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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. This lower perceived risk is likely due to adaptive normalization as the volatility during the shock is compared to volatility experienced in real markets (which was low in December 2019, but very high in March 2020). Lower investments during the crash can be supported by higher risk aversion, not by changes in beliefs.

JEL: C91, G01, G11, G41
Keywords: Experimental finance, countercyclical risk aversion, finance professionals, COVID-19

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1 Introduction

How are risk taking, beliefs about an asset's riskiness, and price expectations affected by extreme "shocks" like the COVID-19 pandemic? In this paper we show evidence from investment experiments conducted with finance professionals in December 2019 and March 2020. With our experimental approach, we are able to control various confounding factors that are active during real-world economic crises and stock market crashes. We find that finance professionals' investments in the experiment were 12 percent lower during the stock market crash than before. Their 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 & 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 & Nagel, 2008; Calvet & 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 & Cochrane, 1999; Barberis et al., 2001). Cohn et al. (2015) show experimental evidence of countercyclical risk aversion and identify fear as the key mediating factor, 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 & Page (2017) also find evidence for countercyclical risk aversion in experimental asset markets with students, König-Kersting & Trautmann (2018) and Alempaki et al. (2019) show that countercyclical risk aversion does not necessarily hold for subjects outside the finance industry.

With regard to the COVID-19 shock, in particular, a few studies have compared risk-taking before and after (or during) the pandemic and the associated market correction, yielding mixed results. The earliest reports can be found in Bu et al. (2020), in which the authors compare answers by students in Wuhan in an unincentivized survey in October 2019 and February 2020. They report a negative relationship between exposure to the pandemic and hypothetical allocations to a risky asset. Shachat et al. (2020) present evidence from an incentivized experiment, showing an

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

increase in student's risk tolerance during the early stages of the COVID-19 crisis. Completing the set of lower, higher, and unchanged risk preferences, Angrisani et al. (2020) report no change in risk preferences among professional traders or students in an abstract risk elicitation task, between 2019 and April 2020.

Our first main contribution with this paper is that we merge both approaches: (i) the investigation of a naturally occurring shock such as the COVID-19 stock market crash and (ii) the method of running controlled and incentivized experiments with finance professionals to reduce identification problems. Hence, we ask the research question whether and how risk-taking behavior and the perception of risk changes during a stock market crash like the one that occurred during the COVID-19 pandemic? Our design allows to isolate risk taking by distinguishing it from beliefs about asset risk (risk perception) and from beliefs about future prices.

In particular, we utilize the stock market crash in March 2020 as a natural experiment 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 artefactual field experiment (Harrison & List, 2004) online with 315 financial professionals from the before.world[2] subject pool 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.

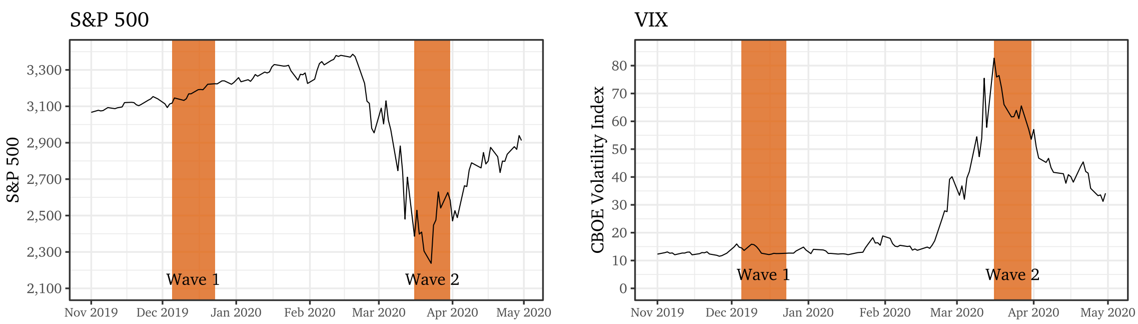

Figure 1: Time series of the S&P 500 stock index (left panel) and the CBOE Volatility Index (VIX, right panel) from November 2019 to May 2020 and the data collection periods. WAVE 1 of the experiment was conducted from December 5 to December 23, 2019; data for WAVE 2 were collected between March 16 and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

Figure 1 outlines the timing of the two experimental waves. During data collection in WAVE 1 in December 2019, the VIX remained within a very narrow range at low levels from only 12.1 to 16.0, and the S&P 500 increased by more than 3 percent. In the month leading up to the data collection

[2]See www.before.world for more information.

in WAVE 2, however, the CBOE Volatility Index (VIX, right panel) increased 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 remained exceptionally high until the end of the wave. In the same time period, the U.S. S&P 500 stock index (left panel) lost 25.5 percent and markets in Europe crashed by 36.1 percent (Euro Stoxx 50 stock index).

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 five periods with returns based on historical data. Each period, 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, and stock price/return forecasts.

We report, first, substantial changes in risk-taking behavior between the two 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 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 can be explained by elevated levels of risk aversion, pointing at a similar finding as Cohn et al. (2015) with countercyclical risk aversion. This general finding is in contrast to the behavior of non-professionals (i.e., students), as these 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 stock market developments), we conjecture that they did not experience the extreme volatility cluster in the stock market to the same extent as professionals.

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 (identical) experimental asset to be less risky in March 2020 than in December 2019. This can be explained by the neuroscientific concept of adaptive normalization (e.g. 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 December 2019, in contrast, the very same volatility of the asset appears to be large compared to the experiences of a years-long tranquil bull phase in real-world markets. Similar to Sitkin & 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 taking. Risk perception is elicited by asking subjects about their perceived riskiness of a particular stock, and thus it 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.

