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Market risk aversion under volatility shifts: An experimental study

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ABSTRACT

We propose an experiment to analyze the relationship between volatility regimes and investors' behavior and explore the mechanism by which aggregated risk aversion is configured. We design a market in which the volatility of the fundamentals is controlled and exogenously manipulated. Then we analyze the participation and trading behavior of participants under different volatility states. We observe a decrease in the market risk aversion during high volatility periods. In these periods, relatively more risk-averse investors do not participate in the risky market while less risk-averse investors trade. The individual risk aversion level of agents does not change during the experiment which leads us to conclude that the changes in market risk aversion during high volatility periods are mainly due to a participation effect.

1. Introduction

We analyze how changes in the volatility or state of the market affect investor behavior in an experimental environment. The understanding of investor behavior and, more specifically, attitude towards risk during different economic cycles/market states has been introduced in regulatory decisions (MiFID) and it is widely debated in the academic literature (e.g. asset pricing models). The flight-to-safety/quality or liquidity literature (Baele et al., 2018) emerges from the observation of investor behavior during periods of market stress. Considering the conclusions of portfolio choice models (Merton, 1969), investors are expected to reduce their holdings on risky investments during periods of uncertainty. From these models, investors with greater risk aversion are expected to "*fly*" to safer markets, with the least risk-averse agents remaining in the markets. One important open question is the influence of this "*flight*" on aggregate risk aversion. The results in our paper show the effects of different market environments on the individual risk aversion, the participation rate in the risky market and the aggregate market risk aversion.

There are three main methods to study empirically whether the investor's risk aversion level (or attitude towards risk) is constant over time and its relationship with the economic cycle,[2] (Schildberg-Hörisch, 2018): self-report or surveys (Guiso et al., 2018; Weber et al., 2013), asset pricing models (Cochrane, 2017), and incentivized experiments (Cohn et al., 2015; Guiso et al., 2018; König-Kersting & Trautmann, 2018). Results across methodologies are not conclusive and therefore this field of research remains open (Mehra, 2012).

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2 This relationship can be counter-cyclical or pro-cyclical.

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The evidence of the papers based on self-report methods is mixed. Guiso et al. (2018) used a methodology based on a survey of beliefs, expectations, risk perceptions and individual risk attitudes done by an Italian Bank between September 2007 and June 2009. They found evidence for counter cyclical risk aversion. Weber et al. (2013) surveyed UK-online-brokerage customers at 3 month intervals for self-reported risk attitude, 3 month expectations of returns and risks for the market and their own portfolio and their willingness to take risk and concluded that the risk aversion level is pretty stable across different periods. Sahm (2012) used the biennial survey of the Health and Retirement Study and also concluded that the risk aversion level is constant over time.

The second method implies the estimation of the risk aversion level of the representative investor in asset pricing models using quoted prices from financial assets. Most of these models (e.g. CAPM), assume investors' behavior not to be sensitive to the uncertainty/risk state in the market.[3] However, there are certain theoretical models that introduce time-varying risk aversion in investors' behavior/preferences or their utility functions. Campbell and Cochrane (1999) develop a habit formation model where the risk aversion of the agent increases when the levels of consumption approach the level of habit. Mayfield (2004) defines the intertemporal component in the ICAPM model of Merton (1973), i.e., the shifts in the investment opportunity set, as changes in the level of market volatility. Whitelaw (2000) modifies the dynamics of consumption and allows for a state-dependent consumption-generating process. Recent empirical studies have also emphasized the state-dependent feature of risk aversion and its importance for describing the empirical risk-return trade-off. By applying different methodologies to different financial markets, several papers find evidence of such dependence (e.g. Bliss & Panigirtzoglou, 2004; Kim & Lee, 2008; Lundblad, 2007; Salvador et al., 2014).

Within the papers using incentivized experiments, Cohn et al. (2015) and Guiso et al. (2018)[4] found evidence for counter cyclical risk aversion or risk taking. In both papers, subjects in the experiment were primed by a sentiment of fear. Cohn et al. (2015) primed their participants with financial boom and bust images while Guiso et al. (2018) showed them a horror film. The participants primed with a fear sentiment (financial bust and horror film) showed lower risk-taking. König-Kersting and Trautmann (2018) replicated the original study of Cohn et al. (2015) but they used a sample of students instead of professional investors. In this case, there is no effect of the fear priming in the investment decision. Andersen et al. (2008) and Harrison et al. (2005) estimated an experimental measure for risk aversion using a multiple price list (Holt & Laury, 2002) and tested the temporal stability of estimates of risk aversion. They concluded that the risk aversion level is constant over time.

Our study relies on the experimental methodology but our design choices differ from previous research. We do not prime the participants nor derive their risk attitude considering how much of the initial endowment they invest in risky versus non-risky investments (Cohn et al., 2015; Guiso et al., 2018; König-Kersting & Trautmann, 2018). Also, we do not derive our results from quoted prices of assets. Instead, we elicited investors' risk attitude (Andersen et al., 2008; Harrison et al., 2005) using a multiple lottery test (Sabater-Grande & Georgantzís, 2002) both at the beginning and at the end of the experiment and we also checked for the temporal stability of aggregated risk aversion[5] depending on the volatility state of the experimental market. In this sense, many studies use the experimental methodology to answer questions related to investors' behavior (Bloomfield & Andersen, 2010; Levy, 2013). However, to the best of our knowledge, no other study has analyzed the dynamics between aggregated risk aversion and market volatility regimes.

