN	9.534*	5.609	2.486	0.971	0.159	0.095	0.478**	−0.036	−12.190**	−13.717**	−13.824**	−15.566**	0.446**	0.818**	0.350*	1.309**
	(3.420)	(3.289)	(2.536)	(1.971)	(0.155)	(0.173)	(0.146)	(0.128)	(1.288)	(0.447)	(1.152)	(1.226)	(0.151)	(0.206)	(0.146)	(0.135)
$t = 1 \times$ UP	1.111	−0.757	−0.707	−0.409	0.082	0.077	0.039	0.164	4.287	2.114**	0.455	2.808*	0.692**	0.711**	0.949**	0.814**
	(2.764)	(2.715)	(2.002)	(2.364)	(0.164)	(0.118)	(0.143)	(0.141)	(3.107)	(0.429)	(1.639)	(1.410)	(0.182)	(0.245)	(0.151)	(0.166)
$t = 2 \times$ UP	2.888	−0.582	−0.745	−1.060	0.168	0.030	0.394**	0.247	0.996	−1.432	−1.491	−3.301*	−0.789**	−0.927**	−1.097**	−1.155**
	(3.114)	(3.579)	(1.990)	(2.453)	(0.151)	(0.120)	(0.134)	(0.127)	(2.073)	(0.816)	(0.781)	(1.598)	(0.176)	(0.249)	(0.164)	(0.173)
$t = 3 \times$ UP	−5.070	−3.676	−3.936	−3.016	−0.110	0.204	−0.397*	−0.207	12.995**	16.765**	14.302**	19.474**	2.048**	2.312**	2.950**	2.880**
	(2.844)	(3.048)	(2.168)	(2.707)	(0.155)	(0.137)	(0.148)	(0.144)	(1.474)	(0.656)	(1.741)	(1.301)	(0.205)	(0.268)	(0.169)	(0.181)
$t = 4 \times$ UP	−2.537	−4.937	−2.003	0.025	−0.084	0.021	−0.273*	−0.033	14.316**	15.672**	13.545**	17.847**	0.713**	0.356*	0.798**	0.317**
	(2.866)	(2.915)	(2.501)	(2.025)	(0.152)	(0.100)	(0.122)	(0.139)	(0.910)	(1.058)	(1.491)	(0.962)	(0.155)	(0.165)	(0.128)	(0.112)
Constant	11.933	24.783	5.073	2.462	3.297**	5.834**	3.871**	5.558**	91.607**	104.498**	119.186**	101.190**	1.327**	0.127	1.202**	0.855*
	(15.912)	(26.088)	(26.370)	(16.109)	(0.610)	(0.965)	(0.710)	(0.732)	(9.108)	(3.338)	(24.920)	(15.310)	(0.440)	(0.564)	(0.372)	(0.395)
Observations	695	660	1,248	1,321	676	651	1,222	1,309	695	660	1,248	1,321	686	653	1,246	1,315
R^2	0.237	0.296	0.169	0.218	0.196	0.150	0.178	0.133	0.224	0.730	0.175	0.262	0.349	0.346	0.433	0.418
Adjusted R^2	0.220	0.279	0.158	0.209	0.176	0.129	0.167	0.122	0.205	0.723	0.164	0.253	0.334	0.330	0.425	0.411

In Tables C9 and C10—outlined on the next two pages –, we run ordinary least squares regression analyses for each subject pool—financial professionals and students—separately and we measure differences in the dependent variables before and after the volatility shock. For each wave, we run separate regressions for the presentation format (RETURNS or PRICES) and for the subject pool. We treat the sample of finance professionals as primary analysis and consider the student sample to be of secondary importance. In particular, we run the following regression model(s):

$$y_{i,t} = \beta_0 + \beta_1 \text{ POST\_SHOCK} + \beta_2 \text{ PRE\_SHOCK} \times \text{DOWN} + \beta_3 \text{ POST\_SHOCK} \times \text{DOWN} \\ + \beta_4 \text{ PRE\_SHOCK} \times \text{UP} + \beta_5 \text{ POST\_SHOCK} \times \text{UP}.$$

