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Evidence for Countercyclical Risk Aversion:
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August, 2014

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JEL classification: G02, C91

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1 Introduction

One of the major puzzles in financial economics is the fact that risk premiums of many asset classes vary strongly and systematically over time. In particular, the equity risk premium seems to be higher during recessions than in business cycle peaks. Over the past decades a high price-dividend ratio of U.S. stocks preceded several years of low returns and vice versa (Shiller 1981; Campbell and Shiller 1988a,b; Cochrane 2011). To account for this pervasive pattern, asset pricing models have evolved that assume that investors exhibit countercyclical risk aversion. In these models, investors are less risk averse during financial booms compared to busts. Investors in consumption-based asset pricing models derive utility from consumption relative to a habit or subsistence level of consumption (e.g., Campbell and Cochrane 1999) and become more risk averse as asset prices decline and consumption approaches the habit level. In the model of Barberis et al. (2001), utility depends not only on consumption, but also on recent investment performance relative to some historical benchmark. They assume that future losses are psychologically more painful if recent investments yielded a relatively poor performance. As Mehra (2012) recently pointed out, however, the question whether investors actually exhibit countercyclical risk aversion as postulated in these models remains open. We address this gap in empirical knowledge by providing evidence in favor of countercyclical risk aversion.[1] Our evidence is based on the risk taking behavior of financial market professionals in a controlled experimental environment that provides a measure of subjects' risk aversion.

In view of the difficulties in identifying countercyclical risk aversion, it is not surprising that only limited evidence exists to date. A key issue is finding ceteris paribus variation in financial market trends. Using actual market data can be problematic be-

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[1]We define countercyclical risk aversion as a lower willingness to buy identical risky assets (i.e., assets with an identical price, identical objective asset returns and identical subjective expectation about these asset returns) in a bust relative to a boom. Subjects who behave in this way apply a higher risk discount to the same assets (i.e., they exhibit higher risk aversion) in the bust compared to the boom treatment.

cause behavior in booms and busts is simultaneously affected by many factors that are often difficult to measure. For example, a decline in asset prices is generally associated with changes in subjective expected asset returns, asset price volatility, overall financial wealth, changes in habits, and background risks that may or may not be correlated with asset prices (Calvet and Sodini 2014; Beaud and Willinger forthcoming). This makes inferring risk aversion from actual asset holdings extremely challenging. For example, in the absence of good expectations data, holding a low share of risky assets may reflect investors' high risk aversion or their pessimistic expectations for future returns (e.g., Malmendier and Nagel 2011). In addition, there is evidence suggesting that inertia governs household asset allocation, i.e., households re-balance their portfolios only slowly in response to capital gains and losses, implying that their portfolio contains too many or too few risky assets for a given level of risk aversion (e.g., Agnew et al. 2003; Brunnermeier and Nagel 2008).

We circumvent these measurement and identification problems in this paper by directly measuring the willingness to take financial risks in a controlled task - adapted from Gneezy and Potters (1997) - with real financial stakes: subjects received an initial endowment of 200 Swiss francs (about 220 USD) and decided how much to invest in a risky asset with a positive expected return, and how much to put on a risk-free account with a zero interest rate. Our subjects are financial professionals who trade assets privately and professionally. One of our investment tasks serves as a measurement tool for risk aversion - the risk task - where we have perfect control over subjects' expected returns and the risks they face because we determine (and subjects know) the probabilities and payoffs in the task. In contrast, in the other investment task - the ambiguity task - subjects do not know the precise probabilities, but we control for their expectations by explicitly measuring them.

Instead of measuring subjects' risk taking in a real financial boom and bust, which is associated with all the measurement and identification problems mentioned above,

we primed half of the subjects with a stock market boom and the other half with a stock market bust. We primed subjects by asking them to fill out a survey before they participated in the investment tasks and they were shown a fictive graph of asset prices in one part of the survey that resembled a stock market boom or a bust, respectively. We then asked them group-specific general questions about their investment strategy during either a boom or a bust, depending on which group they were in. In this way, we mentally activated the concept of a financial boom or bust, i.e., we rendered it mentally salient.

Priming is a well-established and frequently used method in psychology and refers to the mental activation of the primed concepts (Bargh and Chartrand 2000). In recent years, priming has also been increasingly used in economics and finance.[2] Priming enables the measurement of the pure psychological impact of the primed concepts on behavior (and emotions and cognition) in subsequent tasks. This technique allows us to measure the psychological impact of booms and busts on risk preferences without the confounding influence of background risk, wealth effects, changing habits, experienced gains or losses, unknown returns, and volatility expectations, because all these variables remain unchanged across conditions. In other words, subjects in the boom and bust condition face exactly identical choice problems, and random assignment to conditions ensures that the two treatment groups are statistically identical. Thus, any behavioral difference in average risk taking across conditions identifies the psychological impact of boom versus bust on subjects' risk preferences.

Our results show that financial professionals take substantially fewer risks when they are primed with a financial bust as opposed to a boom. When the probabilities with which different payoffs arose are perfectly known (risk task), they invest on average 22 percent less into the risky asset in the bust condition (45 percent of the endowment)

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[2]For example, Gilad and Kliger (2008) primed financial professionals using a fictive story about a person gambling in the casino. See also Benjamin et al. (2010) and Callen et al. (2014) for recent priming studies examining the respective influence of social identity or violent trauma on risk taking.

than in the boom condition (58 percent of the endowment). When subjects do not have perfect information about probabilities (ambiguity task), we observe a similar 17 percent reduction in the amount allocated to the risky asset in the bust treatment. Because the priming could, in principle, also affect subjects' expectations about the probability of the good state of the world in the ambiguity task, we also measured these expectations. However, the priming did not affect expectations. We thus unambiguously observe a countercyclical willingness to take risks, i.e., priming subjects with a bust condition increases their risk aversion relative to the boom prime.[3]

In view of previous studies (e.g., List and Haigh 2005; Cipriani and Guarino 2009) suggesting that psychological forces are attenuated in more experienced market participants, we further examined whether participants with less market experience drive the priming effect. We find no statistically significant differences between subjects with different market experience. If anything, market experience tends to increase the susceptibility to booms and busts.[4] Further analysis suggests that the specific emotion of fear may play a critical role in countercyclical risk aversion. Subjects in the bust condition exhibited a significantly higher level of fear than those in the boom condition. We also find that higher levels of fear predict a significantly lower investment in the risky asset.

The idea that fear may be related to risk taking has been recognized previously in the psychological literature. For example, Lerner and Keltner (2001) found in a correlation study that more fearful individuals are less willing to take risks in a hypothetical choice situation (i.e., in the Asian disease problem). However, evidence for a causal relationship between fear and risk preferences when decisions have real monetary consequences remains scarce.[5] In order to study the causal impact of fear on financial risk taking, we

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[3]The prime could also affect subjects' ambiguity aversion in the ambiguity task. However, as an increase in ambiguity aversion also represents a reduction in the willingness to invest in the risky asset, we use the term risk aversion for both for convenience.

[4]In a similar vein, Haigh and List (2005) find that professional traders exhibit more myopic loss aversion than students.

[5]See, for example, Lee and Andrade (2011) and Lin et al. (2012). In these papers fear is induced exogenously in a market setting where it can affect both subjects' risk preferences and their beliefs about others behavior. Thus, if fear induces behavioral changes, this can be due to changes in subjects'

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conducted a further experiment in which we exposed experimental subjects to fear from random electric shocks during an investment task. All subjects faced low and high fear trials, enabling us to control for individual differences in risk taking and fear perception. A high (low) fear level was implemented by informing subjects that they would receive painful (mild and painless) random electric shocks during the next three investment trials.[6] When participants were exposed to low levels of fear, they were willing to take significantly higher risks than when they were subject to high levels of fear. Interestingly, not the actual shock itself but the expectation of receiving a painful shock during the task diminished risk taking in this study. Taken together, the combined evidence from the priming and the fear induction experiment thus suggests that the emotion of fear may play an important role in countercyclical risk aversion.

Our findings contribute to several strands of the literature. Most importantly, we provide direct support for countercyclical risk aversion, which is a key ingredient of asset pricing models that aim to explain the high volatility of asset prices and the counter-cyclical risk premium for equity (Campbell and Cochrane 1999; Barberis et al. 2001).[7] Higher risk aversion during a bust directly implies that households demand a high equity risk premium, while the required risk premium is lower during a boom. In addition, our findings provide a rationale for self-reinforcing feedback loops that amplify market dynamics and generate excess volatility. For example, a decline in stock prices could evoke feelings of fear among investors, rendering them more risk averse. This may lead to the sale of stocks (i.e., panic sales), which then creates additional downward momentum for the prices. Likewise, a stock market boom could be amplified through a reduction in

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risk preferences or changes in their expectations about other market participants' behavior.

[6]We also measured ex-ante each subject's individual pain threshold in order to be able to calibrate painless and painful electric shocks for each individual.

[7]There have been several attempts in the literature to validate the consumption based habit model by testing one particular prediction of the model. In this model, habits imply that lower wealth is associated with higher risk aversion. Existing studies produced mixed evidence (Brunnermeier and Nagel 2008; Calvet et al. 2009; Chiappori and Paiella 2011). These studies typically rely on the assumption that risky asset holdings are a good proxy of risk aversion, making it necessary to control for many other factors for which good proxies may be difficult to find.

fear and risk aversion.