We implement in the laboratory a double auction experimental financial market in which the participants can decide whether they prefer to trade in a risky asset market (hereafter, traders)[6] or perform a calculus task (hereafter, accountants). As the market operates, we exogenously vary its volatility, and every time we do so, we ask participants to choose their role in the experiment as traders or accountants. Therefore, our design allows us to identify behavioral differences under varying volatility conditions in a within-subjects analysis.[7] This approach enables us to isolate investors' behavior within different volatility regimes from other factors[8] (such as expectations of stock returns and volatility, background risk, futures beliefs).

The asset market we implement here is inspired by the experimental literature on asset market behavior that was originated with the seminal paper by Smith et al. (1988). In their experiment, a homogeneous asset is being traded in a double auction setup where participants act as buyers and sellers for a finite number of periods. In each period, each unit of asset yields a dividend payment from a commonly known distribution. The fundamental value of the asset can then be calculated at each point in time by adding the expected remaining dividend payments if one was to hold the asset until the end of the experiment. This experiment, that was originally designed to be a baseline treatment where no bubbles would occur, turned out to be the perfect blueprint for recreating and studying bubbles in the laboratory, as participants systematically traded at prices higher than fundamentals. One

[3] The risk aversion level of the representative investor and the relationship between the expected return and risk of a financial asset is considered constant and independent of the state of the market.

[4] These authors use a double methodology: self-reporting and incentivized experiments. They found evidence of counter-cyclical risk aversion using both methodologies.

[5] In this study, we define aggregated risk aversion as the average risk aversion of all participants in the market.

[6] In all stages of the experiment, participants conduct a market investment task or an alternative task consisting in solving arithmetic sums. We never mentioned the words "trader" or "accountant" in the experiment to avoid inducing any bias in subjects' choices. However, for readability purposes, we use the labels "trader" and "accountant" in the paper.

[7] In this sense, the "priming" factor that affects the investment decision/sentiment are the changes in the state/volatility of the market.

[8] According to the Efficient Market Hypothesis (EMH), any relevant information about the asset will be reflected immediately in its price. Therefore, any variation in the distribution of the dividends (risk of fundamentals) will be included in the prices or returns of the assets. One of the observed asset pricing puzzles in the literature is the one referring to the high volatility of asset prices compared to the volatility of its fundamentals (excess volatility puzzle; see Shiller, 1981). In an experimental design as the one presented here we reduce this problem. The only information (news) generating an increase/decrease of the asset's risk is the one referring to the dividend distribution. Hence, there are no further influence of additional factors or shocks on future expectations of the agents.

possible explanation that the literature has explored is the presence of risk aversion in the market. Porter and Smith (1995) tested this hypothesis by eliminating the uncertainty of the dividend process, although price patterns did not change. Breaban and Noussair (2015) individually measured the level of risk aversion of market participants and found that a higher average risk aversion in a market correlates with lower prices, even though bubbles subside. This result is in line with what we expect to find in our data, where more risk averse individuals will be less likely to participate in the risky market when the volatility is high. And in order to avoid possible confounding effects of risk aversion related to bubbles and crashes, in this paper we chose to simplify the market design by having a working capital and inventory, rather than assets and cash that carry over from one period to the next. By doing this, we intend to limit the implications of risk aversion to the effect that higher vs. lower volatility regimes may have on behavior.

The main contribution of the paper is the documentation of the participation effect as an explanation for the differences in market risk aversion. Firstly, we find a reduction of the aggregate risk aversion in the high volatility state compared to the low volatility state. Secondly, we find that this reduction is not induced by changes in risk aversion on the individual level, but instead by a survivorship bias or participation effect: the more risk averse investors do not participate in the market during high volatility states and only the less risk-averse do trade. Besides, we observe that at the individual level the risk attitudes before and after the experimental market remain stable over time.

The analysis of the temporal stability of risk attitudes is an open topic and it is crucial for economic models and theories on decision making under risk. The results obtained in this type of studies suggest a common conclusion: risk attitudes are constant except when exceptional events (covariate shocks) occur (e.g. economic shocks, natural disasters, violent conflicts or war) (Malmendier & Nagel, 2011). However, idiosyncratic shocks (unemployment, health, changes in income, assets or wealth) have no effect on risk attitudes (Brunnermeier & Nagel, 2008). This consensus can be explained by the notion that insurance mechanisms for consumption are more effective in idiosyncratic shocks than in covariate shocks (Liebenehm, 2018).

In our case, we obtain risk attitudes before and after the experiment using a lottery-choice measure. This allows us to analyze whether volatility shifts (idiosyncratic shocks) have any effect on risk attitudes, without the need to condition the study to the existence of exceptional events (covariate shocks). Andersen et al. (2008) and Harrison et al. (2005) have studied the temporal stability of these estimates of risk aversion in detail.[9] The particularity of our work compared to others that also use a lottery-choice measure (elicitation) is due to the design of the experiment and the time between the test and re-test (our experiment lasts approximately 2 hours). There are two reasons to test the temporal stability of risk attitudes before and after the experiment: (i) to isolate whether changes in the market risk aversion are due to a participation effect or to changes in the individual risk aversion of the participants; (ii) for robustness purposes (the conclusions obtained using the risk aversion levels measured before and after the experiment are the same).

