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

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A B S T R A C T

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 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.

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 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 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.,

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[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.

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2001). Cohn et al. (2015) show experimental evidence of countercyclical risk aversion and identify fear as the key mediating factor, as financial professionals who are primed with a financial bust scenario are 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.

With regard to the COVID-19 shock, in particular, a few studies compare 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 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, i.e., 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 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 for isolating risk-taking by distinguishing it from beliefs about asset risk (risk perception) and from beliefs about future prices.

In particular, we utilize the March 2020 stock market crash 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 and List, 2004) online with 315 financial professionals from the before.world[2] subject pool and 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, 2020.

Fig. 1 illustrates 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 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 addition, Bekaert et al.'s (2021 asset price- and- utility-based index of time-varying risk aversion in financial markets shows similar patterns. This index (BEX) correlates with the variance risk premium in equity markets and existing sentiment indices, and demonstrates that Wave 2 of our study was conducted precisely during a time characterized by extraordinarily high aggregate risk aversion in the market: the index was at a very low level during Wave 1, but spiked sharply at the beginning of Wave 2—indicating a sudden increase in risk aversion—and did not fully revert until data collection was complete (see BEX, right panel).

In both waves of the experiment, subjects are exposed to an identical investment task, in which we present the unfolding of the price or return chart of a risky stock over five periods, with returns based on historical data. For each period, subjects have to make a number of decisions: which percentage of their endowment to invest in the risky stock (incentivized), how risky they perceive the stock to be, and how to forecast the stock price or stock return.

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 are 12 percent lower in March 2020 than in December 2019 (or 9 percentage points, down from 77 to 68 percent of their endowment). 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 to a finding similar to Cohn et al. (2015) with regard to countercyclical risk aversion. This general finding contrasts with the behavior of nonprofessionals (i.e., students), as these do not show any difference in investment behavior during the crash compared to the calm period. As students are less exposed to the stock market (in terms of investments and attention to stock market developments), we conjecture that they do 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 stock (i.e., risk perception) changes substantially from Wave 1 to Wave 2, as they consider the (identical) experimental stock 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., 2021). Compared to the COVID-19-induced crash, the stock's volatility in the experiment appears to be relatively moderate in March 2020. In December 2019, by contrast, the very same volatility appears to be large with respect to the experiences of a years-long tranquil bull phase in real-world markets. Similar to Sitkin and Pablo's (1992) argument, this indicates that decision makers take less risk, because they perceive the potentially negative consequences of doing so. Again, students show 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. We elicit risk perception by asking subjects about their perceived riskiness of a particular stock; thus the concept relies on individual judgments (i.e., beliefs). 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 contribute 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 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, as lower investment levels reduce demand for assets. This could further lower stock prices, which, in turn, further increases risk aversion. Conversely, booming stock prices could be fueled by lower levels of risk aversion and higher investment levels, thus amplifying upward pressure on stock prices. Indeed, Graham and Narasimhan (2005) find