Here, $y_{i,t}$ is a generic placeholder representing the respective dependent variable described above for subject i in period t. POST_SHOCK is a dummy variable taking the value 1 for periods after the volatility shock (i.e., decision at $t = 3$ and $t = 4$), zero otherwise, and PRE_SHOCK stands for a dummy variable taking the value 1 for periods before the shock (i.e., decision at $t = 1$ and $t = 2$), zero otherwise. The interaction terms (e.g., POST_SHOCK × UP) measure the combined effects of the shock phase (i.e., before or after the shock) and the respective treatment (i.e., UP or DOWN). Hence, the effects of treatment STRAIGHT are incorporated in the dummy POST_SHOCK for decision at $t = 3$ and $t = 4$ after the shock and can directly be compared to the pre-shock decision at $t = 1$ and $t = 2$ in Treatment STRAIGHT, measured with the constant. The pre- and post-shock effects of the other treatments are measured through the interaction terms that add on top of the POST_SHOCK dummy. Moreover, we run all specifications with control variables such as a subject's risk tolerance, CRT score, age, and gender. We also run Wald-coefficient tests on treatment differences which we report at the bottom of Table C9. We clustered standard errors at the subject level and we stick to the 0.5%- and the 5%-level, respectively, following Benjamin et al. (2018).

Table C9: Ordinary least squares regression analyses for each subject pool (financial professionals and students) and each presentation format (RETURNS or PRICES) with standard errors clustered at the subject-level for **Wave** 1. POST_SHOCK is a dummy variable taking the value 1 for periods after the volatility shock (i.e., $t = 3$ and $t = 4$), zero otherwise, and PRE_SHOCK stands for a dummy variable taking the value 1 for periods before the shock (i.e., $t = 1$ and $t = 2$), zero otherwise. The interaction terms (e.g., POST_SHOCK × UP) measure the combined effects of the shock phase (i.e., before or after the shock) and the respective treatment (i.e., UP or DOWN). All specifications are run with control variables such as a subject's risk tolerance, CRT score, age, and gender. The analogous estimates without control variables are provided in tables **??** through **??** in the Supplementary Data and Analyses. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	INVESTMENT				RISK PERCEPTION				PRICE FORECAST				SATISFACTION			
	Fin. Prof.		Students		Fin. Prof.		Students		Fin. Prof.		Students		Fin. Prof.		Students	
	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS	PRICES	RETURNS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
POST_SHOCK	0.630	1.015	0.988	0.542	0.868**	0.518**	0.683**	0.183*	1.415	−0.161	1.681*	−0.0003	−0.490**	−0.899**	−0.738**	−0.929**
	(1.395)	(1.415)	(1.287)	(1.325)	(0.085)	(0.101)	(0.093)	(0.088)	(0.724)	(0.237)	(0.741)	(0.455)	(0.075)	(0.117)	(0.096)	(0.080)