With this study, we add to different research strands. First, 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 & 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, 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. Graham & Narasimhan (2005) indeed find that those who experienced the Great Depression as managers were more conservative with leverage in their capital structure decisions, and Guiso et al. (2018) report a substantial increase in risk aversion during the financial crisis in 2008, which led to reduced portfolio holdings in risky assets among private investors. We contribute by running an artefactual 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. Moreover, extending the findings of Cohn et al. (2015), König-Kersting & 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 subjects in the experiment.

Second, we add to studies on risk and volatility perception. Payzan-LeNestour et al. (2016) explore "variance after-effects" and 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 from changes in beliefs about the asset's riskiness (risk perception) in a controlled manner.

In a companion paper to this study, Huber et al. (2021), we examine how professionals and students adapt their investment behavior, risk perception, and return expectations, among a number of other variables, to an experimental volatility shock and investigate how this is affected by varying the presentation format and direction of such a shock (a price crash, a price surge, or a neutral development). Professionals' investments in this experiment are negatively correlated with the price shock while their risk perception increases significantly regardless of its direction; presenting either prices or returns has no significant effect on subjects' investments or on their risk and return assessment adaptions to market shocks, respectively.

2 The Experiment

2.1 The Investment Task

We sequentially presented subjects with 100 daily returns of a risky stock over five periods, whose returns were based on historical data from the NASDAQ and DAX indices, respectively. Returns in four of the five periods are constructed from comparatively tranquil periods while in the remaining period, we induce a "shock" as returns are drawn from a more volatile distribution (see the left panel of Figure 2). The right panel of Figure 2 depicts the representative sequence of action for one exemplary 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.

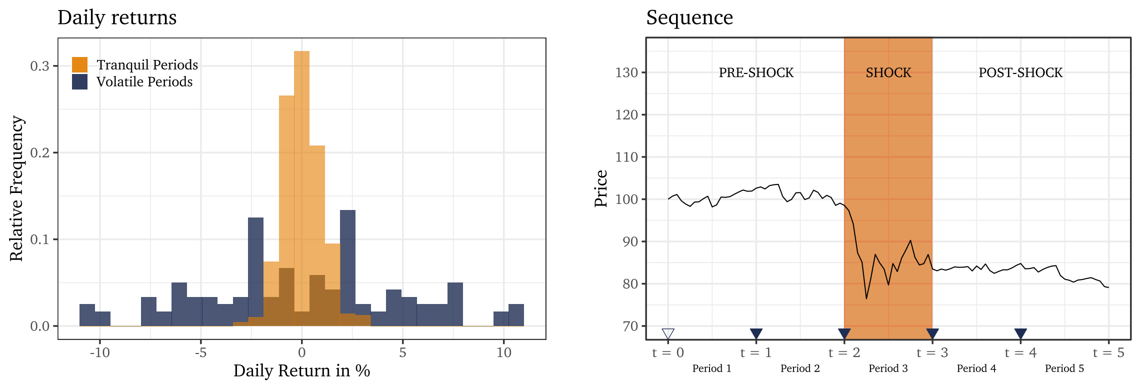

Figure 2: Left panel ('Daily returns'): Histograms of daily returns of the time series used in the experiment pooled across all three treatments. The returns from the volatile periods (blue) represent the shock period (period 3), and the returns from the calm (tranquil) periods (orange) were used in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

Each period, i.e. every 20 return draws for each stock, subjects had to make a number of decisions, which allow us to elicit the following variables (also see the experimental instructions in Online Appendix A for further details):[3]

[3]In the experiment, we also asked questions about a subject's satisfaction ("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.'"), its 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 its optimistic/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 subjects' satisfaction, their recommendations, and 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/RETURN FORECAST ("What is your estimate of the most likely ... price at the end of next month?" (if prices are displayed) / "... monthly return in the next month?" (if returns are displayed)).

In this investment experiment, we introduced two treatment variations: we varied the "presentation format" (showing either price line charts or return bar charts) between subjects, and the direction or particular path of the "experimental shock" of the stock within subjects (DOWN, STRAIGHT, or UP).[4] In a companion paper to this study, we investigate both treatment variations in detail: see Huber et al. (2021), for further details on the particular experimental design and the corresponding analyses.

2.2 Experimental Procedure

In both waves of the experiment, subjects were exposed to the identical investment task. In particular, we invited financial professionals from the before.world subject pool, 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., 2020). In total, 315 financial professionals and 498 economics and business students from the Innsbruck EconLab at the University of Innsbruck completed the experiment. 202 professionals (282 students) participated in WAVE 1 in December 2019; 113 professionals (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 main reason for this choice was that subjects could have remembered the experiment in which they participated three months earlier, 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 experimental crashes).

[4]In particular, 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. 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.

Therefore, we decided to recruit new subjects for WAVE 2 from the same subjects pools used in WAVE 1 (i.e., before.world and Innsbruck EconLab). Table C1 in the Online Appendix outlines socio-demographic 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. They are based in Europe 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 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.

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 significantly 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 periods (investment decisions) from one of the three stocks for payment. A subject's percentage return from the randomly selected period times three was added to an endowment of EUR 20. Student subjects' endowment was EUR 5.[5] 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.[6]

[5]For instance, if a subject invested 70% of her wealth in the risky stock in the randomly selected period and the stock's return in this period was 15%, then the return from this period 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.