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

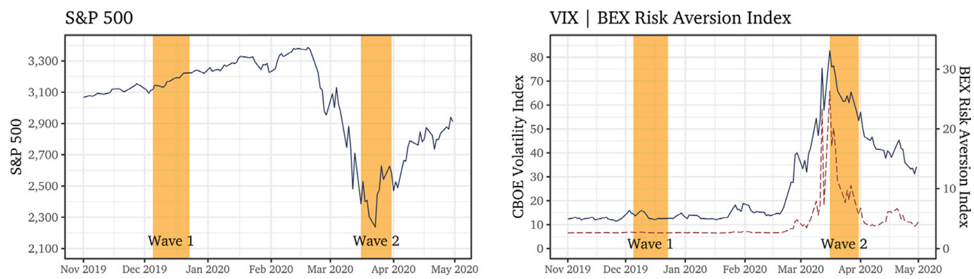

Fig. 1. Time series of the S&P 500 stock index (left panel), the CBOE Volatility Index (VIX, right panel, solid blue, left scale), and the daily risk aversion index of Bekaert et al. (2021, BEX, right panel, dashed red, right scale) from November 2019 to May 2020 and the data collection periods. WAVE 1 of the experiment was conducted from December 5, to December 23, 2019; WAVE 2 of the experiment was conducted from March 16, to March 31, 2020. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 that allows us to control for potentially confounding factors (e.g., changes in wealth levels and stock price expectations) that render identification with empirical data difficult. Additionally, 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 subjects in the experiment. With our observation of lower risk-taking among professionals during the COVID-19 crash, we also provide external validation for Bekaert et al.'s (2021) risk aversion measure.

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. (2021) find that people systematically underestimate risk after prolonged exposure to high risk, as they become 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 we 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 adaptations to market shocks, respectively.

2. The experiment

2.1. The investment task

We sequentially present subjects with 100 daily returns of a risky stock over five periods, the returns of which are 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 Fig. 2). The right panel of Fig. 2 depicts the representative sequence of action for one exemplary time series. In all time series, we model the pre-shock phase in periods 1 and 2, the shock in period 3, and the post-shock phase in periods 4 and 5.

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

- 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 introduce two treatment variations: we vary 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 an 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

[3] We also elicit a subject's satisfaction, its investment recommendation, and its optimistic/pessimistic forecasts (see the Screenshot in Figure A1 (Online Appendix) for the precise wording and possible answers). To keep the paper concise, we report results for these additional variables in the Online Appendix.

[4] In particular, in a between-subjects design, subjects are randomly assigned to one of two conditions. That is, each subject is presented with each of the path types DOWN, STRAIGHT, and UP with price charts only or return charts only in random order. The DOWN shock is either the NASDAQ crash from April to May 2000 or the DAX crash from September to October 2008; for UP and STRAIGHT shocks we mirror/permute the identical returns to arrive at price paths with an analogue positive or net-zero return, respectively, while keeping volatility constant.

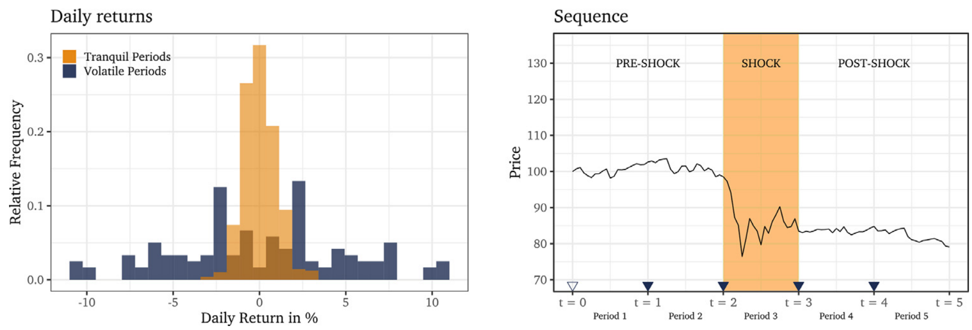

Fig. 2. Left panel ('Daily returns'): Histograms of daily returns of the time series used in the experiment pooled across all three treatments. The returns from the volatile periods (blue) represent the shock period (period 3), and the returns from the calm (tranquil) periods (orange) were used in the 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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, and 113 professionals (216 students) participated in WAVE 2 between March 16 and March 31, at the climax of the COVID-19 stock market crash.

It is important to note that we consciously refrained from running the experiment with the same professionals and students in both waves and that, therefore, no subject participated in both waves. The main reason for this was that subjects might have been able to remember the experiment in which they had participated three months earlier and might, therefore, have been able to anticipate the experimental shocks from the beginning in WAVE 2. This argument applies especially to the professionals, as professionals rarely take part in experiments. This increases the likelihood they will remember parts of the experiment, in particular the experimental crashes.