PRE_SHOCK × DOWN	−3.381	2.061	2.844	0.351	−0.064	−0.158	−0.432**	−0.183*	1.006	0.721**	0.984	1.081	−0.061	−0.147	−0.161	−0.264**
	(1.881)	(1.343)	(1.457)	(1.451)	(0.096)	(0.113)	(0.114)	(0.083)	(0.874)	(0.166)	(1.140)	(0.678)	(0.069)	(0.080)	(0.082)	(0.085)
POST_SHOCK × DOWN	4.966**	6.462**	2.350	0.651	0.204	0.094	0.310**	0.310**	−13.892**	−15.722**	−14.575**	−19.406**	−0.673**	−0.245*	−0.587**	−0.077
	(1.690)	(1.909)	(1.949)	(1.635)	(0.110)	(0.099)	(0.098)	(0.090)	(1.460)	(0.389)	(1.039)	(0.620)	(0.094)	(0.113)	(0.098)	(0.083)
PRE_SHOCK × UP	0.581	2.421	0.190	−1.945	0.126	−0.113	−0.154	−0.171	1.632	0.589**	−0.558	0.478	0.086	−0.099	−0.037	−0.044
	(1.479)	(1.555)	(1.649)	(1.459)	(0.092)	(0.098)	(0.110)	(0.089)	(1.204)	(0.164)	(0.972)	(0.473)	(0.061)	(0.086)	(0.091)	(0.065)
POST_SHOCK × UP	−7.694**	−5.874*	−4.514*	−3.180*	0.085	−0.026	−0.551**	−0.396**	15.325**	16.785**	12.042**	17.867**	1.390**	1.450**	1.629**	1.533**
	(2.392)	(2.247)	(2.028)	(1.592)	(0.092)	(0.104)	(0.111)	(0.099)	(0.837)	(0.338)	(1.115)	(0.584)	(0.117)	(0.129)	(0.130)	(0.100)
Constant	36.104*	58.334**	13.916	41.026*	2.676**	4.387**	4.188**	4.199**	99.350**	98.732**	93.048**	119.501**	−0.660	0.628	−0.911*	−0.501
	(15.213)	(16.907)	(13.977)	(17.081)	(0.569)	(0.636)	(0.683)	(0.563)	(3.420)	(0.990)	(8.098)	(9.964)	(0.521)	(0.523)	(0.371)	(0.476)
Observations	1,485	1,545	1,980	2,250	1,172	1,220	1,560	1,776	1,188	1,236	1,584	1,800	1,186	1,227	1,580	1,794
R^2	0.178	0.123	0.168	0.141	0.181	0.096	0.123	0.043	0.345	0.906	0.238	0.354	0.173	0.115	0.167	0.107
Adjusted R^2	0.172	0.117	0.164	0.137	0.174	0.089	0.118	0.037	0.340	0.905	0.234	0.350	0.165	0.108	0.161	0.102
Wald-tests between coefficients:																
POST_SHOCK + POST_SHOCK × DOWN − PRE_SHOCK × DOWN	**	**	n.s.	n.s.	**	**	**	**	**	**	**	**	**	**	**	**
POST_SHOCK + POST_SHOCK × UP − PRE_SHOCK × UP	**	**	*	n.s.	**	**	*	n.s.	**	**	**	**	**	**	**	**
POST_SHOCK × DOWN − PRE_SHOCK × DOWN	**	*	n.s.	n.s.	*	*	**	**	**	**	**	**	**	n.s.	**	n.s.
POST_SHOCK × UP − PRE_SHOCK × UP	**	**	*	n.s.	n.s.	n.s.	**	n.s.	**	**	**	**	**	**	**	**
(POST_SHOCK × DOWN − PRE_SHOCK × DOWN)− (POST_SHOCK × UP − PRE_SHOCK × UP)	**	**	n.s.	n.s.	*	n.s.	**	**	**	**	**	**	**	**	**	**

Table C10: Ordinary least squares regression analyses for each subject pool (financial professionals and students) and each presentation format (RETURNS or PRICES) with standard errors clustered at the subject-level for **WAVE** 2. POST_SHOCK is a dummy variable taking the value 1 for periods after the volatility shock (i.e., $t = 3$ and $t = 4$), zero otherwise, and PRE_SHOCK stands for a dummy variable taking the value 1 for periods before the shock (i.e., $t = 1$ and $t = 2$), zero otherwise. The interaction terms (e.g., POST_SHOCK × UP) measure the combined effects of the shock phase (i.e., before or after the shock) and the respective treatment (i.e., UP or DOWN). All specifications are run with control variables such as a subject's risk tolerance, CRT score, age, and gender. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	INVESTMENT				RISK PERCEPTION				PRICE FORECAST				SATISFACTION			