The fact that booms and busts affect subjects' fear differently and that fear may directly affect their risk preferences has potentially intriguing implications for how economists should model the individual. In standard theory, expectations typically do not affect preferences. If, however, price expectations affect fear levels, they may also directly affect risk preferences. In this context, we would like to emphasize that nothing in our findings rules out that expectations may also have a direct amplifying effect on market dynamics. If, for example, a substantial share of traders has optimistic price expectations during a boom, this may not only increase their investments in risky assets through a decrease in risk aversion but also because they expect higher returns.[8]

Our evidence for time varying risk aversion may also have implications that go beyond providing an explanation for countercyclical risk premiums and excess volatility in asset prices. Cochrane (2011) pointed out that time varying risk premiums have implications for finance applications, accounting, cost of capital, capital structure, compensation, and macroeconomics.[9]

Our study is also related to an interesting paper by Guiso et al. (2013) who examined time varying risk aversion. They administered a questionnaire to customers of an Italian bank before the financial crisis in 2007 and after the crisis in 2009. They find that customers reported a lower certainty equivalent for a hypothetical lottery following the 2008 financial crisis. Due to the fact that many variables (e.g., wealth, expectations of returns and volatility, experienced losses and gains, etc.) could have changed simultaneously between 2007 and 2009, the authors face the difficult task of controlling for them by finding appropriate proxies. Our study differs from theirs by randomly assigning financial pro-

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[8]The findings in Malmendier and Nagel (2011) suggest that historical experiences may also play a role in investment behavior. They show that individuals which experienced low stock returns in their early lives report more pessimistic expectations of future returns and exhibit a lower willingness to take risks even after decades. See Dillenberger and Rozen (2014) for a formal model of history-dependent risk taking behavior.

[9]Cochrane (2011) uses the term time varying discount rate which includes time discounting and the discounting of the value of risky assets because of risk aversion. In this view, time varying risk aversion is a key cause of time varying discount rates.

fessionals to a boom or bust condition. While our priming approach ensures that there are no observable or unobservable differences between the subjects in the two conditions, it also comes with the potential drawback that behavior and emotions are not measured during an actual boom and bust. Instead, we merely rendered the state of a boom or a bust salient in subjects' minds. However, actual booms and busts are likely to constitute much more powerful primes (i.e., they are emotionally more salient). It seems therefore plausible that the influence of real booms and busts may be even stronger. Our study further differs from Guiso et al. (2013) because we measure risk aversion in an incentive compatible way, i.e., subjects' decisions implied sizable financial consequences for them. We are aware of the concern that the size of preference parameters estimated in laboratory experiments cannot be extrapolated to field settings without caveats (Harrison et al. 2007; Charness et al. 2013). However, because we are interested in the comparative static effects of booms versus busts rather than the absolute levels of risk aversion, we feel confident that our results are generalizable to field settings.[10] Finally, a notable feature of our experiment is that, unlike in most laboratory experiments, we analyze the behavior of financial professionals who actively participate in financial markets. Overall, it is reassuring that both studies, Guiso et al. (2013) and ours, arrive at the same conclusion: the subjective willingness to take risks is lower during a recession. The fact that this conclusion emerges from different studies with different research designs, subject pools, and methods strengthens the evidence for countercyclical risk aversion.

Finally, our study is also related to the small but growing literature on the effects of emotional or traumatic events on risk taking and other economic behaviors (e.g., Saunders 1993; Hirshleifer and Shumway 2003; Knutson et al. 2008; Kuhnen and Knutson 2011; Lin et al. 2012; Bassi et al. 2013; Cameron and Shah 2013; Callen et al. 2014). This literature generally suggests that emotional and/or traumatic events can have con-

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[10]Many studies found significant correlations between lottery choices and field behavior, including health-related behaviors (Anderson and Mellor 2008; Sutter et al. 2013), career choices (Masclet et al. 2009; Bellemare and Shearer 2010), and financial decisions (Dohmen et al. 2011; Guiso et al. 2013; Vieider et al. forthcoming).

siderable effects on preferences and behavior. Although these studies suggest that emotionally significant events can affect preferences, none of them examines countercyclical risk aversion, i.e., how booms and busts affect risk preferences.

The remainder of this paper is organized as follows. Section 2 outlines the experimental design. Section 3 describes the sample and presents a randomization check. Section 4 summarizes the empirical findings, and Section 5 concludes the paper.

2 Experimental Design

We conducted the experiment at a large financial trade fair where exhibitors presented their financial products and services. We installed a mobile laboratory in a quiet corner of the fairground, ensuring that the experiment was run under controlled conditions. To investigate the behavior of real financial market participants, we recruited our subjects on the day when the trade fair was only open to financial professionals. Subjects were asked to fill out a short computerized financial market survey in which they could earn money.[11] The computer stations were separated by partition walls to guarantee privacy (see Figure A1 in the appendix).

The first part of the survey contained a few icebreaker questions. The second part comprised our key experimental manipulation. The computer randomly assigned subjects to one of two treatments. In treatment "Boom", subjects first saw an animated, fictive chart of a booming stock market (see left panel of Figure 1). They subsequently answered five questions about their investment strategy during a stock market boom (e.g., "Imagine you find yourself in a continuing stock market boom and you expect the development to continue as indicated by the arrow in the picture. Would you buy or sell particular stocks? Explain your answer briefly."). In treatment "Bust", subjects faced the opposite situation, i.e., a stock market bust (see right panel of Figure 1), and answered an analogous set of questions about their investment behavior during a bust. Following

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[11]The instructions for the investment task and the survey are available upon request.

these questions, subjects reported their current emotional state. We elicited their general affective state and fear as a more specific emotion. General affect was elicited with a widely used and validated non-verbal measure, where subjects have to select one out of nine manikins (see online appendix) which best expresses their current affective state ranging from very negative (encoded as "-4") to very positive (encoded as "4") (Bradley and Lang 1994). Fear was measured by asking subjects to report the intensity of fear on a 7-point Likert scale (Bosman and Van Winden 2002).[12]

Figure 1: Boom and Bust treatment

(a) Treatment Boom   (b) Treatment Bust
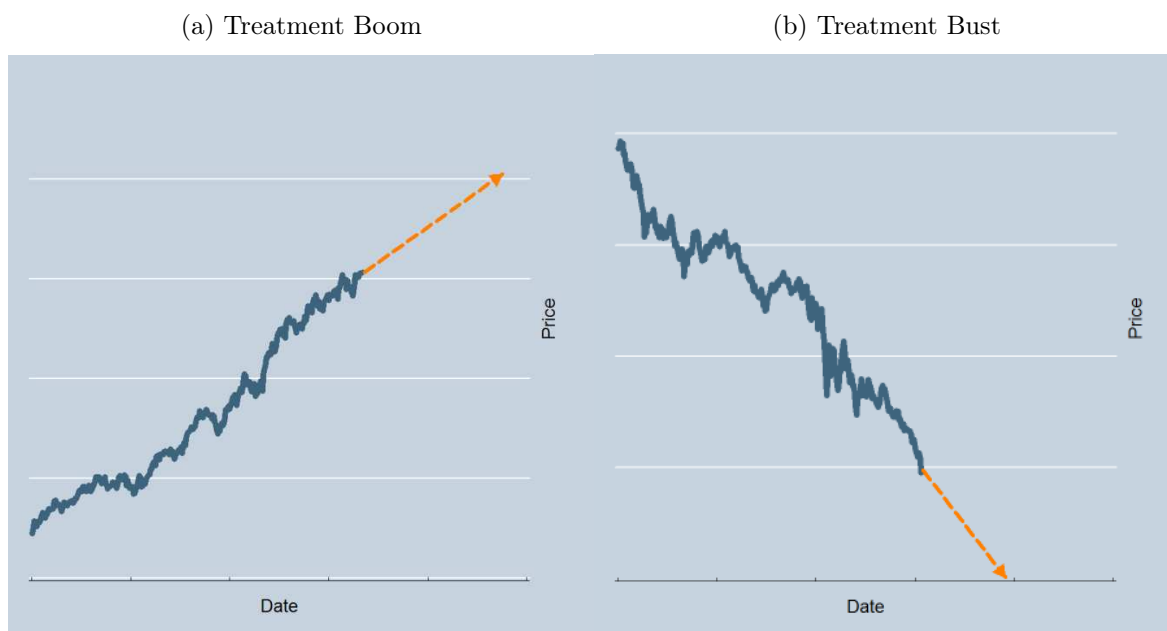
These animated charts were used to increase the mental saliency of financial booms and busts. We deliberately did not label the time and price axes to prevent subjects from thinking about a specific stock market event, but about booms and busts in general. The orange arrows were used to illustrate that the market trends were not expected to revert in the near future.

Subjects could subsequently earn up to 500 Swiss francs (or 546 US dollars at the time of the experiment) in an investment task (adapted from Gneezy and Potters 1997). They were endowed with 200 Swiss francs and decided how much to invest in a risky asset. If the good state of the world occurred, subjects won two and a half times the

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[12]Self-reported emotional experiences have been shown to be consistently correlated with different physiological measures such as heart rate and facial muscle contraction (Bradley and Lang 2000).

invested amount. If the bad state occurred, subjects lost the invested amount. The remaining amount that was not invested in the risky asset was automatically credited to a safe account with a zero interest rate. We implemented two variants of the investment task, which differed only by the extent to which subjects knew the probability of success for the risky asset. In the risk task, subjects knew the probability of success. They saw a picture of a plastic box on their computer screens which contained one red and one yellow ball (see left panel of Figure A2 in the appendix). The real box was visibly placed on the instructor's table and used to determine whether the good or the bad state occurred for each subject. At the end of the experiment, the instructor drew one of the two balls blindly. If the yellow ball was drawn, the good state occurred, i.e., the risky investment was successful. In the ambiguity task, the probability of success for the risky asset was uncertain for the subjects. We introduced uncertainty using a second plastic box filled with a large, unknown number of blue, red, and yellow balls (see right panel of Figure A2 in the appendix). Analogous to the risk task, the good state occurred if a yellow ball was drawn at the end of the experiment. We set the share of yellow balls at 50 percent, i.e., at the same level as in the risk task. After the ambiguity task, subjects guessed the share of yellow balls, which provides a measure of their expectations.