[6]This hourly wage of approximately EUR 60 for professionals is comparable to, for instance, Haigh & List (2005), Kirchler et al. (2018), and Weitzel et al. (2020), 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.

3 Results

Figure 3 and Table 1 show the main results of this study on the percentage invested, risk perception, and return forecasts. The data of the professionals are shown in the left columns and those of student subjects are displayed in the right columns. 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.

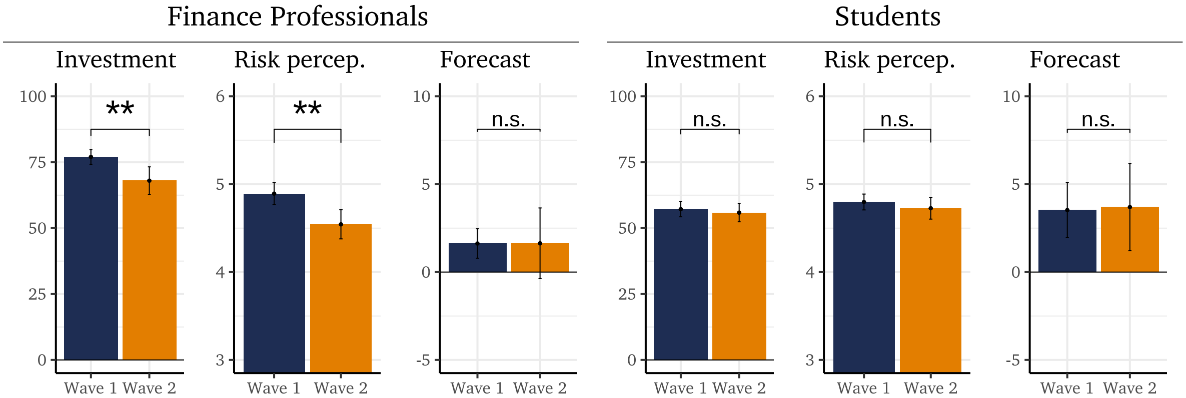

Figure 3: Descriptive overview for INVESTMENT, RISK PERCEPTION, and RETURN FORECAST for WAVE 1 (December 2019) and WAVE 2 (March 2020) for financial professionals (left panel) and student subjects (right panel). Columns WAVE 1 (blue bars) and WAVE 2 (orange bars) show the mean values for each variable. The whiskers indicate the 95% confidence intervals. * and ** indicate the 5% and the 0.5% significance levels, respectively, from double-sided t-test.

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 1, 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.[7] Moreover, we show that the return and price forecasts in the experiment are indifferent between the two waves (see line 3 in Table 1). 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 2, 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 specifications.[8] We run separate regressions for each subject pool, and we add control variables

[7] 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 1 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 Table 2 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).

[8] 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.

Table 1: 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), and RETURN FORECAST (open question) 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)
Observations	202	113		282	216	

like answers to the questions on general and financial risk taking from the GSOEP, CRT score, age, and gender next to a dummy variable indicating observations from the second wave (dummy WAVE 2). We find a statistically significant drop of 8.9 percentage points (6.9 percentage points 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. While this finding is consistent with previous studies, who also report a correlation between self-reported risk attitudes and investment behavior (e.g. Nosić & Weber, 2010), this survey measure of attitudes towards risk has been shown to be stable over time (Lönnqvist et al., 2015). We therefore interpret general and financial risk tolerance as long-term measures, i.e., basic inclinations that are not strongly affected by short-term effects.[9] Our results are in line with this conjecture, as 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), while actual risk taking, i.e., investments, is significantly lower in WAVE 2. Thus, one can conservatively infer

[9]Lönnqvist et al. (2015) and Crosetto & Filippin (2016), for example, also report only weak, if any, correlations between the GSOEP survey measure of risk attitudes and common, incentivized risk elicitation methods, indicating that those methods might not be measuring the same concept of one's attitude towards risk. Also see Jaspersen et al. (2020), for a more general, extensive discussion on what type of risk attitudes are measured by the general risk (GSOEP) question.

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.[10]

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. (2020). The absence of behavioral differences across the waves in the student sample further corroborates 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. This claim is backed up by survey questions asked at the end of the experiment.[11] Only roughly one third of students 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.

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 1). 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 the middle panel of Table 2, we run OLS regressions and control for general and financial risk taking from the GSOEP, CRT score, age, and gender next

[10]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 (2) in Table 2, 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.

[11]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").

Table 2: Ordinary least squares regressions on INVESTMENT, RISK PERCEPTION, and RETURN FORECAST for each subject pool (financial professionals and students) for both waves. The upper panel shows estimates from regressions on INVESTMENT; the middle panel on RISK PERCEPTION, and the lower panel on RETURN FORECAST. WAVE 2 is a dummy variable taking the value 1 for observations from the second wave (March 2020), zero otherwise. Models 2, 4, 6, and 8 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.