The implications of our results are manifold. First, we provide an explanation for the Flight to Safety or Flight to Quality concepts documented in Baele et al. (2018), Caballero and Krishnamurthy (2008) or Ghysels et al. (2016). Second, the role of stock market participation (risk taking), rather than time-varying individual risk aversion can play a major role in explaining the time-variation of the aggregate risk premia/aversion (Brunnermeier & Nagel, 2008). Third, the existence of a pro-cyclical risk-aversion/price of risk in financial markets reported by Bliss and Panigirtzoglou (2004), Ghysels et al. (2014), Rossi and Timmermann (2010) and Salvador et al. (2014) is plausible when the more risk averse investors do not participate in the market during periods of high volatility. Fourth, the concept of risk taking used in Cohn et al. (2015), Guiso et al. (2018) and Weber et al. (2013) and the participation effect in our paper have similar implications: lower participation in risky assets during stress markets or fear. This effect has also been reported in other situations; e.g. Malmendier and Nagel (2011) for individual experiences in risk taking or Brunnermeier and Nagel (2008) considering changes in liquid wealth of households and risk taking.

The remainder of the paper is structured as follows. Section 2 introduces the hypotheses. We explain the experimental design and describe the data obtained in Section 3. Section 4 discusses the main results of the study. Finally, Section 5 concludes.

2. Hypotheses

The theoretical model proposed for the experiment follows closely the papers of Mayfield (2004) and Merton (1969). According to these models, the decision of the investor to trade the risky asset (risk taking decision) in period t is directly proportional to the return of the asset but inversely proportional to the volatility of the asset (Heaton & Lucas, 2000). This decision to trade is also inversely proportional to the risk aversion of the investor.

$$Trade_t = \frac{\mu_t^*}{\sigma_t^2 RRA} \tag{1}$$

where $\mu_t^* = \mu_t - r_t$ is the expected excess return of the asset over the risk-free asset; σ_t^2 is the variance (risk) of the risky asset and RRA the relative risk aversion of the investor.

The hypotheses in our experiment follow variations of this relationship together with empirical evidence on the evolution of average returns and volatilities of US stock returns.

[9] Other studies have analyzed the temporal stability of risk aversion measured with an experimental task or surveys and consider larger periods between test and re-test, ranging from weeks to years (Galizzi et al., 2016). For studies obtaining risk attitudes from long-term panel data that consider surveys or questionnaire measures, see Brunnermeier and Nagel (2008); Malmendier and Nagel (2011); or Sahm (2012). See Chuang and Schechter (2015), Lönnqvist et al. (2015) for studies that consider both experimental tasks and survey measures.

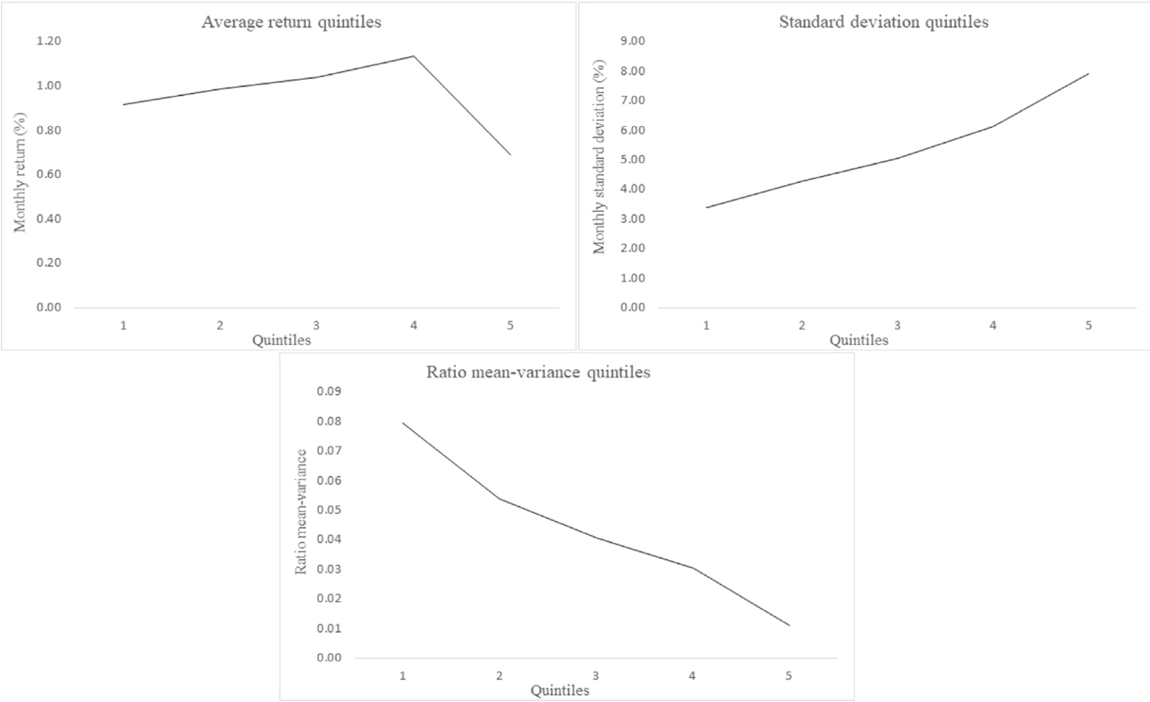

Fig. 1. Sorted portfolios by variance. This figure shows the average return (top left plot), the standard deviation of the returns (top right plot) and the ratio between the average return and the variance of five portfolios sorted on the level of variance of its constituent stocks (bottom plot). These portfolios include all stocks available in the CRSP (Centre for Research in Securities Prices) database and cover the period from July 1963 to September 2017.