The final part of the survey included a question on general optimism borrowed from the standard Life Orientation Test, a commonly used test in psychology (Scheier et al. 1994). Subjects indicated the extent to which they agreed with the statement "Overall, I expect more good things to happen to me than bad." on a 7-point Likert scale. We used this question as a second, more general measure of expectations. Subjects next completed a financial literacy test. We created our own test because existing financial literacy tests were primarily developed for the general population (e.g., van Rooij et al. 2011). Our financial literacy test is a multiple choice test and asked subjects to rank order different financial products according to their volatility, identify the advantages of traded funds, select the correct term for purchasing a put option, and finally, to recognize

which companies are currently listed on the Swiss Market Index. The survey concluded with questions collecting information on subjects' socio-economic backgrounds.

Several features of the experimental design are noteworthy. First, the risk task, where subjects knew the exact probability of success, was always presented after the ambiguity task. This prevented them from using the probability of success in the risk task as an anchor for their decisions in the ambiguity task (e.g., Tversky and Kahneman 1974). Second, it was common knowledge that only one of the two investment decisions would become payoff relevant. The instructor drew a ball from the small or the large box for each subject. Which box was used was determined randomly by the computer at the end of the survey. This prevented subjects from pursuing hedging strategies across decisions (e.g., Blanco et al. 2010). Finally, due to budget constraints, we randomly selected 20 percent of the subjects for actual payment at the end of the survey.[13] The payment modality was common knowledge. Considering that the survey took only about 15 minutes to complete, the stake size was nevertheless quite sizable.

3 Descriptive statistics and randomization check

3.1 Descriptive statistics

Table A1 presents the summary statistics of our sample consisting of 162 financial professionals. Their average age was 36.4 years. 75 percent were male. Their average monthly income was 11'041 Swiss francs, which is representative for Switzerland's financial industry (Office 2010). 54 percent of the participants owned liquid assets worth 100'000 Swiss francs or more. Many worked as financial advisors, but the sample also covers other typical professional functions in the financial industry, such as traders, analysts,

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[13]Payment schemes with random components are commonly used in experiments on individual decision-making and there is solid evidence showing that these schemes do not change behavior (Starmer and Sugden 1991; Cubitt et al. 1998; Hey and Lee 2005).

and product managers.[14] More than half of the participants indicated that they trade assets at least once per month. We find individual heterogeneity in financial literacy, but overall, the level of financial knowledge was rather high. 64 percent correctly solved three or all four problems in the financial literacy test, while only 11 percent ended up with a score of one or zero. This heterogeneity in financial literacy is related to market participation: subjects who reported trading assets frequently achieved a higher test score compared to those who indicated they were less active in financial markets (p = 0.013, t-test).[15]

3.2 Randomization check

We tested whether the computerized randomization successfully resulted in a balanced sample using rank-sum tests, or χ^2-tests in case of binary variables. With the exception of male subjects being slightly over-represented in treatment Boom (p = 0.069, χ^2-test), we cannot reject the null hypothesis that the socio-economic and financial background of the subjects is balanced between treatments based on conventional significance levels (see Table A1 in the appendix). We always control for gender in our regression analysis.

4 Experimental results

4.1 Investment decisions

Figure 2 displays the average investment share in the risky asset by treatment. In both variants of the investment task, subjects made considerably more conservative investment decisions in treatment Bust compared to treatment Boom. Panel A presents the treatment effect in the risk task. Investments into the risky asset decreased on average by 22 percent from an investment share of 57.7 percent in treatment Boom down to 45.2

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[14]The job function question was asked in open format and therefore does not permit a precise classification of professional functions in some cases.

[15]We report two-sided p-values throughout the entire paper.

percent in treatment Bust. The treatment effect is similar in the ambiguity task, as shown in Panel B. The share invested in the risky asset is on average 50.3 percent in treatment Boom compared to 41.9 percent in treatment Bust, which corresponds to a 17 percent reduction in risk taking.

Figure 2: Booms, busts and investment decisions
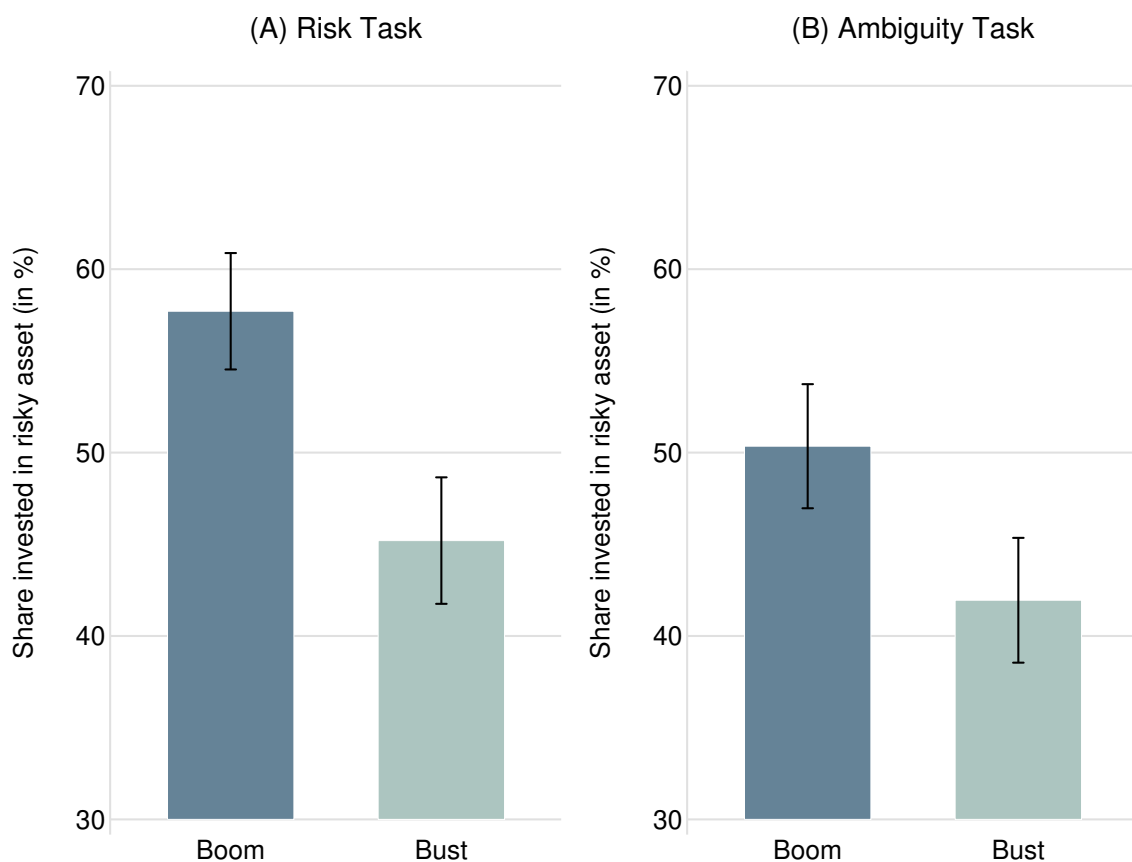
The figure shows average investments in the risk task (Panel A), and the ambiguity task (Panel B), by treatments. Error bars indicate standard errors of the mean.

In order to underpin the treatment differences statistically and to control for individual differences in socio-economic and financial background, we conducted a regression analysis. Our regression model is specified as follows:

$$y_{ik} = \beta_0 + \beta_1 Bust_{ik} + \beta_2 Ambiguity_i + \beta_3 X_i + \epsilon_{ik}, \tag{1}$$

where the dependent variable y_{ik} is the share individual i invested in the risky asset (in percent of the endowment) in investment task k. $Bust_{ik}$ is a dummy for treatment Bust, and $Ambiguity_i$ is a dummy for decisions made in the ambiguity task. We estimate an alternative model where we include the interaction term $Bust_{ik} \times Ambiguity_i$. This allows us to examine whether treatment Bust had a differential impact on investments in the two variants of the task. X_i is the set of control variables for subjects' socio-economic and financial backgrounds. We control for age, gender, financial literacy, and trading frequency.[16] Finally, ϵ_{ik} is the idiosyncratic error term. We estimate our regression model using OLS and correct the standard errors for clustering at the individual level. The results are the same if we use a Tobit model instead.

The estimation results reported in Table 1 corroborate our main finding. Column (1) reveals that investments are significantly lower in treatment Bust than in treatment Boom (p = 0.020, t-test). This difference also holds if we include the interaction term between treatment Bust and the ambiguity task, as shown in column (2). According to this model, in the risk task, subjects invested on average 12 percentage point less in the risky asset in treatment Bust compared to treatment Boom (p = 0.012, t-test). The interaction term between treatment Bust and the ambiguity task is not significantly different from zero (p = 0.368, t-test). This means that we cannot reject the null hypothesis that the treatment effect is similar in both variants of the task. We further find that subjects invested significantly less in the risky asset when its success probability was uncertain (p = 0.018 in column (1) and p = 0.012 in column (2), t-tests). This is consistent with the notion that ambiguous prospects are valued less because of ambiguity aversion.[17] The control variables for financial knowledge and trading frequency have no

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[16]Due to item non-response, we do not use the income and wealth measures as control variables in the regression analysis. Both measures are uncorrelated with risk taking and the results are qualitatively the same if we include these variables.