	Financial Professionals		Students	
Investment	(1)	(2)	(3)	(4)
WAVE 2	−8.925**	−6.866*	−1.486	−1.247
	(2.969)	(2.548)	(2.240)	(1.997)
Constant	76.945**	40.302**	57.473**	17.341*
	(1.413)	(8.545)	(1.418)	(8.476)
Controls	No	Yes	No	Yes
Observations	315	315	498	498
R^2	0.033	0.261	0.001	0.218
Adjusted R^2	0.030	0.247	−0.001	0.209

	Financial Professionals		Students	
Risk perception	(5)	(6)	(7)	(8)
WAVE 2	−0.350**	−0.325**	−0.079	−0.066
	(0.106)	(0.106)	(0.078)	(0.077)
Constant	4.892**	4.067**	4.797**	4.861**
	(0.064)	(0.352)	(0.046)	(0.356)
Controls	No	Yes	No	Yes
Observations	315	315	498	498
R^2	0.033	0.073	0.002	0.022
Adjusted R^2	0.030	0.055	0.000	0.010

	Financial Professionals		Students	
Return forecast	(5)	(6)	(7)	(8)
WAVE 2	0.012	0.002	0.170	0.413
	(1.107)	(1.205)	(1.495)	(1.431)
Constant	1.625**	−2.000	3.527**	8.606
	(0.427)	(2.873)	(0.800)	(7.677)
Controls	No	Yes	No	Yes
Observations	315	315	498	498
R^2	0.000	0.006	0.000	0.039
Adjusted R^2	-0.003	-0.014	-0.002	0.027

to a dummy variable depicting observations from the second wave (WAVE 2).[12] We find that the estimated coefficients and significance levels remain nearly unchanged when we add control variables (see also Table C8 in the Online Appendix as a robustness check).[13] Risk perception seems to be partly driven by CRT scores with high-CRT professionals perceiving the asset as riskier. Again, sensitivity analyses following Oster (2019) show that it is unlikely that the estimated effect between the waves is driven by unobservable variable selection.[14]

Again, student subjects do not show any differences in risk perception before and during the stock market crash. Interestingly, their 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. These findings are nicely in line with Payzan-LeNestour et al. (2020), who provide a neurologically founded explanation for why people perceive e.g., moderate volatility as rather low after a high-volatility phase and as rather high after a low-volatility phase. Again, students exhibit no differences in risk perception between December 2019 and March 2020.

Result 3: Finance professionals' price and return forecasts do not differ between the two experimental waves. Students' behavior does not differ across waves either.

Support: As shown in Table 1 and Table 2 (lower panel), we observe no statistically significant differences in professionals' beliefs about the future development of the risky asset in the experiment. 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

[12] 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.

[13] One could expect differential effects of the COVID-19 crisis: for example, low risk-tolerant subjects might be more significantly impacted than high risk-tolerant subjects. As a robustness check and to test this proposition, we also added – separately and combined – five interaction terms in the regressions shown in Table 2. Only one of the ten coefficients was significant at the 5%-level (general risk tolerance x WAVE2 in the investments-regression), but this did not change the significance of the WAVE 2-coefficient. When we put all five interaction terms in the regression at the same time none of them was significant and the coefficient for WAVE2 remained almost unchanged; see Table C8 in the Online Appendix.

[14] Assuming a maximum attainable R^2 of 0.10 ($= 1.3R^2$ from Model (6) in Table 2, 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.

with the findings for investment levels (Result 1), that the crash likely has a more general impact on professionals' risk-taking behavior.

4 Conclusion

In this paper, we investigated how the experience of the onset of the COVID-19 pandemic and the associated stock market crash influenced 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. In line with countercyclical risk aversion, this finding suggests that the drop in investments was not driven by a change in beliefs, but by a shift in risk preferences. 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, and therefore, the students' financial risk-taking behavior did not change.

Second, we found an 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.

Naturally, our findings are subject to some limitations. First, one might argue that a within-subjects design might have strengthened the drawn inference. Nevertheless, we consciously refrained from running the experiment with the same subjects in both waves. The major reason was avoiding learning effects between the two waves: experienced subjects in WAVE 2 could have anticipated the experimental shocks, as they saw a shock in WAVE 1, making identification of any causal effect of either the experimentally-induced (within-waves) or naturally occurring shock (between-waves) impossible. Reassuringly, subjects' characteristics across waves do not differ significantly, and we demonstrate that it is highly unlikely that unobservables drive our results.

Second, the economic crisis and the stock market crash around the COVID-19 pandemic are certainly 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). As with any other major economic crisis, however, 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 the experiment. In contrast, we utilize this extreme real-world event to investigate changes in risk taking 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.

Our findings emphasize the importance of the concept of countercyclical risk aversion for investors' risk-taking behavior and their perception of risk. We believe that the investigation of this amplification mechanism 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) is an important avenue 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'

Christoph Huber, Jürgen Huber, Michael Kirchler[15]

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

[15] All materials of the experiment (e.g., source codes, data files) can be found public in the Open Science Framework (OSF) repository osf.io/9chg8.

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.

——————— (new page) ———————

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.