Fig. 1 displays the performance of five portfolios using all US stocks sorted by variance during the last 50 years. These portfolios are formed monthly on the variance of daily returns, estimated using 60 days (minimum 20 days) of lagged returns.[10] The portfolios are divided into five quintiles. The lowest quintile (quintile 1) corresponds to the portfolio holding the stocks with the lowest level of variance while the highest quintile (quintile 5) corresponds to the portfolio holding the stocks with the highest level of variance.

We can clearly observe a non-linear relationship between return and risk in the top left plot of Fig. 1. As expected, average returns increase monotonically with increases in the levels of risk. However, this direct relationship between return and risk does not hold for very high levels of volatility. The bottom plot reveals an interesting implication for our theoretical model. We can observe that the mean–variance return ratio (μ_t^*/σ_t^2) strictly decreases with the level of risk of the portfolio. According to our expression (1), if we decrease the value of the mean–variance ratio (assuming RRA is constant), the probability of trading (value of the decision variable $Trade_t$) will be lower. Therefore, we conjecture that there will be less investors interested in the high volatility portfolios than in the low volatility portfolios.

In our experiment, this hypothesis concerns the participation rate in the risky asset market when volatility is exogenously varied. We expect that fewer subjects will prefer trading in the risky asset (*trader* role) compared to the calculus task (*accountant* role) when volatility is higher. This hypothesis, is also based on the models supporting the concept of Flight to Safety (Baele et al., 2018).[11]

Hypothesis 1. In the high-volatility regime, there will be fewer traders participating in the stock market compared to the low-volatility regime.

Re-arranging slightly our expression (1), we can define the trading decision variable weighted by the coefficient of relative risk aversion as a function of the characteristics of the assets. Obviously, the higher level of risk aversion on the left hand side will require a higher value of the mean–variance ratio on the right hand side:

$$Trade_t \cdot RRA = \frac{\mu_t^*}{\sigma_t^2} \tag{2}$$

[10] We thank professor Kenneth French for making this data available through his library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[11] There is a considerable number of theoretical models analyzing the relationship between participation in financial markets, risk pricing/risk aversion behavior and periods of market instability. Most of these papers can be classified under the concepts of Flight to Safety or Flight to Quality (see for instance Baele et al., 2018; Bekaert & Engstrom, 2015).

From this relationship, we propose our remaining hypotheses. Only investors with a lower RRA will be trading in the different risk states (both where the mean–variance ratio shows a higher and a lower value), supporting the idea that the most risk-averse investors will not participate in the market in periods of high risk. This will also decrease the aggregated level of risk aversion in the market during periods of high risk.

The second hypothesis is also motivated by the empirical results in several papers where market risk aversion decreases during high volatility periods (Bliss & Panigirtzoglou, 2004; Salvador et al., 2014). These studies, using quoted returns for different asset markets, show that market risk aversion is not constant but shows a state-dependent behavior. During low volatility states market risk aversion is higher than during high volatility states. Even more interesting than establishing the correlational relationship between average risk aversion and the volatility regime in the market, which is an empirically tested result, is establishing a causality relationship between the two variables. Our experimental design allows us to test this relationship by exogenously altering the risk regime. By doing so and considering Eq. (2), we can argue that a volatility shift causes the observed change in the market average risk aversion.

Hypothesis 2. Market average risk aversion will be lower in the high-volatility regime than in the low-volatility regime.

To further investigate the mechanism through which this phenomenon occurs, we formulate our third hypothesis regarding individual behavior. The change (decrease) in market risk aversion depending on the state of the market may be due to two different effects: *(a)* participation effect (presented in Hypothesis 1) or *(b)* changes in the individual risk aversion level. In order to get a better understanding about which is the leading factor driving the variation of the market risk aversion, we also analyze differences in the individual risk aversion levels before and after the experiment. The study of both concepts (market participation and dynamics of individual risk aversion levels) allows us to disentangle whether the variation in market risk aversion are due to a pure participation effect or to a combination of both effects.

Hypothesis 3. At the individual level, agents with higher risk-aversion will tend to exit the stock market when a high-volatility regime arrives.

3. The experiment methodology

3.1. Experiment design

The experiment consisted of two treatments, corresponding to the two volatility states of the market, and four experimental sessions (both treatments were implemented in each session).[12] There were a total of 180 volunteer participants and each of them was randomly assigned to one market. Each market was formed by 9 subjects, making a total of 20 markets. In each session, 5 independent markets operated simultaneously. All 180 participants (91 women) were undergraduate students at University Jaume I (Castellon, Spain), and most of them were enrolled in Economics or Business Administration courses. Each session took approximately two hours on average. The experiment was programmed using Z-tree software, developed by Fischbacher (2007).