[17]Reduced risk taking in the ambiguity task (i.e., ambiguity aversion) could be due to pessimistic expectations or to an aversion to ambiguous success probabilities. Subjects guessed that the share of winning balls in the ambiguous lottery is 43.3 percent on average (95% confidence interval: [41.2%, 45.4%]). Thus, they were more pessimistic in the ambiguity task than in the risk task where they knew they would win with a probability of 50 percent. We ran an additional regression where the

significant correlation with investment decisions.[18]

Table 1: Regression analysis of investment decisions

| Dependent variable:	Share invested in risky asset	
	(1)	(2)
Bust	-9.827**	-11.879**
	(4.177)	(4.699)
Bust × Ambiguity		4.106
		(4.544)
Ambiguity	-5.407**	-7.359**
	(2.255)	(2.891)
Age	-0.080	-0.080
	(0.188)	(0.188)
Male	5.181	5.181
	(4.153)	(4.160)
Financial literacy	0.660	0.660
	(2.470)	(2.474)
High trading frequency	-1.766	-1.766
	(4.439)	(4.446)
Constant	54.585***	55.561***
	(8.676)	(8.706)
N	324	324

This table reports OLS coefficient estimates (robust standard errors corrected for clustering on the individual level in parentheses). The dependent variable is the share invested in the risky asset (in percent of the endowment). "Bust" is a dummy for treatment Bust. "Ambiguity" is a dummy indicating decisions from the ambiguity task. The interaction term "Bust × Ambiguity" allows the treatment effect to differ across the two variants of the investment task. "Age" is the individual's age in years, and "Male" is a gender dummy. "Financial literacy" is the score on the financial literacy test, ranging from 0 to 4. "High trading frequency" is a dummy for individuals who trade assets at least once per month. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Given that some studies (e.g., List and Haigh 2005; Cipriani and Guarino 2009) report that market experience diminishes the importance of psychological forces in financial decisions, we further examined whether the observed change in risk aversion is stronger in

within-subject difference of the investment share between the risk and the ambiguity task is regressed on subjects' beliefs about the success probability of the ambiguous lottery (and other control variables). We find a negative yet insignificant ($p = 0.238$, t-test) correlation between investment differences across risk and ambiguity task and the expected number of winning balls in the ambiguity task. This suggests that while pessimistic expectations in the ambiguity task may have lowered investments in this task, an aversion to ambiguous success probabilities may also have played a role.

[18] We also find that male participants tended to invest more than their female counterparts, but not significantly so ($p = 0.214$ in column (1) and $p = 0.215$ in column (2), t-tests).

subjects with less market experience. We used subjects' financial knowledge and trading frequency as a proxy for their market experience. Panel A of Figure 3 presents average investments in the risk task by treatment and level of financial literacy. We divided the sample into two equally sized groups: subjects with below-median financial literacy and those above-median. The picture shows that both groups responded similarly to our manipulation. If anything, the treatment effect seems to be even slightly stronger in

Figure 3: The role of market experience
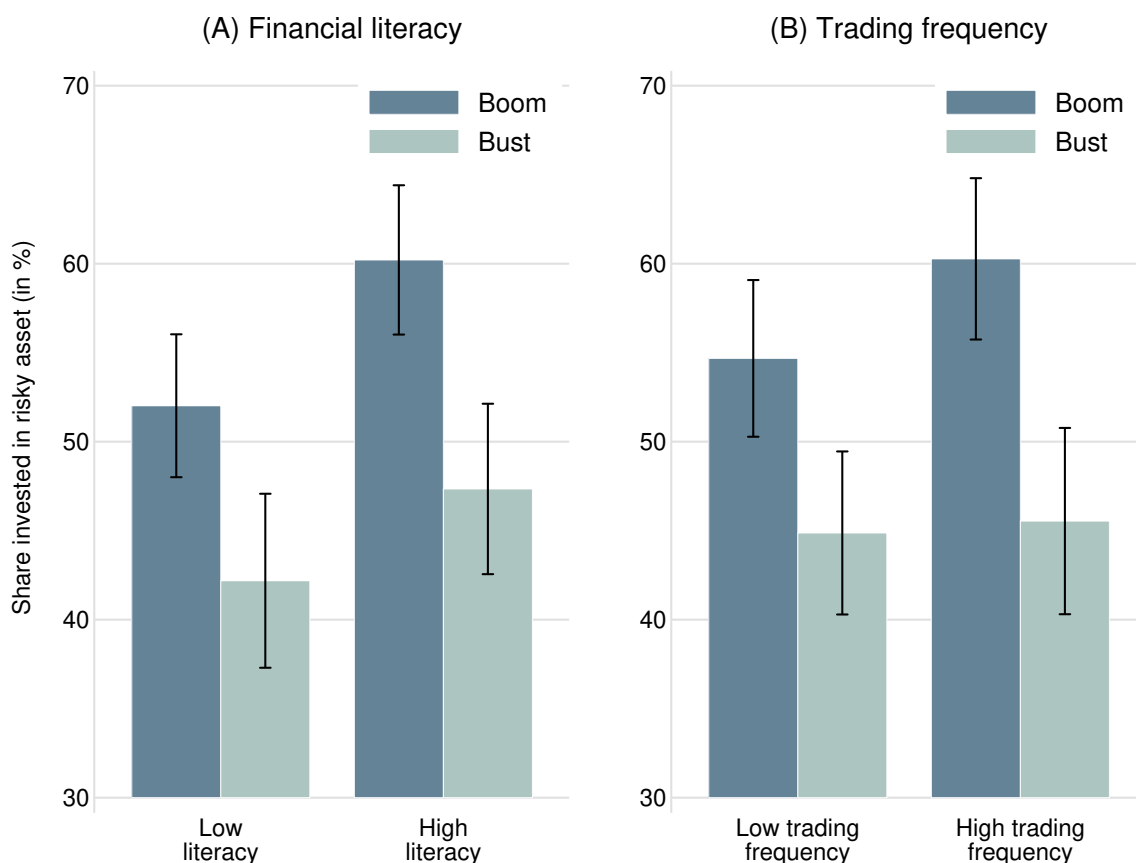
The figure displays the impact of the boom and the bust prime on average investments made in the risk task as a function of the level of financial literacy (Panel A), and trading frequency (Panel B). Error bars indicate standard errors of the mean.

subjects who scored higher on the financial literacy test. We make a similar comparison based on trading frequency in Panel B of Figure 3. We divided the sample into two

groups of roughly the same size: subjects who trade assets at least on a monthly basis and those who trade assets less frequently. The more active market participants exhibited a slightly more pronounced reaction, but the difference is again not very large. A similar pattern emerges in the ambiguity task (see Figure A3 in the appendix). We also ran OLS regressions based on model (1), where we additionally include an interaction term between the priming condition and financial literacy, respectively trading frequency. The estimation results indicate that market experience tends to enhance the treatment effect, but none of the coefficients on the interaction terms reaches statistical significance.[19]

4.2 Expectations

In addition to risk aversion, expectations may be another important determinant of peoples' risk taking behavior. We designed the risk task in such a way that expectations should not matter. Subjects knew all parameters of this task, which eliminated any kind of uncertainty. In contrast, the ambiguity task involved some uncertainty because subjects did not know the share of winning balls. This enables us to study the role of expectations in an environment that is comparable to the risk task.

The fact that we find a similar effect in both variants of the investment task is a preliminary indication of a change in risk preferences, rather than a change in expectations. If the mental saliency of booms and busts had an impact on subjective expectations, we should observe a stronger treatment effect in the ambiguity task because the absence of perfect certainty about the share of winning balls leaves more room for expectations to play a role in that task (e.g., Klibanoff, Marinacci, and Mukerji 2005).

In order to directly test whether our manipulation affected expectations, we estimated an OLS regression model in which we regressed the subjects' guessed share of winning balls in the ambiguity task on a dummy for treatment Bust, and our set of control variables. Column (1) of Table 2 shows that while subjects were slightly more

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[19]The t-statistics and p-values for trading frequency are t = -1.02, p = 0.310 and t = -0.01, p = 0.989 for financial literacy. The interaction term "Bust × Ambiguity" was excluded from the regression model.

pessimistic concerning the probability of success in treatment Bust than in treatment Boom, the difference is rather small and statistically insignificant (p = 0.209, t-test). We additionally considered the subjects' general levels of optimism as an alternative

Table 2: Regression analysis of expectations

Dependent variable:	Guessed probability of success (1)	General optimism (2)
Bust	-2.777	0.216
	(2.203)	(0.229)
Age	0.178*	0.004
	(0.091)	(0.011)
Male	-1.505	-0.022
	(2.830)	(0.286)
Financial literacy	1.299	0.215*
	(1.564)	(0.122)
High trading frequency	-1.101	-0.029
	(2.183)	(0.233)
Constant	36.414***	3.548***
	(5.440)	(0.569)
N	162	162

This table reports OLS coefficient estimates (robust standard errors in parentheses). In column (1), the dependent variable is the guessed percentage of winning balls in the ambiguity task. In column (2), the dependent variable is the degree of agreement to the statement "Overall, I expect more good things to happen to me than bad.", which ranges from 0 (strongly disagree) to 6 (strongly agree). "Bust" is a dummy for treatment Bust. "Age" is the individual's age in years, and "Male" is a gender dummy. "Financial literacy" is the score on the financial literacy test, ranging from 0 to 4. "High trading frequency" is a dummy for individuals who trade assets at least on a biweekly basis. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

measure of expectations. The results in column 2 show that subjects were slightly more optimistic in treatment Bust than in treatment Boom, although the coefficient is small and statistically insignificant (p = 0.346, t-test).[20] Thus, regardless of which measure of expectations one refers to, the findings support the key result that increasing the mental saliency of booms and busts causes a change in risk aversion rather than a change in

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[20]We also asked subjects whether they believed the Swiss Market Index (SMI) would tend to rise or fall in the following two years and whether they thought they would lose their jobs within the next six months. Our conclusion that the mental saliency of booms and busts did not influence expectations remains the same if we use these alternative measures instead.

the expectation of a successful outcome from the investment. The reduced willingness to invest in the risky asset in the bust treatment indicates an increase in risk aversion, i.e., a lower valuation of the risky asset for given subjective expectations about the state of the world (the share of winning balls).