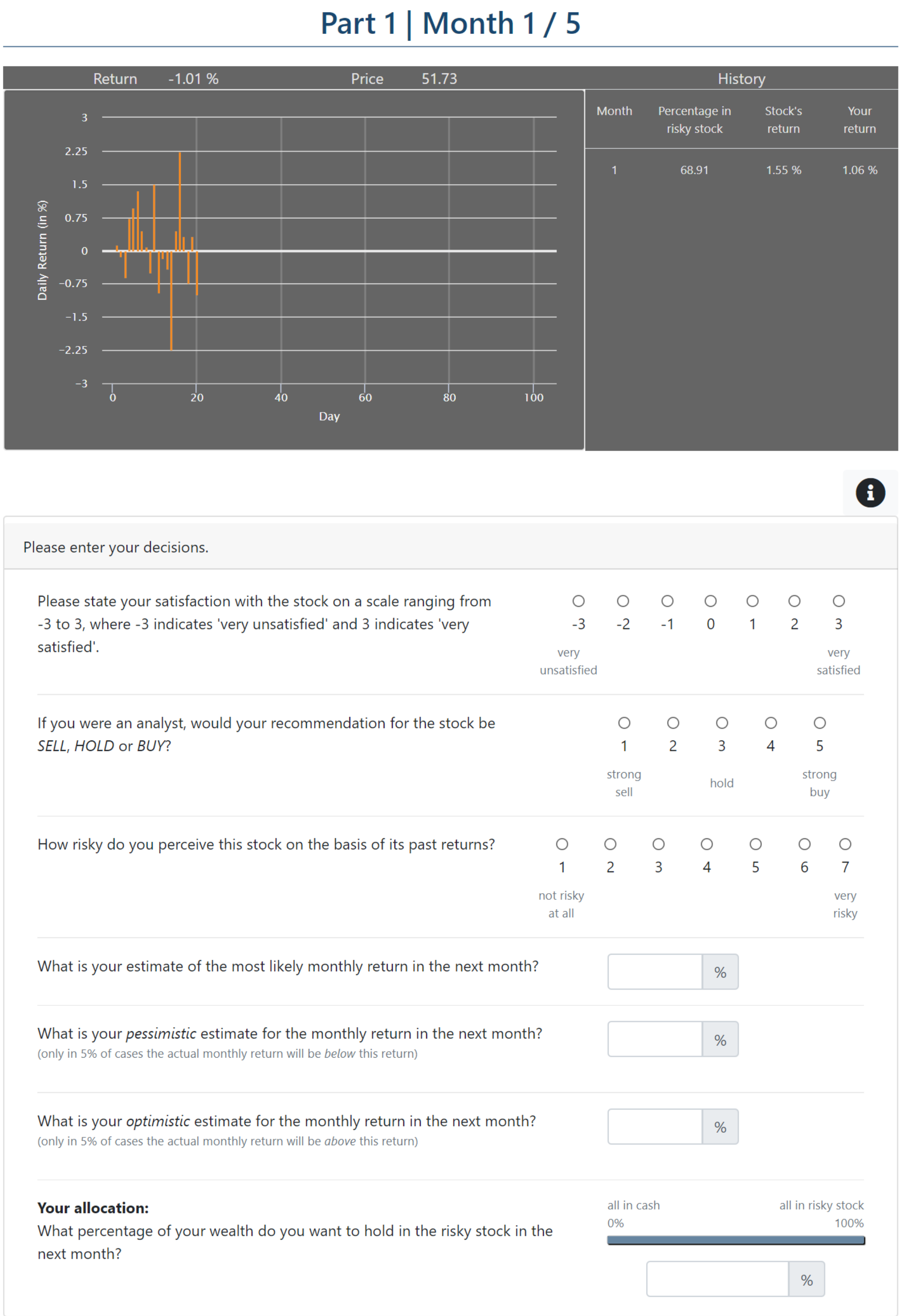
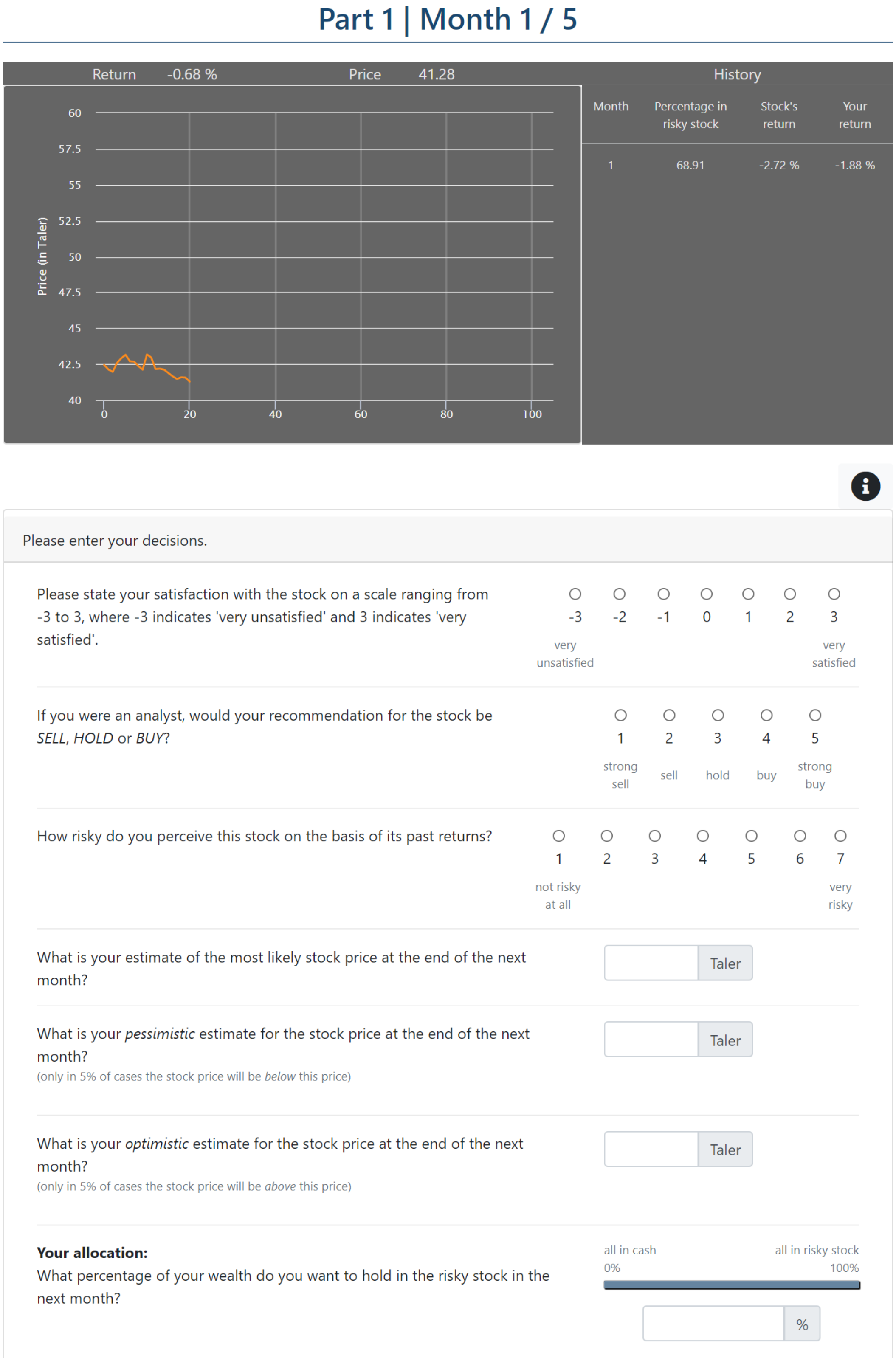