Therefore, we recruited new subjects for WAVE 2 from the same subject pools used in WAVE 1 (i.e., before.world and Innsbruck EconLab). Table C1 in the Online Appendix outlines the subjects' socio-demographic information across the waves. On average, participating 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; and the fraction of professionals with a university degree was 86 percent. The professionals are based in Europe, and nearly 30 percent of them selected investment and portfolio management as their primary job function, followed by trading and financial advice. Notably, at the 5%-level, none of the demographic differences between the two waves were statistically significant, indicating no impact of the professionals' sample compositions on behavioral differences between the two waves. Similarly, the student samples for both waves did not differ from another, 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) suggested approach, outlined in Section 3.

Following 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). Furthermore, we evaluated 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 more correct answers than the students' average ($p < .005$, Mann-Whitney U-test, $N = 813$). Moreover, professionals' self-reported general (7.5 across the two waves) and financial (7.7) risk tolerance levels were significantly higher than those reported by students (general: 6.6; financial: 5.5; $p < .005$ 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' endowments were EUR 5.[5] Financial professionals received, 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]

3. Results

Fig. 3 and Table 1 show the main results of this study on the percentage invested, risk perception, and return forecasts. The professionals' data are shown in the left columns and the students' data 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.

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

As outlined in Table 1, we find a drop in investment levels of 9 percentage points (from 77 to 68 percent of their endowment, $p < .005$ following Benjamin et al., 2018) from December 2019 to March 2020, although the investment task is identical.[7] Moreover,

[5] For instance, if a subject invests 70% of her wealth in the risky stock in the randomly selected period and the stock's return in this period is 15%, then the return from this period will be 70% × 15% = 10.5%. Her payment from the experiment will be 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 and 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, respectively, for their professionals.

[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).

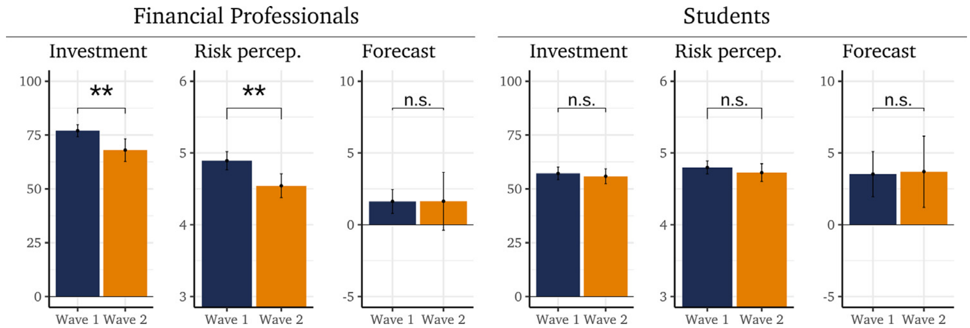

Fig. 3. Descriptive overview for INVESTMENT, RISK PERCEPTION, and RETURN FORECAST for WAVE 1 (December 2019) and WAVE 2 (March 2020) for financial professionals (left panel) and student subjects (right panel). Columns WAVE 1 (blue bars) and WAVE 2 (orange bars) show the mean values for each variable. The whiskers indicate the 95% confidence intervals. * and ** indicate the 5% and the 0.5% significance levels, respectively, from double-sided *t*-test. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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	

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.

An alternative interpretation of this result could be that subjects might expect a rebound of stocks in the near future but consider the present time too early to invest because, as the short-term crash risk is elevated, the next few days may present even better buying opportunities. However, over 71 percent of all data in WAVE 2 came in during the first three days, i.e., from March 16, to 18. During these three days, stock markets were still falling: both the Euro Stoxx 50 and DAX reached their respective nadir on March 18. Thus, at least in these first three days, when most of our data for WAVE 2 came in, stock market prospects did not appear already to have improved.