Each session consisted of three parts: The first and the third part of the experiment consisted of a risk aversion test developed by Sabater-Grande and Georgantzís (2002).[13] This task was constructed to compensate riskier options with higher risk-return trade-offs in each of its four lottery panels and is capable of capturing two dimensions of individual risky decision-making: subjects' average willingness to take risk and their sensitivity towards variations in the return to risk (Barreda-Tarrazona et al., 2020). As shown in Table 1, the SGG lottery task was presented to students in a four-panel format, with each containing ten different lotteries. In each lottery, the subjects can earn a payoff x with a probability p or a zero payoff with probability $(1-p)$. In the first panel, the amount x increases in each lottery from 1 euro to 10.90 euros as probability p decreases from 1, 0.9, 0.8, …, to 0.1. In panels 2, 3 and 4, the amount x increases for each lottery from 1 euro to 19 euros, 55 euros and 100 euros, respectively. The payoff x associated with each lottery i and panel j is constructed using the following rule:

$$x_{i,j} = \frac{c_j + (1 - p_{i,j} t_j)}{p_{i,j}} \tag{3}$$

where c_j is the sure payoff of 1 euro in this case, $p_{i,j}$ is the probability of winning the lottery, and $t_j \in \{0.1, 1, 5, 10\}$ is a panel-specific risk premium, which generates an increase in the expected values of the lotteries as we move from safer to riskier options within the same panel.

The task was computerized, and the four panels were simultaneously displayed on the computer screen, so that individuals could revisit and revise their responses to previous questions in light of subsequent decisions. The choice consisted in selecting one of the ten lotteries in each of the four panels. When they were satisfied with all their responses, they submitted all four of them simultaneously. At the end of the session, a volunteer flipping a coin determined whether the first or the third part of the sessions

[12] In order to control for possible order effects we ran 2 sessions that started with high volatility regime and 2 sessions starting with low volatility regime.

[13] The test by Sabater-Grande and Georgantzís (2002) was developed in our laboratory and is our standard measure of risk aversion. Using this test, Barreda-Tarrazona et al. (2011) obtain an estimate of a CRRA coefficient that is perfectly in line with the one estimated by Harrison et al. (2009) based on the more common Holt and Laury (2002) test. Details on the characteristics, advantages and limitations, and implementation of the test can be found in Barreda-Tarrazona et al. (2020).

Table 1
The SGG lottery-panel test and example of subject choices.

Panel 1										
Prob	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
Die	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Euros	1.00	1.10	1.30	1.50	1.70	2.10	2.70	3.60	5.40	10.90
Choice			X							
Panel 2										
Prob	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
Die	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Euros	1.00	1.20	1.50	1.90	2.30	3.00	4.00	5.70	9.00	19.00
Choice				X						
Panel 3										
Prob	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
Die	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Euros	1.00	1.70	2.50	3.60	5.00	7.00	10.00	15.00	25.00	55.00
Choice					X					
Panel 4										
Prob	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
Die	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Euros	1.00	2.20	3.80	5.70	8.30	12.00	17.50	26.70	55.00	100.00
Choice								X		

This table shows the payoffs (expressed in euros) for each of the four panels of the SGG lottery according to the probability of winning the lottery. The participant chooses one option in each one of the panels. The outcome of the lottery is conducted by a double draw. First, a four-sided die decides which of the four panels determines the payoffs of the lottery. Second, a ten-sided die determines the probability p of winning, for which the participants with an equal or higher probability than that shown by the die would win the lottery.

would be paid. Then, one of the four panels of the lottery test was randomly selected to add up to each individual's earnings, a task that was performed by a second volunteer student rolling a four-sided die. Then, a ten-sided die cast by another volunteer participant determined p: the minimum winning probability, according to which each participant would win the amount specified in the chosen lottery option or not. The outcome of the lotteries was only revealed at the end of the session.

The SGG test was conducted at the beginning (SGGpre) and at the end of the experiment (SGGpost) and no change has been detected in the individual risk aversion level before and after the experiment (see Table 7). We consider this testing a robustness check of our results but, for the sake of brevity, we only display the results when considering the SGGpre measurements in the baseline results since we reach the same conclusions using SGGpost.[14]

In the second and main part of the experiment, subjects made investment decisions or arithmetic computations. They could opt to participate in the asset market, choosing "task A" (*trader* role), or, alternatively, participate in "task B" solving arithmetic sums[15] (*accountant* role). Every five periods, coinciding with a change of regime, subjects were asked to choose whether they preferred "task A" or "task B". Therefore, at the beginning of periods 1, 6, 11 and 16, each participant chose a role for the immediate 5 periods and would have the chance to reverse that decision after those periods had elapsed.

We provided all subjects with specific written instructions to follow at each stage of the experiment.[16] Additionally, we showed a presentation illustrating how to trade using the experimental screen. Before starting the experiment, there was a trial period that did not count towards the final earnings. In this period, the participants could experiment with the interface of the asset market, submitting offers and making transactions, and also asked questions to the experimentalist if there was something they were not understanding.