Figure A1: Screenshot of the decision screen with a RETURN chart.



Part 1 | Month 1 / 5

Return -0.68 % Price 41.28

History

Month	Percentage in risky stock	Stock's return	Your return
1	68.91	-2.72 %	-1.88 %

Please enter your decisions.

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'.

-3 -2 -1 0 1 2 3

very unsatisfied ... very satisfied

If you were an analyst, would your recommendation for the stock be *SELL*, *HOLD* or *BUY*?

1 strong sell | 2 sell | 3 hold | 4 buy | 5 strong buy

How risky do you perceive this stock on the basis of its past returns?

1 2 3 4 5 6 7

not risky at all ... very risky

What is your estimate of the most likely stock price at the end of the next month? Taler

What is your *pessimistic* estimate for the stock price at the end of the next month? Taler

(only in 5% of cases the stock price will be *below* this price)

What is your *optimistic* estimate for the stock price at the end of the next month? Taler

(only in 5% of cases the stock price will be *above* this price)

Your allocation:
What percentage of your wealth do you want to hold in the risky stock in the next month?

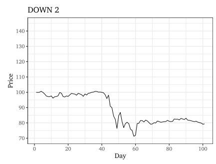
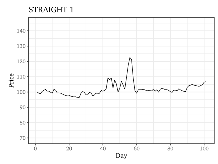
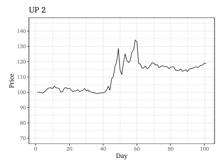
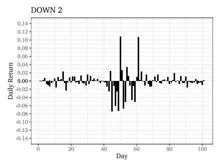
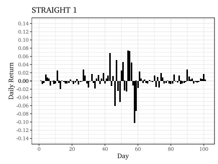
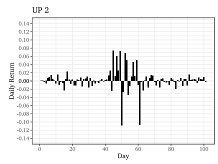
all in cash 0% ... all in risky stock 100%

%

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

B Additional Figures

Table B1: 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.

<table>
<tr><th></th><th></th><th colspan="3">Experimental shock (within-subjects)</th></tr>
<tr><th></th><th></th><th>DOWN</th><th>STRAIGHT</th><th>UP</th></tr>
<tr><td rowspan="2">Presentation format (between-subjects)</td><td>PRICES</td><td>
</td><td>
</td><td>
</td></tr>
<tr><td>RETURNS</td><td>
</td><td>
</td><td>
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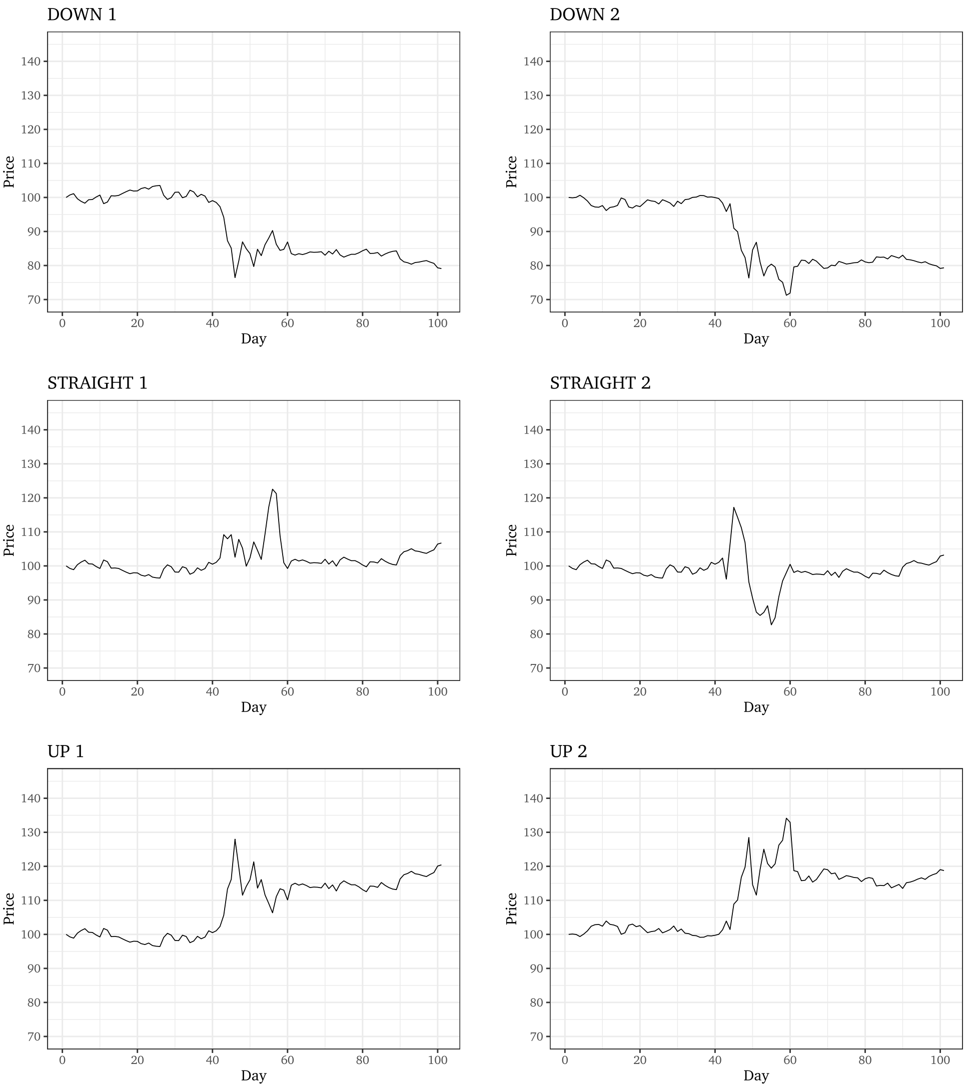