4.3 Emotions

Our final piece of evidence sheds light on the possible mechanism underlying countercyclical risk aversion. Most economic theories do not explicitly model emotions such as fear. However, this does not mean that these theories are necessarily inconsistent with emotion-driven mechanisms. For example, the mechanism underlying countercyclical risk aversion in Barberis et al. (2001) can be easily reconciled with the notion of fear. In this theory, investors have a mental cushion that regulates their psychological capacity to deal with investment losses. A decline in asset prices reduces this mental cushion and renders investors more fearful, which translates into a higher degree of risk aversion. Likewise, the theory of Campbell and Cochrane (1999) is, in principle, also consistent with a fear based explanation. In this theory, individuals' increase in risk aversion after a fall in financial wealth may arise because they fear being unable to maintain their habitual level of consumption. The association of risk taking with fear is also in accordance with recent brain imaging and hormone studies, which suggest a link between a key fear processing unit of the brain (i.e., the amygdala) and risk taking (e.g., Bossaerts 2009).[21] Moreover, studies with professional traders indicate that even highly trained market participants exhibit strong psychophysiological reactions typically associated with strong emotions (e.g., variations in the heart rate and the blood volume pressure) in response to price fluctuations, and that these emotional responses are related

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[21]See also Kandasamy et al. (2013) who show that exogenously administrating the stress hormone cortisol increases risk aversion. Furthermore, the results from Knutson et al. (2008) suggest that activity in the nucleus accumbens (a neuronal marker for positive arousal) mediates the influence of incidental positive emotions on subsequent risk taking. See also Apicella et al. (2014) on the role of testosterone in financial risk taking.

to trading performance (Lo and Repin 2002; Lo et al. 2005).

We therefore examined whether our treatments evoked different emotional reactions, and, in addition, whether emotions are related to investment decisions. Figure 4 visualizes treatment differences in general affect and the specific emotion of fear. The figure reveals that subjects felt generally worse (Panel A) and they also reported a higher level of fear (Panel B) in treatment Bust compared to treatment Boom. To examine the

Figure 4: Booms, busts and emotions
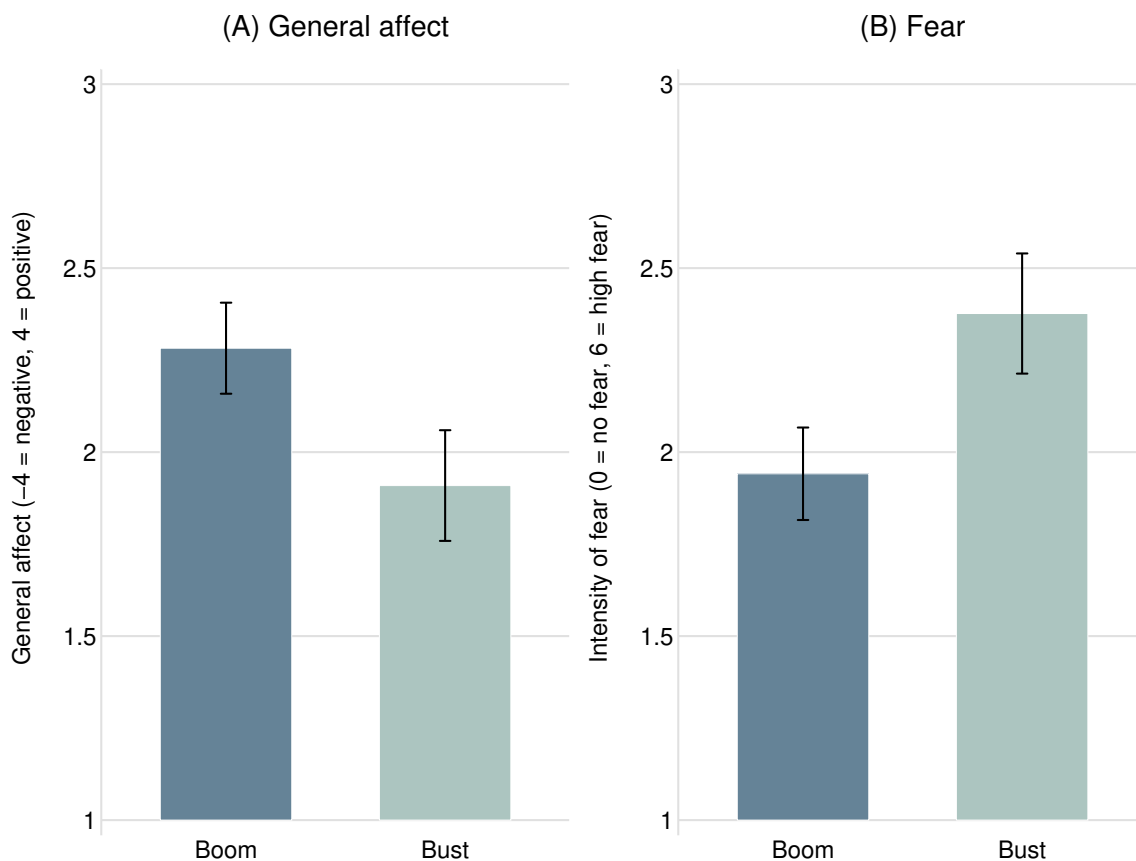
This figure presents averages in subjects' general affect (Panel A) and fear (Panel B) in the treatments Boom and Bust. Error bars indicate standard errors of the mean.

statistical significance of these treatment differences, we estimated an OLS regression model in which we separately regressed our two measures of emotions on a dummy for treatment Bust, and our set of control variables. The estimation results are reported in

Table 3: Regression analysis of emotions

Dependent variable:	General affect	Fear		Share invested in risky asset	
	(1)	(2)	(3)	(4)	(5)
Bust	-0.351*	0.474**			-8.561**
	(0.193)	(0.206)			(4.126)
General affect			2.395		
			(1.645)		
Fear				-3.256**	-2.668*
				(1.344)	(1.372)
Age	-0.003	0.002	-0.082	-0.082	-0.075
	(0.009)	(0.011)	(0.195)	(0.191)	(0.185)
Male	0.110	0.182	6.350	7.092*	5.666
	(0.273)	(0.262)	(4.355)	(4.254)	(4.172)
Financial literacy	0.030	0.139	0.693	1.210	1.031
	(0.125)	(0.124)	(2.559)	(2.544)	(2.471)
High trading frequency	0.104	-0.005	-1.927	-1.701	-1.780
	(0.195)	(0.214)	(4.470)	(4.441)	(4.419)
Ambiguity			-5.407**	-5.407**	-5.407**
			(2.255)	(2.255)	(2.259)
Constant	2.151***	1.353**	44.063***	54.038***	58.194***
	(0.509)	(0.539)	(9.189)	(9.247)	(9.299)
N	162	162	324	324	324

This table reports OLS coefficient estimates. Robust standard errors are reported in parentheses. In column (1), the dependent variable is subjects' general affect state, ranging from -4 (negative) to 4 (positive). In column (2), the dependent variable is subjects' level of fear, ranging from 0 (no fear at all) to 6 (high level of fear). In columns (3) to (5), the dependent variable is the share invested in the risky asset (in percent of the endowment). Standard errors are corrected for clustering on the individual level in columns (3) to (5). "Bust" is a dummy for treatment Bust. "Age" is the individual's age in years, and "Male" is a gender dummy. "Financial literacy" is the score on the financial literacy test, ranging from 0 to 4. "High trading frequency" is a dummy for individuals who trade assets at least on a biweekly basis. "Ambiguity" is a dummy indicating decisions from the ambiguity task. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

the first two columns of Table 3. Column (1) shows that while the treatment variable Bust is only marginally significant in the equation for general affect (p = 0.070, t-test), the second column shows that treatment Bust caused a highly significant increase in fear (p = 0.023, t-test). This indicates that the priming of financial market trends has a causal effect on the specific emotion of fear.

We also find a stronger relationship between investment decisions and fear than with the general affective state, as columns (3) and (4) of Table 3 indicate. In these columns, we report OLS regressions in the spirit of model (1) in Table 1, with the difference that one of our emotion measures replaces the treatment dummy. Column (3) shows that the coefficient for general affect has the expected positive sign - i.e., a generally more positive emotional state is associated with larger investments - but the estimate is statistically insignificant (p = 0.147, t-test). In contrast, column (4) shows that the relation between fear and investments is highly significant (p = 0.017, t-test), indicating that higher levels of fear predict lower investments in the risky asset. Thus, taken together, we have shown that the mere priming of financial market trends causes significant changes in fear and that higher levels of fear are associated with less risk taking. To study the extent to which the treatment effect is mediated by fear we also estimated a model where we simultaneously control for treatment Bust and our measure of fear (column 5 in Table 3). The results of this regression show that fear reduces the share invested in the risky asset by roughly 2.7 percentage points per "unit of fear" (p = 0.054, t-test) and that the effect of Bust is reduced relative to regression (1) in Table 1 in which we do not control for fear. Moving from "no fear at all" to the average level of fear reduces investments by 4.4 percentage points, which corresponds to 44.5% of the treatment effect. Yet, the treatment variable is still positive which could mean that fear does not fully mediate the treatment effect, or that there is measurement error in the fear variable. In our view, it is likely that there is measurement error in the fear variable because emotions are notoriously difficult to measure in a precise way. Nevertheless, our measure of fear at

least partly explains the effect of the bust treatment.