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 like answers to the questions on general and financial risk tolerance 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; $p < .005$ and $p < .05$, respectively) in the fraction invested in the risky stock 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, which also report a correlation between self-reported risk attitudes and investment behavior (e.g. Nosić and 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 align with this conjecture, as we do not find statistically significant differences in self-reported survey measures of risk tolerance in general or financial matters across the waves for each subject pool (see Table C1 in the Online Appendix), whereas actual risk-taking, i.e., investments, is significantly lower in WAVE 2. 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 were those with higher investment levels in the experiment.

[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.

[9] Lönnqvist et al. (2015) and Crosetto and 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.

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	(9)	(10)	(11)	(12)
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

As we find no statistically significant differences between professionals' characteristics in WAVE 1 and WAVE 2, we expect selection on *observables* not to influence our results (see Table C1 in the Online Appendix for the non-statistically significant differences in subject characteristics across both waves). To corroborate this notion, we apply sensitivity analyses following Altonji et al. (2005) and Oster (2019) and examine coefficient movements with respect to movements in R^2 to rule out potential omitted variable biases. The intuition underlying these analyses is that coefficient and R^2 movements, after including observable covariates, are informative of the extent of potential bias arising from omitting unobservable variables. Assuming a maximum attainable R^2 of 0.34, we compute a relative degree of selection on observed and unobserved controls of $\delta = 7.71$.[10] This can be interpreted as selection on unobservables having 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. We thus argue that it is unlikely that the estimated effect between the two waves is driven by *unobservable* variables.

In explaining participants' risk-taking behavior, one might also consider their elicited beliefs and risk perceptions in the cross-section. From the results of, for instance, Huber and Huber (2019) and Nosić and Weber (2010), we would expect individuals to invest more when they possess higher overall return forecasts and lower overall risk perceptions, respectively. However, in additional, explorative regression analyses, neither of these two coefficients is statistically significant at the individual level across both experimental waves (see Tables C9 and C10 in the Online Appendix). Thus, while individuals' average risk-taking is consistent with their self-reported risk tolerance, the picture is more blurred when it comes to their elicited period-to-period beliefs. For more detailed analyses at the period-level, adding a time dimension within each experimental wave, we refer to Huber et al. (2021).

Importantly, student subjects do not show any differences in investment behavior before or 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 for the professionals' changes in risk-taking behavior, which 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, mostly because the majority of them are not invested in the stock market and those who are invested are probably minimally affected. This claim is backed up by survey questions asked at the end of the experiment, in which only around one third of students indicate they had invested in financial products at least once during the preceding five years—which is a very weak measure of intense stock market participation. Furthermore, more than two-thirds of students report that they consulted financial news only once a week or less often. Students who declare having invested in financial markets and/or regularly check financial news on average take more risk in the experiment, but their risk-taking decisions are not significantly different between the two waves (see Table C11). However, we do not believe that those students who invested at least once during the last five years or who have some interest in stock markets are comparable to finance professionals in their exposure to the COVID-19 crash. The latter were exposed in their delegated decisions with large sums of client money, and probably also in their private investment decisions.

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

We show evidence of professionals' decrease in risk perception of the experimental stock 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 stock (drop from 4.89 to 4.55, $p < .005$) from December 2019 to March 2020. In the middle panel of Table 2, we run OLS regressions and control for general and financial risk tolerance from the GSOEP, CRT score, age, and gender next to a dummy variable depicting observations from the second wave (WAVE 2).[11] 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). One could expect differential effects of the COVID-19 crisis: for example, low risk-tolerant subjects might be significantly more impacted than high risk-tolerant

[10] A maximum attainable R^2 of 0.34 represents $1.3R^2$ from Model (2) in Table 2. Related investment tasks, such as Ehm et al., 2014, Cohn et al., 2017, and Kirchler et al., 2018 also report R^2s between 0.08 and 0.26.