Figure B1: Price Charts: Overview over the six price paths run in the experiment. The shocks are modelled in period three. Each subject is presented with each of the path-types DOWN, STRAIGHT, and UP in random order in such a way that a subject either sees DOWN 1 and UP 2 or vice versa.

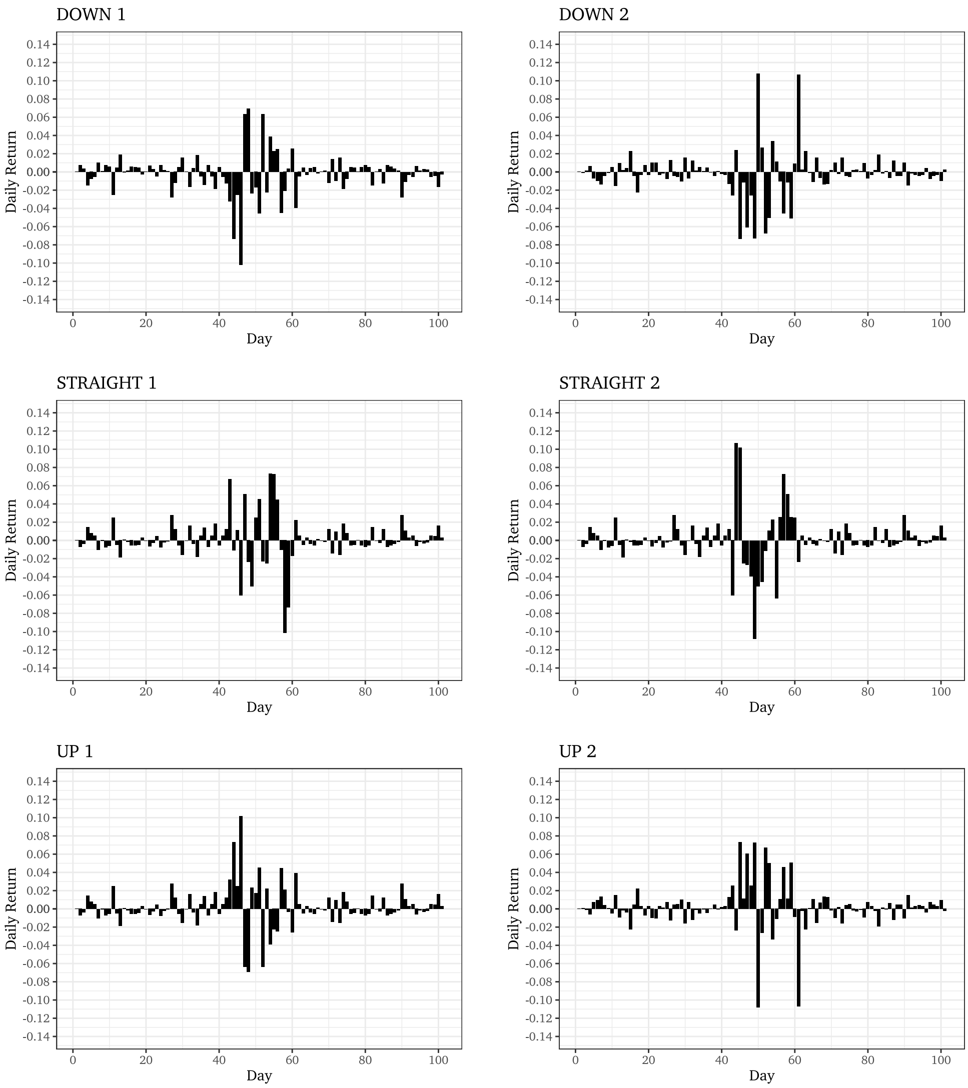

Figure B2: Return Charts: Overview over the six return paths run in the experiment. The shocks are modelled in period three. Each subject is presented with each of the path-types DOWN, STRAIGHT, and UP in random order in such a way that a subject either sees DOWN 1 and UP 2 or vice versa.