	Fin. Prof.		Students		Fin. Prof.		Students		Fin. Prof.		Students		Fin. Prof.		Students	
	PRICES (1)	RETURNS (2)	PRICES (3)	RETURNS (4)	PRICES (5)	RETURNS (6)	PRICES (7)	RETURNS (8)	PRICES (9)	RETURNS (10)	PRICES (11)	RETURNS (12)	PRICES (13)	RETURNS (14)	PRICES (15)	RETURNS (16)
POST_SHOCK	−1.612	−1.765	−0.223	0.619	0.934**	0.271*	0.877**	0.373**	0.838	−0.363	1.018	−0.970	−0.627**	−0.815**	−0.667**	−0.926**
	(2.323)	(2.561)	(1.529)	(1.676)	(0.144)	(0.122)	(0.104)	(0.087)	(0.833)	(0.333)	(0.891)	(0.546)	(0.123)	(0.140)	(0.092)	(0.092)
PRE_SHOCK × DOWN	−2.043	0.398	0.111	1.077	0.030	−0.134	0.085	0.080	0.382	0.720	−0.097	0.612	−0.084	−0.272*	−0.194*	−0.306**
	(2.638)	(2.402)	(1.801)	(1.799)	(0.129)	(0.108)	(0.131)	(0.110)	(0.647)	(0.563)	(1.187)	(1.221)	(0.107)	(0.111)	(0.080)	(0.089)
POST_SHOCK × DOWN	9.664**	8.444**	3.383	0.208	0.175	0.160	0.523**	0.400**	−13.180**	−14.958**	−13.871**	−18.178**	−0.501**	−0.354*	−0.647**	−0.079
	(2.847)	(2.818)	(2.178)	(1.613)	(0.115)	(0.111)	(0.126)	(0.090)	(1.051)	(0.636)	(0.991)	(1.044)	(0.122)	(0.149)	(0.110)	(0.093)
PRE_SHOCK × UP	2.011	−0.670	−0.742	−0.734	0.125	0.055	0.215	0.206	2.628	0.341	−0.525	−0.247	−0.050	−0.126	−0.081	−0.176
	(2.116)	(2.217)	(1.634)	(1.778)	(0.143)	(0.083)	(0.112)	(0.117)	(2.497)	(0.406)	(1.000)	(1.378)	(0.112)	(0.117)	(0.087)	(0.092)
POST_SHOCK × UP	−3.804	−4.306	−2.970	−1.495	−0.103	0.120	−0.339**	−0.119	13.655**	16.218**	13.923**	18.660**	1.388**	1.334**	1.874**	1.599**
	(2.485)	(2.498)	(1.988)	(2.038)	(0.127)	(0.084)	(0.110)	(0.105)	(1.019)	(0.499)	(1.447)	(1.045)	(0.132)	(0.153)	(0.115)	(0.108)
Constant	13.183	25.857	3.447	2.019	3.307**	5.752**	3.997**	5.660**	90.113**	102.148**	118.027**	98.055**	0.679	−0.830	0.076	−0.310
	(15.785)	(25.798)	(26.306)	(15.953)	(0.606)	(0.961)	(0.702)	(0.732)	(9.119)	(3.060)	(24.873)	(15.157)	(0.438)	(0.529)	(0.362)	(0.385)
Observations	695	660	1,248	1,321	676	651	1,222	1,309	695	660	1,248	1,321	686	653	1,246	1,315
R^2	0.236	0.292	0.166	0.215	0.162	0.075	0.129	0.090	0.222	0.719	0.174	0.256	0.193	0.137	0.217	0.117
Adjusted R^2	0.224	0.281	0.159	0.209	0.149	0.060	0.122	0.083	0.211	0.714	0.168	0.250	0.181	0.124	0.210	0.111
Wald-tests between coefficients:																
POST_SHOCK + POST_SHOCK × DOWN − PRE_SHOCK × DOWN	**	*	n.s.	n.s.	**	**	**	**	**	**	**	**	**	**	**	**
POST_SHOCK + POST_SHOCK × UP − PRE_SHOCK × UP	*	*	n.s.	n.s.	**	**	**	n.s.	**	**	**	**	**	**	**	**
POST_SHOCK × DOWN − PRE_SHOCK × DOWN	**	*	n.s.	n.s.	n.s.	n.s.	*	**	**	**	**	**	*	n.s.	**	n.s.