In order to test whether fear has a causal impact on the willingness to take financial risks, we conducted an additional experiment in which we exogenously induced fear during an investment task. In psychology and neuroscience, a reliable and frequently used method for inducing fear is to expose subjects to the threat of painful electric shocks (Schmitz and Grillon 2012). In our experiment 41 university students participated in an investment task in which they could invest between 0 and 24 Swiss francs. The experiment had two parts, each consisting of 42 investment trials (see appendix B for details). In part 1 the subjects knew that on average the lotteries offered a 40 to 60 percent chance of winning an equal or greater amount than the investment. The maximum amount a lottery could return was 24 Swiss francs plus three times the invested amount. Coarse information about the expected payoff frequencies was given at the end of part 1, where subjects were told how often they could earn a positive return rate at the various investment levels. This means that in part 2 subjects were much better informed about the expected distribution of returns, implying that the ambiguity concerning the probability of success was substantially reduced. At the end of the experiment two randomly chosen trials were paid out.

During both parts of this investment task each subject faced randomly ordered blocks of low and high fear trials, where one block consisted of three investment trials. A high (low) fear level was implemented by informing subjects that they would receive painful (painless) electric shocks that would arrive unpredictably during the next three trials. Before the experiment, we measured individual pain thresholds so that we could ensure that each subject received both painful and painless shocks. Subjects received written information on their computer screens at the beginning of each block of three trials about whether they were in a low or high pain block. In addition, they received a reminder shock (either low or high) at the beginning of a block in order to ensure that they were absolutely certain about the treatment condition.

The results show that in part 1 (part 2) average investment shares decreased by 7 (10) percent from 54.6 (48.4) to 50.8 (43.7) percent when subjects were exposed to a high level of fear than when they were subject to low fear. Table B2 in the appendix reports the OLS-regression results. We regressed the investment shares (measured in percent of CHF 24) on the treatment condition ("Threat of shock") and a dummy variable "Information" indicating whether the decisions were made in part 2 after coarse distributional information about payoffs was provided. In order to control for the actual experience of electric shocks, we also included dummies for the experience of either painful or non-painful electrical stimulation ("Painful shock" and "Non-painful shock") shortly before individuals made the decision in a given trial. In addition, we control for age and gender. The regression results show that the threat of painful shocks significantly reduced investments ($p < 0.001$, t-test). Interestingly, however, it is only the threat of a random shock, i.e., the expectation of an adverse event, and not the previous experience of painful shocks that reduces risk taking.

These results highlight that fear per se, even if it is completely unrelated to economic events, decreases the willingness to take risks. Thus, taken together, the facts (i) that the priming of a bust causes fear, (ii) that this fear negatively predicts a lower investment in risky assets, and (iii) that exogenously induced fear directly causes a reduction in risky investments, lend coherent support to the hypothesis that fear is one of the key mechanisms behind the changes in risk aversion during a financial cycle.

5   Conclusion

This paper presents experimental evidence on countercyclical risk aversion. We primed financial professionals either with the scenario of a financial boom or a bust and then measured their risk aversion using incentivized investment tasks. We show that thinking of busts, as opposed to booms, substantially reduces risk taking. Because we have

perfect control over expectations about probabilities and payoffs in the risk task - and good measures of expectations in the ambiguity task - we can unambiguously attribute the behavioral change induced by the boom and bust scenarios to a change in risk preferences. Finally, we find evidence that fear is a plausible explanation for why risk aversion is higher during a bust than a boom. In fact, if we exogenously induce fear in subjects during an investment task by exposing them to the threat of an aversive electric shock, we observe a significant reduction in risk taking. This suggests that fear directly causes a lower willingness to take risks even if that fear is completely unrelated to economic events. Together, these findings support a critical component of asset pricing models that assume countercyclical risk aversion in order to fit empirical observations of aggregate market behavior.

Our evidence further suggests that countercyclical risk aversion might produce feedback loops that amplify market trends. For example, a decline in stock prices that renders investors more fearful, and consequently, more risk averse, could lead to an increased number of sales which pushes the prices further down. Several factors might exacerbate this amplification mechanism. For example, analogous to a contagious disease, emotions may rapidly spread within investors' social networks and amplify emotional responses to market trends (de Gelder et al. 2004). Moreover, social projection bias - people's tendency to project their own emotions onto others - might have a similar reinforcing effect (Lee and Andrade 2011). We believe that improving our understanding of how institutional and behavioral factors moderate such an amplification mechanism provides a promising avenue for future research.

References

Agnew, Julie, Pierluigi Balduzzi, and Annika Sunden (2003): Portfolio Choice and Trading in a Large 401(k) Plan, *American Economic Review*, Vol. 93, No. 1, pp. 193–215.

Anderson, Lisa R and Jennifer M Mellor (2008): Predicting health behaviors with an experimental measure of risk preference, *Journal of health economics*, Vol. 27, No. 5, pp. 1260–1274.

Apicella, Coren L, Anna Dreber, and Johanna Mollerstrom (2014): Salivary testosterone change following monetary wins and losses predicts future financial risk-taking, *Psychoneuroendocrinology*, Vol. 39, pp. 58–64.

Barberis, Nicholas, Ming Huang, and Tano Santos (2001): Prospect theory and asset prices, *Quarterly Journal of Economics*, Vol. 116, No. 1, pp. 1–53.

Bargh, John A. and Tanya L. Chartrand (2000): The Mind in the Middle: A Practical Guide to Priming and Automaticity Research, in: H. T. Reis and C. M. Judd (Eds.), *Handbook of Research Methods in Social Psychology*, pp. 253–285, New York: Cambridge University Press.

Bassi, Anna, Riccardo Colacito, and Paolo Fulghieri (2013): 'O Sole Mio: An Experimental Analysis of Weather and Risk Attitudes in Financial Decisions, *Review of Financial Studies*, Vol. 26, No. 7, pp. 1824–1852.

Beaud, Mickael and Marc Willinger (forthcoming): Are People Risk-Vulnerable?, *Management Science*.

Bellemare, Charles and Bruce Shearer (2010): Sorting, incentives and risk preferences: Evidence from a field experiment, *Economics Letters*, Vol. 108, No. 3, pp. 345–348.

Benjamin, Daniel J., James J. Choi, and A. Joshua Strickland (2010): Social Identity and Preferences, *American Economic Review*, Vol. 100, No. 4, pp. 1913–28.

Blanco, Mariana, Dirk Engelmann, Alexander K. Koch, and Hans-Theo Normann (2010): Belief Elicitation in Experiments: Is There a Hedging Problem?, *Experimental Economics*, Vol. 13, No. 4, pp. 412–438.

Bosman, Ronald and Frans Van Winden (2002): Emotional Hazard in a Power-to-take Experiment, *Economic Journal*, Vol. 112, No. 476, pp. 147–169.

Bossaerts, Peter (2009): What Decision Neuroscience Teaches us about Financial Decision Making, *Annual Review of Financial Economics*, Vol. 1, No. 1, pp. 383–404.

Bradley, Margaret M and Peter J Lang (1994): Measuring Emotion: The Self-assessment Manikin and the Semantic Differential, *Journal of Behavior Therapy and Experimental Psychiatry*, Vol. 25, No. 1, pp. 49–59.

Bradley, Margaret M and Peter J Lang (2000): Measuring Emotion: Behavior, Feeling, and Physiology., in: Richard Lane, Lynn Nadel, and Geoffrey Ahern (Eds.), *Cognitive Neuroscience of Emotion*, pp. 242–276, Oxford University Press.

Brooks, Andrew M., Chandrasekhar V.S. Pammi, Charles Noussair, Monica C. Capra, Jan B. Engelmann, and Gregory S. Berns (2010): From Bad to Worse: Striatal Coding of the Relative Value of Painful Decisions, *Frontiers in Neuroscience*, Vol. 4, No. 176, pp. 1–8.

Brunnermeier, Markus K and Stefan Nagel (2008): Do Wealth Fluctuations Generate Time-Varying Risk Aversion? Micro-Evidence on Individuals' Asset Allocation, *American Economic Review*, Vol. 98, No. 3, pp. 713–736.

Callen, Michael, Mohammad Isaqzadeh, James D Long, and Charles Sprenger (2014): Violence and risk preference: Experimental evidence from Afghanistan, *American Economic Review*, Vol. 104, No. 1, pp. 123–148.

Calvet, Laurent E, John Y Campbell, and Paolo Sodini (2009): Fight or Flight? Portfolio Rebalancing by Individual Investors, *Quarterly Journal of Economics*, Vol. 124, No. 1, pp. 301–348.

Calvet, Laurent E. and Paolo Sodini (2014): Twin Picks: Disentangling the Determinants of Risk-Taking in Household Portfolios, *The Journal of Finance*, Vol. 69, No. 2, pp. 867–906.

Cameron, Lisa and Manisha Shah (2013): Risk-taking Behavior in the Wake of Natural Disasters, NBER Working Paper No. 19534.

Campbell, John Y. and John H. Cochrane (1999): By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior, *Journal of Political Economy*, Vol. 107, No. 2, pp. 205–251.

Campbell, John Y. and Robert J. Shiller (1988a): The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors, *Review of Financial Studies*, Vol. 1, No. 3, pp. 195–228.

Campbell, John Y. and Robert J. Shiller (1988b): Stock prices, earnings, and expected dividends, *Journal of Finance*, Vol. 43, No. 3, pp. 661–676.

Charness, Gary, Uri Gneezy, and Alex Imas (2013): Experimental methods: Eliciting risk preferences, *Journal of Economic Behavior & Organization*, Vol. 87, pp. 43–51.

Chiappori, Pierre-André and Monica Paiella (2011): Relative Risk Aversion is Constant: Evidence from Panel Data, *Journal of the European Economic Association*, Vol. 9, No. 6, pp. 1021–1052.

Cipriani, Marco and Antonio Guarino (2009): Herd behavior in financial markets: an experiment with financial market professionals, *Journal of the European Economic Association*, Vol. 7, No. 1, pp. 206–233.