The asset market

The asset market operated for 20 periods, and it was open for a fixed 2 minute time interval every period, during which subjects were able to trade units of an asset. The asset was a homogeneous stock that earned a dividend for its holder at the end of each period. The transaction prices were determined in a continuous double-auction market (Smith, 1962). This type of market operates in the following manner. In each period, at any time while the market was open, any trader could submit offers to sell or offers to purchase an asset. These offers were posted publicly on the computer screens of all subjects who were operating as traders, ordered

[14] These results are available upon request.

[15] The motivation for using this task is to develop a framework to analyze the decision of participating in financial markets. A plausible alternative for this task could have been a risk-free asset investment, although this could lead to behavioral distortions as subjects might decide to participate in the risky market simply to be doing something.

[16] The experimental instructions can be found in Appendix A.

such that the best current bids and asks would be on the top of the list. Additionally, any trader could at any time accept an offer that another trader had submitted. When a bid or ask was accepted by a trader, a transaction for one unit of asset at the offered price occurred between the trader who posted the offer and the trader who accepted it. There was no automatic clearing, short selling or leverage. Within a period, it was possible for different transactions to occur at different prices and all traders received information about all realized transactions as they occurred. The subjects could trade as much as they wished, provided that they had sufficient cash and units of the asset to do so. The participants in any of the formed markets remained anonymous at all times.

Each subject participating in the asset market was endowed with an identical portfolio of 10 assets and 340 ECUs (Experimental Currency Units) at the beginning of each trading period. The assets would not carry over from one period to the next, and the 340 ECUs were not included in the traders' money balance; therefore, the purpose of this endowment was strictly working capital.

A subject's final earnings in the asset market were determined by the accumulated dividend payments for each asset the subject held at the end of each period plus (minus) any capital gains (losses) resulting from the trading activity. The currency used in the asset market was defined as an "experimental currency unit", such that prices, cash and dividends were expressed in terms of ECUs. At the end of the experiment, the accumulated number of ECUs during all periods was converted into Euros using the following exchange rate: 100 ECUs = 1 Euro.

During the 20 periods when the market was operating, different risk regimes were implemented. This was done by varying the dividend distribution. Every 5 periods, the potential values of these dividend payoffs were changed to generate states of high and low risk in the asset markets. It is just in these periods (period 1, 6, 11 and 16) when the participants may change their decision whether to participate in the market or not. More specifically, in the low-risk regime, labeled "regime A", there was a 50–50 chance that the dividend paid at the end of each period would be either 17 ECUs or 0 ECUs per asset held in the inventory. However, in the high-risk regime, labeled "regime B", the dividends took values of 25 ECUs or −2 ECUs per asset, with a 50% probability.[17] A computer randomly generated the draw at the end of each period, which determined whether the dividend for that period was 0 ECUs or 17 ECUs for regime A and 25 ECUs or −2 ECUs for regime B.[18] Then, the true value of the dividend was announced, the dividend was paid to the asset holders, and the cash was added to their money balance. This information was displayed on the participants' screen as their accumulated earnings. They were also shown information about the average earnings of traders in the asset markets in each period and the average earnings of accountants in that period.[19] Both regimes were alternated such that, in each session, both high- and low-risk treatments were implemented twice over 5 periods each time. To control for order effects, two of the sessions started with regime B and the other two with regime A.

Arithmetic sums

During the main part of the experiment, the second one, subjects also had the possibility to perform an alternative task that consisted in solving arithmetic sums. The earnings in this task were determined by the number of sums that were correctly solved during the 2 minute periods. These sums consisted of adding five two-digit numbers that appeared on the screen. For every sum that was correctly solved, the subject operating as an accountant received 5 ECUs. At the end of each period, the number of correct sums that one achieved, the corresponding earnings for that period and the accumulated earnings were displayed on the computer screen. There was also information provided about the average earnings of accountants in the session in that period and the average earnings of traders.

An individual's payoff for this second part of the experiment was the sum of the earnings in each of the 20 periods, regardless of the role that she decided to play in each period. These earnings were converted into euros and were added to the lottery gains to obtain the final earnings for the experiment. The total amount was anonymously paid in cash at the end of the session.

3.2. Experimental data

We construct our dataset linking the observations from three different parts of the experiment. First we obtain the individuals' risk aversion level measured by the SGG test performed both at the beginning (*SGGpre*) and at the end (*SGGpost*) of each session. The level of risk aversion derived from each of the two implementations of the test is obtained through a scale considering the decisions made by the subjects for each one of the panels 1 to 4 in Table 1. This variable represents the individual risk-aversion level for each participant, with higher values of the variable associated to lower risk-aversion levels up to a maximum of risk neutrality (the scale does not measure risk-lovingness).

In particular, the SGG variable in our regression models in Section 4 is an adjusted-alpha risk aversion level for each of the participants in the experiment based on their decisions in the lotteries played at the beginning of the experiment. Psychological research involving scale construction requires for a test of the reliability of the measurements. One of the most popular metrics used as an estimate of the reliability of a psychometric test is Cronbach's alpha[20] (Cronbach, 1951). In our case, the average inter-item

[17] As Merton (1973) highlights, a riskier investment should demand a higher expected return. Regimes A and B comply with this premise.