POST_SHOCK × UP − PRE_SHOCK × UP	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	**	*	**	**	**	**	**	**	**	**
(POST_SHOCK × DOWN − PRE_SHOCK × DOWN)− (POST_SHOCK × UP − PRE_SHOCK × UP)	**	**	n.s.	n.s.	*	n.s.	**	**	**	**	**	**	**	**	**	**

Table C11: Ordinary least squares regression analyses for each subject pool (financial professionals and students) and each shock type (DOWN, STRAIGHT, and UP) with standard errors clustered at the subject-level for **WAVE** 1. INVESTMENT is the dependent variable, POST_SHOCK is a dummy variable taking the value 1 for periods after the volatility shock (i.e., decision at $t = 3$ and $t = 4$), zero otherwise, and PRE_SHOCK stands for a dummy variable taking the value 1 for periods before the shock (i.e., decision at $t = 1$ and $t = 2$), zero otherwise. The interaction terms (e.g., POST_SHOCK × RETURNS) measure the combined effects of the shock phase (i.e., before or after the shock) and the respective treatment (i.e., RETURNS). PRE_SHOCK and the presentation format PRICES act as the reference categories. All specifications are run without or with control variables such as a subject's risk tolerance, CRT score, age, and gender. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	Dependent variable: INVESTMENT											
	Financial Professionals						Students					
	DOWN		STRAIGHT		UP		DOWN		STRAIGHT		UP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
POST_SHOCK	8.977**	8.977**	0.630	0.630	−7.645**	−7.645**	0.494	0.494	0.988	0.988	−3.715*	−3.715*
	(1.779)	(1.784)	(1.389)	(1.393)	(2.124)	(2.130)	(1.644)	(1.647)	(1.283)	(1.285)	(1.842)	(1.845)
PRE_SHOCK × RETURNS	8.645*	9.696**	3.202	4.203	5.042	6.052*	1.121	0.156	3.614	2.640	1.479	0.749
	(3.145)	(2.880)	(3.205)	(3.036)	(3.063)	(2.872)	(3.040)	(2.728)	(2.967)	(2.707)	(3.045)	(2.769)
POST_SHOCK × RETURNS	5.083	6.134*	3.587	4.588	5.407	6.416	1.469	0.505	3.168	2.195	4.502	3.772
	(2.987)	(2.794)	(3.485)	(3.308)	(3.900)	(3.706)	(3.602)	(3.119)	(3.406)	(3.066)	(3.405)	(3.081)
Constant	71.556**	41.395**	74.937**	43.183**	75.518**	46.997**	58.295**	25.293*	55.451**	29.916*	55.640**	20.027
	(2.255)	(10.705)	(2.264)	(11.444)	(2.283)	(12.062)	(2.210)	(12.589)	(2.111)	(11.093)	(2.207)	(11.968)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,010	1,010	1,010	1,010	1,010	1,010	1,410	1,410	1,410	1,410	1,410	1,410
R^2	0.042	0.176	0.004	0.134	0.027	0.134	0.001	0.171	0.004	0.150	0.004	0.134
Adjusted R^2	0.039	0.169	0.001	0.127	0.024	0.127	-0.002	0.166	0.002	0.145	0.002	0.129

Table C12: Ordinary least squares regression analyses for each subject pool (financial professionals and students) and each shock type (DOWN, STRAIGHT, and UP) with standard errors clustered at the subject-level for **WAVE** 2. INVESTMENT is the dependent variable, POST_SHOCK is a dummy variable taking the value 1 for periods after the volatility shock (i.e., decision at $t = 3$ and $t = 4$), zero otherwise, and PRE_SHOCK stands for a dummy variable taking the value 1 for periods before the shock (i.e., decision at $t = 1$ and $t = 2$), zero otherwise. The interaction terms (e.g., POST_SHOCK × RETURNS) measure the combined effects of the shock phase (i.e., before or after the shock) and the respective treatment (i.e., RETURNS). PRE_SHOCK and the presentation format PRICES act as the reference categories. All specifications are run without or with control variables such as a subject's risk tolerance, CRT score, age, and gender. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	Dependent variable: INVESTMENT											