Cochrane, John H. (2011): Presidential Address: Discount Rates, *Journal of Finance*, Vol. 66, No. 4, pp. 1047–1108.

Cubitt, Robin P, Chris Starmer, and Robert Sugden (1998): On the validity of the random lottery incentive system, *Experimental Economics*, Vol. 1, No. 2, pp. 115–131.

Dillenberger, David and Kareen Rozen (2014): History-Dependent Risk Attitude, University of Pennsylvania Working Paper.

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G Wagner (2011): Individual risk attitudes: Measurement, determinants, and behavioral consequences, *Journal of the European Economic Association*, Vol. 9, No. 3, pp. 522–550.

de Gelder, Beatrice, Josh Snyder, Doug Greve, George Gerard, and Nouchine Hadjikhani (2004): Fear fosters flight: a mechanism for fear contagion when perceiving emotion expressed by a whole body, *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 101, No. 47, pp. 16 701–16 706.

Gilad, Dalia and Doron Kliger (2008): Priming the Risk Attitudes of Professionals in Financial Decision Making, *Review of Finance*, Vol. 12, No. 3, pp. 567–586.

Gneezy, Uri and Jan Potters (1997): An experiment on risk taking and evaluation periods, *Quarterly Journal of Economics*, Vol. 112, No. 2, pp. 631–645.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2013): Time Varying Risk Aversion, NBER Working paper.

Haigh, Michael S and John A List (2005): Do professional traders exhibit myopic loss aversion? An experimental analysis, *Journal of Finance*, Vol. 60, No. 1, pp. 523–534.

Harrison, Glenn W, John A List, and Charles Towe (2007): Naturally occurring preferences and exogenous laboratory experiments: A case study of risk aversion, *Econometrica*, Vol. 75, No. 2, pp. 433–458.

Hey, John D and Jinkwon Lee (2005): Do subjects separate (or are they sophisticated)?, *Experimental Economics*, Vol. 8, No. 3, pp. 233–265.

Hirshleifer, David and Tyler Shumway (2003): Good day sunshine: Stock returns and the weather, *Journal of Finance*, Vol. 58, No. 3, pp. 1009–1032.

Kandasamy, Narayanan, Ben Hardy, Lionel Page, Markus Schaffner, Johann Graggaber, Andrew S Powlson, Paul Fletcher, Mark Gurnell, and John Coates (2013): Cortisol shifts financial risk preferences, *Proceedings of the National Academy of Sciences of the United States of America (PNAS)*.

Klibanoff, Peter, Massimo Marinacci, and Sujoy Mukerji (2005): A smooth model of decision making under ambiguity, *Econometrica*, Vol. 73, No. 6, pp. 1849–1892.

Knutson, Brian, G Elliott Wimmer, Camelia M Kuhnen, and Piotr Winkielman (2008): Nucleus accumbens activation mediates the influence of reward cues on financial risk taking, *NeuroReport*, Vol. 19, No. 5, pp. 509–513.

Kuhnen, Camelia M and Brian Knutson (2011): The influence of affect on beliefs, preferences, and financial decisions, *Journal of Financial and Quantitative Analysis*, Vol. 46, No. 3, pp. 605–626.

Lee, Chan Jean and Eduardo B Andrade (2011): Fear, social projection, and financial decision making, *Journal of Marketing Research*, Vol. 48, No. SPL, pp. S121–S129.

Lerner, Jennifer S and Dacher Keltner (2001): Fear, anger, and risk., *Journal of personality and social psychology*, Vol. 81, No. 1, p. 146.

Lin, Shengle, Terrance Odean, and Eduardo B Andrade (2012): Bubbling with Excitement: An Experiment, Working paper.

List, John A and Michael S Haigh (2005): A Simple Test of Expected Utility Theory Using Professional Traders, *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 102, No. 3, pp. 945–948.

Lo, Andrew W and Dmitry V Repin (2002): The Psychophysiology of Real-time Financial Risk Processing, *Journal of Cognitive Neuroscience*, Vol. 14, No. 3, pp. 323–339.

Lo, Andrew W., Dmitry V. Repin, and Brett N. Steenbarger (2005): Fear and Greed in Financial Markets: A Clinical Study of Day-Traders, *American Economic Review*, Vol. 95, No. 2, pp. 352–359.

Malmendier, Ulrike and Stefan Nagel (2011): Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?, *Quarterly Journal of Economics*, Vol. 126, No. 1, pp. 373–416.

Masclet, David, Nathalie Colombier, Laurent Denant-Boemont, and Youenn Loheac (2009): Group and individual risk preferences: A lottery-choice experiment with self-employed and salaried workers, *Journal of Economic Behavior & Organization*, Vol. 70, No. 3, pp. 470–484.

Mehra, Rajnish (2012): Consumption-Based Asset Pricing Models, *Annual Review of Financial Economics*, Vol. 4, No. 1, pp. 385–409.

Office, Swiss Federal Statistical (2010): Swiss Earnings Structure Survey.

van Rooij, Maarten, Annamaria Lusardi, and Rob Alessie (2011): Financial literacy and stock market participation, *Journal of Financial Economics*, Vol. 101, No. 2, pp. 449–472.

Saunders, Edward M (1993): Stock prices and Wall Street weather, *American Economic Review*, Vol. 83, No. 5, pp. 1337–1345.

Scheier, Michael F, Charles S Carver, Michael W Bridges, et al. (1994): Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): A reevaluation of the Life Orientation Test, *Journal of personality and social psychology*, Vol. 67, No. 6, pp. 1063–1078.

Schmitz, Anja and Christian Grillon (2012): Assessing Fear and Anxiety in Humans using the Threat of Predictable and Unpredictable Aversive Events (the NPU-Threat Test), *Nature Protocols*, Vol. 7, No. 3, pp. 527–532.

Shiller, Robert J (1981): Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?, *American Economic Review*, Vol. 71, No. 3, pp. 421–436.

Starmer, Chris and Robert Sugden (1991): Does the random-lottery incentive system elicit true preferences? An experimental investigation, *American Economic Review*, Vol. 81, No. 4, pp. 971–78.

Sutter, Matthias, Martin G Kocher, Daniela Glatzle-Rutzler, and Stefan T Trautmann (2013): Impatience and uncertainty: Experimental decisions predict adolescents' field behavior, *American Economic Review*, Vol. 103, No. 1, pp. 510–531.

Tversky, Amos and Daniel Kahneman (1974): Judgment Under Uncertainty: Heuristics and Biases, *Science*, Vol. 185, No. 4157, pp. 1124–1131.

Vieider, Ferdinand M, Mathieu Lefebvre, Ranoua Bouchouicha, Thorsten Chmura, Rustamdjan Hakimov, Michal Krawczyk, and Peter Martinsson (forthcoming): Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries, *Journal of the European Economic Association*.

Appendix

A Figures and Tables

Figure A1: Mobile laboratory

This picture shows the mobile laboratory at the financial trade fair.

Figure A2: Plastic boxes for the investment task

(a) Ambiguity task   (b) Risk task

The pictures show the plastic boxes filled with colored balls that were used in the risk and the ambiguity task to determine whether the good state of the world prevails. At the end of the study, the instructors fully covered the boxes. Then one of the instructors (who could not see inside the box) randomly picked a ball.

Figure A3: The role of market experience in the presence of uncertainty
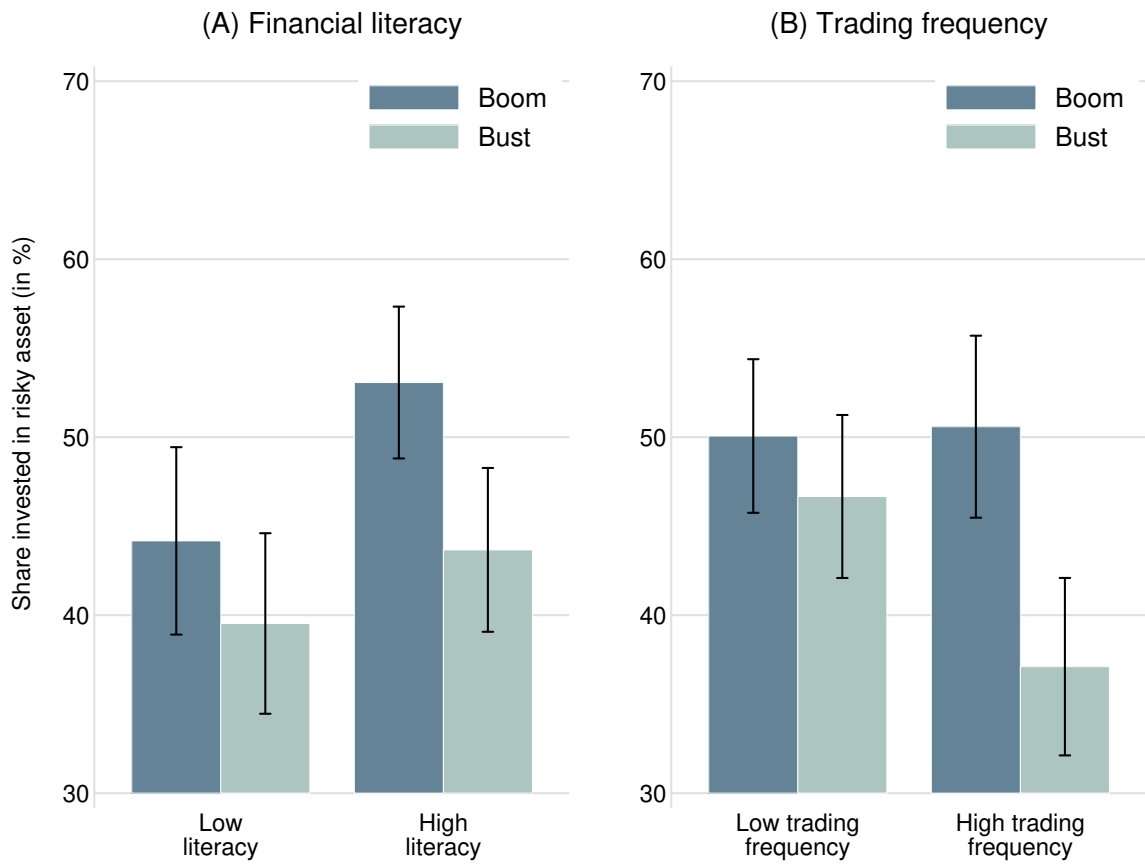
This figure displays the impact of booms and busts on average investments made in the ambiguity task as a function of the level of financial literacy (Panel A) and trading frequency (Panel B). Error bars indicate standard errors of the mean.