[11] 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.

subjects. As a robustness check and to test this proposition, we also add, separately and combined, five interaction terms in the regressions shown in Table 2. Only one of the ten coefficients is significant at the 5%-level (general risk tolerance x WAVE 2 in the investments-regression), but this does 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 is significant, and the coefficient for WAVE 2 remains almost unchanged; see Table C8 in the Online Appendix. Risk perception seems to be partly driven by CRT scores, with high-CRT professionals perceiving the stock 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.[12]

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

Summing up the findings from both subject pools, we conclude that professionals consider the stock 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 experiences of different magnitudes of volatility. Compared to the COVID-19 stock market crash, the experimental stock's volatility in the experiment obviously appears to be comparatively moderate in March 2020. By contrast, in December 2019, the stock'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 align nicely with Payzan-LeNestour et al. (2021), 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.

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 stock in the experiment. This is interesting, as professionals experience a downturn of 30 to 40 percent on 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.

4. Conclusion

In this study, 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 a risky experimental asset dropped by 9 percentage points (or 12 percent) 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 and with the spike in overall risk aversion in financial markets (see Fig. 1), 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). Students 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 considered 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. By 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, several factors simultaneously influence behavior. For instance, the crisis could trigger a wealth decline and a lower expected path for future labor income. Classic background risk, i.e., 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. Rather, 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 contribute to an even more severe crisis and slower price recovery) is an important avenue for future research. From a methodological standpoint with a focus on external validity, combining controlled experiments with industry professionals and private investors alongside naturally occur-

[12] Assuming a maximum attainable R^2 of 0.10 (= $1.3R^2$ from Model (6) in Table 2, we compute $\delta = 9.58$. Related risk perception elicitations, such as Holzmeister et al., 2020, for example, report an R^2 of 0.05.

ring events, such as real-world booms or crashes, can be a fruitful avenue for future work and provide better understanding in this particular area.

Declaration of Competing Interest

None.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2021.106247

CRediT authorship contribution statement

Christoph Huber: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Jürgen Huber:** Conceptualization, Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing, Funding acquisition. **Michael Kirchler:** Conceptualization, Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing, Funding acquisition.

References

Alempaki, D., Starmer, C., Tufano, F., 2019. On the priming of risk preferences: the role of fear and general affect. J Econ Psychol doi:10.1016/J.JOEP.2018.12.011.

Altonji, J.G., Elder, T.E., Taber, C.R., 2005. Selection on observed and unobserved variables: assessing the effectiveness of catholic schools. Journal of Political Economy 113 (1), 151–184. doi:10.1086/426036.

Angrisani, M., Cipriani, M., Guarino, A., Kendall, R., de Zarate Pina, J. O., 2020. Risk preferences at the time of COVID-19: An experiment with professional traders and students. Working Paper.

Barberis, N., Huang, M., Santos, T., 2001. Prospect theory and asset prices. Q J Econ 116 (1), 1–53. doi:10.1162/003355301556310.

Bekaert, G., Engstrom, E.C., Xu, N.R., 2021. The time variation in risk appetite and uncertainty. Manage Sci. Forthcoming

Benjamin, D.J., Berger, J.O., Johannesson, M., Nosek, B.A., Wagenmakers, E.-J., Berk, R., Bollen, K.A., Brembs, B., Brown, L., Camerer, C.F., Cesarini, D., Chambers, C.D., Clyde, M., Cook, T.D., De Boeck, P., Dienes, Z., Dreber, A., Easwaran, K., Efferson, C., Fehr, E., Fidler, F., Field, A.P., Forster, M., George, E.I., Gonzalez, R., Goodman, S., Green, E., Green, D.P., Greenwald, A.G., Hadfield, J.D., Hedges, L.V., Held, L., Hua Ho, T., Hoijtink, H., Hruschka, D.J., Imai, K., Imbens, G., Ioannidis, J.P.A., Jeon, M., Jones, J.H., Kirchler, M., Laibson, D., List, J., Little, R., Lupia, A., Machery, E., Maxwell, S.E., McCarthy, M., Moore, D.A., Morgan, S.L., Munafó, M., Nakagawa, S., Nyhan, B., Parker, T.H., Pericchi, L., Perugini, M., Rouder, J., Rousseau, J., Savalei, V., Schönbrodt, F.D., Sellke, T., Sinclair, B., Tingley, D., Van Zandt, T., Vazire, S., Watts, D.J., Winship, C., Wolpert, R.L., Xie, Y., Young, C., Zinman, J., Johnson, V.E., 2018. Redefine statistical significance. Nat. Hum. Behav. 2 (1), 6–10. doi:10.1038/s41562-017-0189-z.