	Financial Professionals						Students					
	DOWN		STRAIGHT		UP		DOWN		STRAIGHT		UP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
POST_SHOCK	10.095**	10.095**	−1.624	−1.544	−7.426**	−7.426*	3.183	3.055	−0.309	−0.228	−2.363	−2.425
	(2.605)	(2.620)	(2.298)	(2.324)	(2.641)	(2.656)	(1.889)	(1.890)	(1.532)	(1.526)	(2.149)	(2.154)
PRE_SHOCK × RETURNS	15.520*	10.732*	13.067*	9.294*	10.398	6.176	3.472	4.305	2.281	3.003	2.462	3.295
	(5.624)	(5.019)	(5.507)	(4.683)	(5.683)	(4.860)	(3.791)	(3.504)	(3.851)	(3.423)	(3.818)	(3.522)
POST_SHOCK × RETURNS	11.705*	6.917	12.926*	9.073	12.423*	8.201	−0.014	0.994	3.209	3.850	4.683	5.578
	(5.695)	(5.075)	(6.077)	(5.494)	(5.970)	(5.317)	(4.092)	(3.518)	(4.058)	(3.564)	(3.980)	(3.635)
Constant	59.596**	24.101	61.651**	18.038	63.650**	17.410	54.510**	12.453	54.572**	3.899	53.657**	−2.065
	(3.990)	(15.503)	(3.760)	(14.689)	(3.763)	(14.329)	(2.664)	(14.637)	(2.616)	(15.007)	(2.680)	(15.055)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	452	452	451	451	452	452	857	857	855	855	857	857
R^2	0.063	0.279	0.040	0.246	0.041	0.266	0.002	0.198	0.002	0.196	0.004	0.149
Adjusted R^2	0.057	0.266	0.033	0.233	0.035	0.253	-0.001	0.190	-0.001	0.189	0.001	0.141

Table C13: Ordinary least squares regression analyses for each subject pool (financial professionals and students) and each shock type (DOWN, STRAIGHT, and UP) with standard errors clustered at the subject-level for **WAVE** 1. RISK PERCEPTION is the dependent variable, POST_SHOCK is a dummy variable taking the value 1 for periods after the volatility shock (i.e., decision at $t = 3$ and $t = 4$), zero otherwise, and PRE_SHOCK stands for a dummy variable taking the value 1 for periods before the shock (i.e., decision at $t = 1$ and $t = 2$), zero otherwise. The interaction terms (e.g., POST_SHOCK × RETURNS) measure the combined effects of the shock phase (i.e., before or after the shock) and the respective treatment (i.e., RETURNS). PRE_SHOCK and the presentation format PRICES act as the reference categories. All specifications are run without or with control variables such as a subject's risk tolerance, CRT score, age, and gender. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	Dependent variable: RISK PERCEPTION											
	Financial Professionals						Students					
	DOWN		STRAIGHT		UP		DOWN		STRAIGHT		UP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
POST_SHOCK	1.139**	1.136**	0.870**	0.870**	0.829**	0.828**	1.425**	1.426**	0.683**	0.683**	0.285*	0.288*
	(0.115)	(0.115)	(0.085)	(0.085)	(0.095)	(0.095)	(0.102)	(0.102)	(0.092)	(0.093)	(0.103)	(0.103)
PRE_SHOCK × RETURNS	0.477**	0.463*	0.568**	0.533**	0.328	0.292	0.677**	0.673**	0.430**	0.429**	0.410**	0.434**