Table A1: Summary statistics and randomization check

Variable	Total sample (N = 162)	Boom (N = 85)	Bust (N = 77)	p-value
Age	36.395 (10.232)	36.447 (11.274)	36.338 (9.015)	0.971
Male	0.753 (0.433)	0.812 (0.393)	0.688 (0.466)	0.069
Monthly income	11'041.267 (13'899.983)	10'576.429 (10'582.771)	11'560.000 (16'920.469)	0.977
Wealth (> CHF 100'000)	0.541 (0.500)	0.566 (0.499)	0.514 (0.503)	0.508
Financial literacy	2.673 (0.918)	2.729 (0.793)	2.610 (1.041)	0.536
High trading frequency	0.519 (0.501)	0.541 (0.501)	0.494 (0.503)	0.544

This table reports means and standard deviations (in parenthesis) in the total sample and in treatments Boom and Bust. The last column displays p-values for the null hypothesis of perfect randomization (X^2 tests in case of binary variables and Mann-Whitney tests in case of interval variables). "Age" is the individual's age in years. "Male", "Wealth", and "High trading frequency" are dummy variables indicating male subjects, asset ownership of 100'000 Swiss francs or more, and asset trading at a monthly or more frequent rate. "Monthly income" is the monthly income in Swiss francs. "Financial literacy" is the financial literacy test score, ranging from 0 to 4. Due to item non-response for the income and the wealth question, sixteen observations are missing for monthly income, and five for wealth.

B Fear Induction Experiment

The purpose of the additional experiment was to measure the causal impact of fear on financial risk taking. 41 university students participated in the experiment. We induced different levels of fear by informing subjects that they would receive both mild (i.e., painless) and strong (i.e., painful) electric shocks (see Schmitz and Grillon 2012). Electrical stimulation was applied to the dorsum of the left hand in order to deliver a maximally focused and centered tactile stimulus. Prior to the experiment, we determined each subject's pain threshold using standard procedures (Brooks et al. 2010). Once individual stimulation thresholds were identified the experiment started.

The computerized experiment consisted of 84 investment trials, divided into blocks of three trials. In each block, subjects continuously expected to receive mild (strong) electric shocks that were administered at random points in time during the block. The experimental condition (i.e., threat of mild or strong shocks) was announced prior to a block in three ways: (1) via a text cue on the computer screen indicating "strong" for the threat-of-shock condition, and "mild" for the control condition, (2) via a reminder shock that reflected the exact intensity of the shock(s) that could occur throughout the block, and (3) via a specific background color on the screen that was maintained during the block and that was consistently associated with either mild or strong shocks (the color was counterbalanced across subjects). Thus, before each block subjects knew exactly whether they would receive mild or strong electric shocks. The frequency and time points of electric shocks were determined stochastically, and thus were completely unpredictable to subjects. This strengthened the fear manipulation (see Schmitz and Grillon 2012). Subjects knew that they could neither influence the frequency nor the timing of the electric shocks. The length of each trial was fixed at exactly 5.5 seconds, meaning that subjects could not avoid painful shocks by making faster decisions. We explained this in detail to the subjects in written and in oral instructions.

In each trial, subjects could invest between 0 and 24 Swiss francs in a lottery. They

could choose among five options: invest nothing (i.e., 0 Swiss francs), invest all (i.e., 24 Swiss francs), or invest one out of three intermediate amounts. The part of the endowment that was not invested was put on a safe account with a zero interest rate. Intermediate amounts varied stochastically from trial to trial in order to keep subjects focused on the task. In each trial, the intermediate amounts were randomly and independently drawn from three categories (low, medium, high), i.e., one amount was selected from each category. The low category consisted of the amounts 4, 6, and 8 Swiss francs, the medium category included the amounts 10, 12, and 14 Swiss francs, and the high category consisted of the amounts 16, 18, and 20 Swiss francs. So, for example, in a given trial a subject might have been facing the following five options: 0, 4, 10, 20, or 24 Swiss francs.

The lotteries returned any integer payoff between 0 Swiss francs and three times the invested amount plus 24 Swiss francs. Subjects were presented a table illustrating the minimum and maximum lottery payoff for each possible investment level (see Table B1).

Table B1: Lottery payoff table

If you invest ...	the lottery returns a payoff in the range of ...
0	0
4	0 - 36
6	0 - 42
8	0 - 48
10	0 - 54
12	0 - 60
14	0 - 66
16	0 - 72
18	0 - 78
20	0 - 84
24	0 - 96

The experiment was split into two parts (i.e., 42 trials each) which differed in the extent of ambiguity of the lotteries. In the first part of the experiment (the first 42 trials),

subjects only knew that they had an ambiguous 40 to 60 percent chance to receive at least the amount invested. In addition, they knew the minimum and maximum payoffs for any feasible investment level (see Table B1). At the end of the first part, subjects were informed how often they chose a positive investment level in the previous 42 rounds. In addition, the degree of ambiguity was reduced by giving subjects the following coarse information on the payoff distributions for positive investment levels:

(1) the previously realized frequency and the expected relative frequency (0.54) of a payoff that is lower than their investment;

(2) the previously realized frequency and the expected relative frequency (0.35) of a payoff that is zero;

(3) the previously realized frequency and the expected relative frequency (0.33) of a payoff that is larger than their investment;

(4) the previously realized frequency and the expected relative frequency (0.16) of a payoff that is larger than $1.5 \times$ investment.

This information was presented to the subjects both numerically and with bar charts at the end of the first part. After they received this information, they faced another 42 trials (second part). Recall that the information given at the end of part 1 lowered the overall investment level but did not affect the impact of fear on investment levels. The impact remained constant across part 1 and part 2. Thus, the additional information did not have an impact on the fear effect.

To identify the impact of the threat-of-shock treatment on investment decisions, we estimated the following regression model using OLS:[22]

$$y_{it} = \beta_0 + \beta_1 Threat_{it} + \beta_2 PS_{it} + \beta_3 NPS_{it} + \beta_4 I_{it} + \beta_5 X_i + \epsilon_{it}, \qquad (2)$$

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[22]The results remain the same if we use a Tobit model instead.

where the dependent variable is the share invested (in percent of the endowment) into a lottery by individual i in trial t. $Threat_{it}$ is a dummy for the threat-of-shock treatment, i.e., the condition we implemented to induce fear. I_{it} is a dummy for decisions made in the second part, i.e., after providing coarse information about the expected payoff frequencies. PS_{it} and NPS_{it} are dummy variables for the actual experience of either painful or non-painful electrical stimulation within an interval of 4 seconds prior to the display of the choice scenario and until subjects made a choice. We examined shorter and longer intervals ranging from 2 to 10 seconds; the results remain unchanged. X_i is a vector that controls for age and gender. Standard errors are corrected for clustering at the individual level. The estimation results are reported in Table B2 and indicate that the threat of painful shocks significantly reduced investments ($p < 0.001$, t-test). Interestingly, it is only the threat of random shocks that affects risk taking because the actual experience of electric shocks had no impact on subsequent behavior (PS: $p = 0.754$ and NPS: $p = 0.972$, t-tests). Finally, revealing coarse information about the expected payoff frequencies decreased investments ($p < 0.001$, t-test), but column (2) shows that the interaction term between the treatment and information dummy is insignificant ($p = 0.482$, t-test), which means that the fear-of-pain effect does not depend on the degree of ambiguity.

Table B2: Regression analysis of fear induction experiment

Dependent variable:	Share invested in risky asset	
	(1)	(2)
Threat of shock	-4.273***	-3.794***
	(1.234)	(1.189)
Information	-6.353***	-5.869**
	(2.459)	(2.567)
Threat of shock × Information		-0.967
		(1.376)
Painful shock	0.577	0.584
	(1.843)	(1.841)
Non-painful shock	0.061	-0.048
	(1.762)	(1.763)
Age	1.720	1.720
	(1.382)	(1.382)
Male	4.628	4.628
	(6.540)	(6.540)
Constant	14.319	14.077
	(29.118)	(29.041)
N	3399	3399

This table reports OLS coefficient estimates (robust standard errors corrected for clustering on the individual level in parentheses). The dependent variable in both columns is the share invested in a lottery (in percent of the endowment). "Threat of shock" is a dummy for the painful treat-of-shock treatment, i.e., the condition we implemented to induce fear by exposing subjects to the threat of unpredictable, randomly administered painful electric shocks. "Information" is a dummy for decisions made in the second part of the experiment, i.e., after subjects received coarse information about the expected payoff frequencies. "Painful shock" and "Non-painful shock" are dummy variables for the actual experience of either painful or non-painful electrical stimulation within an interval of 4 seconds prior to the display of the choice scenario and until subjects made a choice. "Age" is a subject's age in years, and "Male" is a gender dummy. The number of observations is less than the total number of choice scenarios (3444) because some subjects did not respond within the allotted 5.5 second time limit and one subject ended the experiment early. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$.