Brunnermeier, M.K., Nagel, S., 2008. Do wealth fluctuations generate time-varying risk aversion? micro-evidence on individuals' asset allocation. American Economic Review 98 (3), 713–736. doi:10.1257/aer.98.3.713.

Bu, D., Hanspal, T., Liao, Y., Liu, Y., 2020. Risk Taking, Preferences, and Beliefs: Evidence from Wuhan. Working Paper.

Calvet, L.E., Sodini, P., 2014. Twin picks: disentangling the determinants of risk-Taking in household portfolios. J Finance 69 (2), 867–906. doi:10.1111/jofi.12125.

Campbell, J.Y., Cochrane, J.H., 1999. By force of habit: a consumption-based explanation of aggregate stock market behavior. Journal of Political Economy 107 (2), 205–251. doi:10.1086/250059.

Cohn, A., Engelmann, J., Fehr, E., Maréchal, M.A., 2015. Evidence for countercyclical risk aversion: an experiment with financial professionals. American Economic Review 105 (2), 860–885. doi:10.1257/aer.20131314.

Cohn, A., Fehr, E., Maréchal, M.A., 2017. Do professional norms in the banking industry favor risk-taking? Review of Financial Studies 30 (11), 3801–3823. doi:10.1093/rfs/hhx003.

Crosetto, P., Filippin, A., 2016. A theoretical and experimental appraisal of four risk elicitation methods. Experimental Economics 19 (3), 613–641. doi:10.1007/s10683-015-9457-9.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: measurement, determinants, and behavioral consequences. J Eur Econ Assoc 9 (3), 522–550. doi:10.1111/j.1542-4774.2011.01015.x. arXiv:1011.1669v3.

Ehm, C., Kaufmann, C., Weber, M., 2014. Volatility inadaptability: investors care about risk, but cannot cope with volatility. Rev Financ 18 (4), 1387–1423. doi:10.1093/rof/rft032.

Graham, J.R., Narasimhan, K., 2005. Corporate Survival and Managerial Experiences During the Great Depression. Working Paper doi:10.2139/ssrn.489694.

Guiso, L., Sapienza, P., Zingales, L., 2004. The role of social capital in financial development. American Economic Review 94 (3), 526–556. doi:10.1257/0002828041464498.

Guiso, L., Sapienza, P., Zingales, L., 2008. Trusting the stock market. J Finance 63 (6), 2557–2600. doi:10.1111/j.1540-6261.2008.01408.x.

Guiso, L., Sapienza, P., Zingales, L., 2018. Time varying risk aversion. J financ econ 128 (3), 403–421. doi:10.1016/j.jfineco.2018.02.007.

Haigh, M.S., List, J.A., 2005. Do professional traders exhibit myopic loss aversion? an experimental analysis. J Finance 60 (1), 523–534. doi:10.1111/j.1540-6261.2005.00737.x.

Harrison, G.W., List, J.A., 2004. Field experiments. J Econ Lit 42 (4), 1009–1055. doi:10.1257/0022051043004577.

Hertwig, R., Barron, G., Weber, E.U., Erev, I., 2004. Decisions from experience and the effect of rare events in risky choice. Psychol Sci 15 (8), 534–539. doi:10.1111/j.0956-7976.2004.00715.x.

Holzmeister, F., Huber, J., Kirchler, M., Lindner, F., Weitzel, U., Zeisberger, S., 2020. What drives risk perception? a global survey with financial professionals and laypeople. Manage Sci 66 (9), 3977–4002. doi:10.1287/mnsc.2019.3526.