[18] The design of the dividend distribution seeks that participants perceive different levels of risk between the two regimes (with a higher level of risk for regime B). Although the expected returns in both regimes are positive, the possibility of a negative payoff increases the perception of higher risk in regime B.

[19] The purpose of displaying this information is to create the conditions for a transparent market where participants can make their decisions using all the information available (market efficiency).

[20] Cronbach's alpha is a function of the number of items in a test, the average covariance between item pairs, and the variance in the total score, intended to be used as a test of the reliability of a psychometric test.

Table 2
Descriptive statistics for the variables.

Panel A.- Risk aversion and trading variables				
	Max.	Min.	Std. dev.	Average
Net position (NP)	38	−10	6.63	0
Risk aversion (SGG)	9	2	1.74	5.74
Accumulated earnings	5455.70	635	745.98	2004.15
Earnings per period *accountants*	90	0	12.75	48.97
Earnings per period *traders*	999.90	−412.10	148.49	114.27
Panel B.- Qualitative variables				
	Max.	Min.	Std. dev.	Average
Age	34	18	2.553	21.933
Gender	1	0	0.500	0.494
Studies	1	0	0.239	0.938

This table shows the descriptive statistics for our main variables. Accumulated Earnings are expressed as Experimental Currency Units (ECUs). The total number of *accountants* and *traders* is 720, which is the number of participants (180) times the number of periods (1, 6, 11 and 16) in which there is a regime shift and the participants can select to act as *traders* or *accountants*. Net position refers to the net stock holdings (final stocks–initial stocks) of each subject at every point in time. Risk aversion is the SGG score for each subject according to the Sabater-Grande and Georgantzís (2002) test with higher values showing lower risk aversion. Accumulated earnings show the final monetary balance of each subject at the end of the experiment. Earnings per period accountants/traders show the profits earned by a subject acting as an accountant/trader at every point in time. Age, gender and studies (dummy variable that took value 1 if the field of study was Economics, Finance or Business related).

correlation for the SGG test is 0.53, and the scale reliability coefficient is 0.82. Cortina (1993) shows that a large alpha, as in our case, implies that there is very little item-specific variance, and it can be concluded that the measurement is reliable.

Besides, we collect data on the market activity for the subjects acting as traders, such as purchases, sales and final earnings. Further, we compute the *Net Position* (NP) of a trader by comparing her holdings at the beginning of a period with the holdings at the end of that period. We also compute the *Accumulated Earnings* (Erg) for each trader and for every period. The accumulated earnings show the monetary balance of each subject up to a specific period of the experiment. Finally, we collect the data generated by the subjects operating as accountants who decided to conduct the task of solving sums. With all this available information, we construct a panel dataset with 180 individuals and 20 periods.

Below, Table 2 shows some descriptive statistics regarding the constructed dataset. Additionally, we collect some qualitative data about the participants, such as gender, age and undertaken studies.

The variable net position shows a significant dispersion (standard deviation of 6.63), which means that different subjects hold different numbers of stocks in their portfolios at certain points in time. The number of stocks held reaches a maximum of 38 stocks, whereas there are other subjects who sell their initial endowment of 10 stocks at a certain point in time. Similar to other studies, risk aversion levels in our sample show heterogeneous preferences, allowing us to analyze the relationship between risk aversion and risk regimes. The average earnings made by the participants at the end of the experiments accounted for more than 2000 ECUs, with a maximum of 5455.70 ECUs for the subject with the most profitable strategy. Another interesting fact observed in the experiment is the average return and the standard deviation of the profits made in the stock market and in the accountant task. The accountant task offers not only lower average returns (48.97 ECUs per period) but also lower uncertainty (12.75 ECUs per period). However, the risky asset offers not only higher average returns (114.27 ECUs per period) but also higher uncertainty (148.4 ECUs per period).[21] The qualitative variables show gender parity in our set of participants, the fact that the majority of the subjects in the experiments were enrolled in business/economics-related courses and that the age of the subjects ranged from 18 to 34 years old.[22]

All these statistics show a preliminary picture of our collected variables. In the next section, we provide a deeper analysis of the relationships among net position, risk aversion and earnings and a formal statistical analysis of the hypotheses presented in section two.

4. Results

In this section we present and discuss the results, in correspondence with the hypotheses posed.

***Results for** Hypothesis 1: In the high-volatility regime, there is a significantly lower number of traders participating in the market compared to the low-volatility regime.*

[21] The ratio between the earnings of accountants and traders is approximately 0.42. This ratio is within the range 0.34–0.45 that we obtained for the ratio between the returns of the risk-free asset (1 month T-bill) and the US stock market for the period 1926 to 2012, depending on the sample period considered. Results available from authors upon request.

[22] We find that among the 28 pairwise correlations of the variables used in the paper, 20 show significant values. This finding means that some of these variables co-move together, and they may reflect relationships among them that help illuminate our main hypothesis. Results available from authors upon request.