	(0.167)	(0.166)	(0.161)	(0.160)	(0.168)	(0.168)	(0.129)	(0.129)	(0.127)	(0.128)	(0.131)	(0.132)
POST_SHOCK × RETURNS	0.105	0.096	0.218	0.179	0.100	0.068	−0.072	−0.076	−0.071	−0.071	0.082	0.105
	(0.155)	(0.154)	(0.156)	(0.155)	(0.147)	(0.145)	(0.133)	(0.133)	(0.127)	(0.128)	(0.142)	(0.141)
Constant	4.183**	3.197**	4.250**	3.194**	4.376**	2.888**	4.034**	3.638**	4.465**	4.088**	4.313**	3.682**
	(0.110)	(0.488)	(0.108)	(0.467)	(0.115)	(0.509)	(0.102)	(0.546)	(0.091)	(0.502)	(0.105)	(0.541)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	800	800	791	791	801	801	1,115	1,115	1,113	1,113	1,108	1,108
R^2	0.128	0.157	0.092	0.114	0.081	0.119	0.147	0.150	0.037	0.045	0.014	0.025
Adjusted R^2	0.125	0.148	0.089	0.105	0.077	0.110	0.145	0.144	0.035	0.038	0.011	0.018

Table C14: Ordinary least squares regression analyses for each subject pool (financial professionals and students) and each shock type (DOWN, STRAIGHT, and UP) with standard errors clustered at the subject-level for **WAVE** 2. RISK PERCEPTION is the dependent variable, POST_SHOCK is a dummy variable taking the value 1 for periods after the volatility shock (i.e., decision at $t = 3$ and t = 4), zero otherwise, and PRE_SHOCK stands for a dummy variable taking the value 1 for periods before the shock (i.e., decision at $t = 1$ and t = 2), zero otherwise. The interaction terms (e.g., POST_SHOCK×RETURNS) measure the combined effects of the shock phase (i.e., before or after the shock) and the respective treatment (i.e., RETURNS). PRE_SHOCK and the presentation format PRICES act as the reference categories. All specifications are run without or with control variables such as a subject's risk tolerance, CRT score, age, and gender. The stars * and ** indicate the 5%- and the 0.5%-significance levels, respectively.

	Dependent variable: RISK PERCEPTION											
	Financial Professionals						Students					
	DOWN		STRAIGHT		UP		DOWN		STRAIGHT		UP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
POST_SHOCK	1.080**	1.075**	0.929**	0.934**	0.706**	0.709**	1.315**	1.317**	0.878**	0.873**	0.325**	0.322**
	(0.115)	(0.116)	(0.143)	(0.143)	(0.130)	(0.131)	(0.118)	(0.119)	(0.103)	(0.104)	(0.101)	(0.102)
PRE_SHOCK × RETURNS	0.423*	0.420*	0.576*	0.559*	0.516*	0.513*	0.597**	0.596**	0.598**	0.605**	0.592**	0.599**
	(0.197)	(0.201)	(0.209)	(0.215)	(0.201)	(0.203)	(0.165)	(0.163)	(0.159)	(0.155)	(0.164)	(0.163)
POST_SHOCK × RETURNS	−0.091	−0.089	−0.079	−0.101	0.148	0.139	−0.029	−0.032	0.093	0.104	0.320*	0.327*
	(0.202)	(0.203)	(0.195)	(0.195)	(0.203)	(0.203)	(0.146)	(0.145)	(0.164)	(0.159)	(0.157)	(0.154)
Constant	3.957**	3.880**	3.938**	3.816**	4.053**	4.078**	4.111**	5.159**	4.025**	4.347**	4.239**	4.618**
	(0.138)	(0.556)	(0.156)	(0.542)	(0.143)	(0.600)	(0.109)	(0.579)	(0.103)	(0.579)	(0.114)	(0.537)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	443	443	441	441	443	443	846	846	846	846	839	839
R^2	0.112	0.127	0.080	0.105	0.067	0.091	0.131	0.153	0.070	0.093	0.035	0.060
Adjusted R^2	0.106	0.111	0.074	0.089	0.060	0.075	0.128	0.145	0.067	0.084	0.031	0.051