Huber, C., Huber, J., 2019. Scale matters: risk perception, return expectations, and investment propensity under different scalings. Experimental Economics 22 (1), 76–100. doi:10.1007/s10683-018-09598-4.

Huber, C., Huber, J., Kirchler, M., 2021. Volatility Shocks and Investment Behavior. Working Paper.

Jaspersen, J.G., Ragin, M.A., Sydnor, J.R., 2020. Linking subjective and incentivized risk attitudes: the importance of losses. J Risk Uncertain 1–20. doi:10.1007/s11166-020-09327-4.

Kirchler, M., Lindner, F., Weitzel, U., 2018. Rankings and risk-Taking in the finance industry. J Finance 73 (5), 2271–2302. doi:10.1111/jofi.12701.

Kirchler, M., Lindner, F., Weitzel, U., 2020. Delegated investment decisions and rankings. Journal of Banking & Finance 120, 105952. doi:10.1016/j.jbankfin.2020.105952.

König-Kersting, C., Trautmann, S.T., 2018. Countercyclical risk aversion: beyond financial professionals. J Behav Exp Finance 18, 94–101. doi:10.1016/J.JBEF.2018.03.001.

Lönnqvist, J.-E., Verkasalo, M., Walkowitz, G., Wichardt, P.C., 2015. Measuring individual risk attitudes in the lab: task or ask? an empirical comparison. Journal of Economic Behavior & Organization 119, 254–266. doi:10.1016/j.jebo.2015.08.003.

Malmendier, U., Nagel, S., 2011. Depression babies: do macroeconomic experiences affect risk taking? Q J Econ 126 (1), 373–416. doi:10.1093/qje/qjq004.

Newell, A., Page, L., 2017. Countercyclical Risk Aversion and Self-reinforcing Feedback Loops in Experimental Asset Markets. Working Paper doi:10.13140/RG.2.2.33417.44640.

Nosić, A., Weber, M., 2010. How riskily do I invest? The role of risk attitudes, risk perceptions, and overconfidence. Decision Analysis 7 (3), 282–301. doi:10.1287/deca.1100.0178.

Oster, E., 2019. Unobservable selection and coefficient stability: theory and evidence. Journal of Business and Economic Statistics 37 (2), 187–204. doi:10.1080/07350015.2016.1227711.

Payzan-LeNestour, E., Balleine, B.W., Berrada, T., Pearson, J., 2016. Variance after-Effects distort risk perception in humans. Current Biology 26 (11), 1500–1504. doi:10.1016/J.CUB.2016.04.023.

Payzan-LeNestour, E., Pradier, L., Putniņš, T. J., 2021. The "Waterfall Illusion" in the Perception of Risk. Working Paper. 10.2139/ssrn.2553526

Schwaiger, R., Kirchler, M., Lindner, F., Weitzel, U., 2019. Determinants of investor expectations and satisfaction. a study with financial professionals. Journal of Economic Dynamics and Control 110, 103675. doi:10.1016/J.JEDC.2019.03.002.

Shachat, J., Walker, M.J., Wei, L., 2020. The Impact of the Covid-19 Pandemic on Economic Behaviours and Preferences: Experimental Evidence from Wuhan. Working Paper.

Sitkin, S.B., Pablo, A.L., 1992. Reconceptualizing the determinants of risk behavior. The Academy of Management Review 17 (1), 9–38.

Toplak, M.E., West, R.F., Stanovich, K.E., 2014. Assessing miserly information processing: an expansion of the cognitive reflection test. Thinking and Reasoning 20 (2), 147–168. doi:10.1080/13546783.2013.844729.

Weitzel, U., Huber, C., Huber, J., Kirchler, M., Lindner, F., Rose, J., 2020. Bubbles and financial professionals. Rev Financ Stud 33 (6), 2659–2696.