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: RETURN FORECAST: 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: RETURN FORECAST					
	PRICES	RETURNS	Pooled	PRICES	RETURNS	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
WAVE 2	−0.671	1.203	0.170	−0.649	1.016	0.202
	(1.495)	(2.014)	(1.495)	(2.042)	(1.982)	(1.466)
PROF	1.342	−4.727**	−1.902*	1.187	−3.794*	−1.241
	(0.907)	(1.206)	(0.907)	(2.474)	(1.761)	(1.633)
WAVE 2 × PROF	0.145	−0.590	−0.158	0.341	−0.356	−0.233
	(1.861)	(2.100)	(1.861)	(3.116)	(2.091)	(1.881)
General risk tolerance				0.500	0.429	0.519
				(0.447)	(0.326)	(0.282)
Financial risk tolerance				0.245	0.130	0.127
				(0.314)	(0.387)	(0.260)
CRT score				−0.168	−2.554**	−1.489*
				(0.965)	(0.804)	(0.642)
Age				−0.032	−0.014	−0.030
				(0.138)	(0.069)	(0.080)
Female				1.185	1.814	1.464
				(1.400)	(1.376)	(1.020)
Constant	−0.079	6.700**	3.527**	−4.321	5.245	0.932
	(0.800)	(1.196)	(0.800)	(4.879)	(3.460)	(3.082)
S.e.	robust	robust	robust	robust	robust	robust
Observations	394	419	813	394	419	813
R^2	0.003	0.038	0.005	0.016	0.073	0.025
Adjusted R^2	-0.004	0.031	0.001	-0.005	0.055	0.015

Table C8: Ordinary least squares regression analyses for financial professionals with pooled presentation formats (RETURNS and PRICES) for both waves. WAVE 2 is a dummy variable taking the value 1 for observations from the second wave (March 2020), zero otherwise. INVESTMENT is the dependent variable in models 1–4, RISK PERCEPTION is the dependent variable in models 5–8. All models include control variables as well as interactions terms between one or all control variables and WAVE 2. The stars * and ** indicate the 5% and the 0.5% significance levels, respectively.

	Investment				Risk perception				Return forecast			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WAVE 2	−25.444*	−21.449	−6.048*	−25.273*	0.120	0.235	−0.337**	0.275	0.120	0.235	−0.337**	0.275
	(10.402)	(11.121)	(2.692)	(11.946)	(0.471)	(0.376)	(0.120)	(0.444)	(0.471)	(0.376)	(0.120)	(0.444)
General risk tolerance	0.195	1.092	1.139	0.283	0.074	0.053	0.051	0.061	0.074	0.053	0.051	0.061
	(0.872)	(0.775)	(0.787)	(0.925)	(0.043)	(0.042)	(0.041)	(0.046)	(0.043)	(0.042)	(0.041)	(0.046)
Financial risk tolerance	3.501**	2.851**	3.598**	3.422**	−0.026	−0.0001	−0.028	−0.005	−0.026	−0.0001	−0.028	−0.005
	(0.818)	(0.889)	(0.816)	(0.995)	(0.037)	(0.041)	(0.037)	(0.042)	(0.037)	(0.041)	(0.037)	(0.042)
CRT score	6.792**	6.627**	6.660**	6.760**	0.200**	0.204**	0.203**	0.203**	0.200**	0.204**	0.203**	0.203**
	(1.601)	(1.620)	(1.623)	(1.611)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)
Age	−0.218	−0.226	−0.211	−0.210	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
	(0.137)	(0.138)	(0.140)	(0.138)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Female	−3.372	−3.590	−0.773	−1.585	−0.153	−0.143	−0.192	−0.155	−0.153	−0.143	−0.192	−0.155
	(3.387)	(3.468)	(4.146)	(4.283)	(0.136)	(0.142)	(0.175)	(0.178)	(0.136)	(0.142)	(0.175)	(0.178)
WAVE 2× General risk tol.	2.497*			2.216	−0.060			−0.020	−0.060			−0.020
	(1.273)			(1.713)	(0.059)			(0.094)	(0.059)			(0.094)
WAVE 2× Fin. risk tol.		1.901		0.329		−0.073		−0.059		−0.073		−0.059
		(1.299)		(1.731)		(0.049)		(0.084)		(0.049)		(0.084)
WAVE 2× Female			−5.372	−3.980			0.079	0.024			0.079	0.024
			(7.019)	(6.979)			(0.274)	(0.282)			(0.274)	(0.282)
Constant	47.616**	46.390**	39.261**	47.076**	3.891**	3.833**	4.082**	3.823**	3.891**	3.833**	4.082**	3.823**
	(9.198)	(9.436)	(8.743)	(9.804)	(0.381)	(0.370)	(0.356)	(0.382)	(0.381)	(0.370)	(0.356)	(0.382)
S.e.	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust	robust
Observations	315	315	315	315	315	315	315	315	315	315	315	315
R^2	0.273	0.268	0.263	0.274	0.078	0.080	0.074	0.080	0.078	0.080	0.074	0.080
Adjusted R^2	0.256	0.251	0.246	0.253	0.057	0.059	0.053	0.053	0.057	0.059	0.053	0.053

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Market shocks and professionals' investment behavior - Evidence from the COVID-19 crash

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. This lower perceived risk is likely due to adaptive normalization as the volatility during the shock is compared to volatility experienced in real markets (which was low in December 2019, but very high in March 2020). Lower investments during the crash can be supported by higher risk aversion, not by changes in beliefs.

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