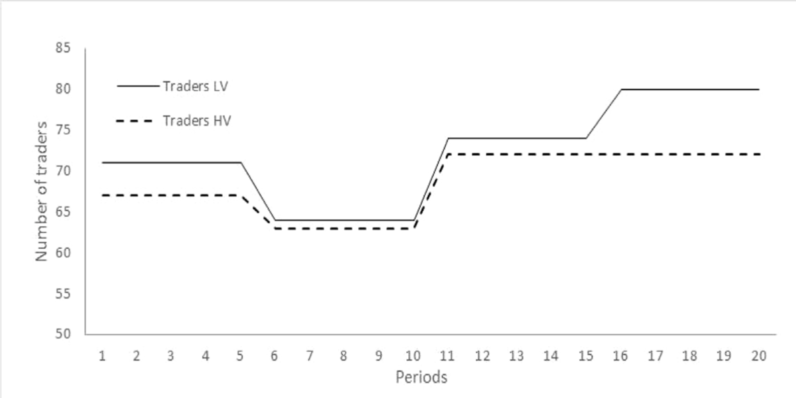

Fig. 2. Number of traders, low vs. high volatility (LV vs. HV). The figure plots the number of traders who operate in a low-volatility state and the traders who operate in high-volatility states for each of the 20 periods of the experiment. Note that for every 5 periods the data for LV regime come from two of the four sessions, while those for HV regime come from the other two sessions, so the traders under each regime are different people within each 5-period block, however, the same pool of people plays each block of 5 periods, where they can participate as traders or exit the market as accountants.

Table 3
McNemar (1947) test for different periods and treatments.

	Periods 15 to 16	Periods 10 to 11	Periods 5 to 6	Periods 10 to 11 plus 15 to 16	Periods 5 to 6 plus 10 to 11 plus 15 to 16
Low to high	0.250	2.460	1.780	0.860	0.050
	(0.803)	*(0.169)*	*(0.234)*	*(0.441)*	*(0.909)*
High to low	4.000**	5.260**	0.290	9.260**	0.230
	(0.076)	*(0.035)*	*(0.720)*	*(0.003)*	*(0.702)*

The table displays the *t*-statistic and *p*-value (in parentheses) for the McNemar (1947) test. The first three columns show the McNemar (1947) test results for the changes in period 16, in period 11 and in period 6, respectively. The fourth column displays the results for the aggregated changes in periods 11 and 16, and the fifth column shows the aggregated changes in periods 6, 11 and 16. We distinguish in rows whether the change in volatility is from states of low-to-high volatility or from states of high-to-low volatility.

Support for Hypothesis 1: We aggregate the number of traders in all markets and the number of accountants for all periods. Fig. 2 plots the total number of traders for every period for each of the volatility regimes. We observe that there is a higher number of traders operating in the markets during low-volatility periods than during high-volatility periods. In the first change of regime (in any direction), many subjects try what it is like to be an accountant but return to similar levels of traders in the next change of regime. The final change of regime (in period 16), which entails for many subjects already having experienced both roles, is the most revealing: many more subjects enter to trade in the market in period 16 when volatility switches to low.

We perform a McNemar (1947) test where we compare whether the number of times that a subject chose to be an accountant in period t and she decided to switch her selection to be a trader when the volatility changed is significantly different from the opposite switch (i.e., a subject who was a trader in period t and who decided to change to an accountant when the volatility experienced the same change of state). The different panels in Table 3 show the results for the different shifting periods, and we distinguish between whether the change in volatility is from states of low-to-high volatility or from states of high-to-low volatility. The switches from accountant to trader are significantly more frequent than the opposite change for the latter shifts from high to low volatility. This finding is in line with Hypothesis 1, although there seems to exist an order effect since we do not find a significant difference in the low-to-high volatility changes. Shifts in the subjects' role in the market, according to our hypothesis, are more evident considering periods 11 and 16, rather than period 6, both individually and in an aggregated manner (see the results in the first, second and fourth columns), suggesting the existence of a learning effect.

This evidence of a learning effect makes us think that, in the first part of the experiment, some subjects may decide to switch from one task to the other to experience both. We expect behavioral patterns to be clearer in the last two blocks,[23] when the participants have gained experience in the game under both volatility regimes. To test the significance of our evidence, we run a series of tests on the mean and the median of the number of traders during low- and high-volatility states. The Wilcoxon rank-sum test suggests that the median number of traders per market in the high-volatility regime is lower than that in the low-volatility regime. The two sample t-tests and the Kolmogorov–Smirnov test also confirm this different number of traders during different volatility regimes. All the results in Table 4 strongly support our Hypothesis 1.

[23] We report results for these last two blocks of the experiment although the conclusions using all the periods in the experiment are qualitatively similar. Results available from authors upon request.

Table 4
Test for equality of means and medians of the number of traders during high- and low-volatility states.

Periods	Wilcoxon rank test	t-test	Kolmogorov–Smirnov test
Last two blocks	4.068***	5.000***	1.000***
(periods 11–20)	*(0.000)*	*(0.000)*	*(0.000)*

The table displays the *t*-statistic and *p*-value for the two-sided Wilcoxon rank-sum test (equality of median), the two-sided t-test (equality of means) and the Kolmogorov–Smirnov test (equality of distribution). We test the null hypothesis that the number of traders operating in low-volatility states and the number of traders operating in high-volatility states are samples from continuous distributions with equal medians (means and distribution) against the alternative that they are not. ***, **, and * represent rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively.

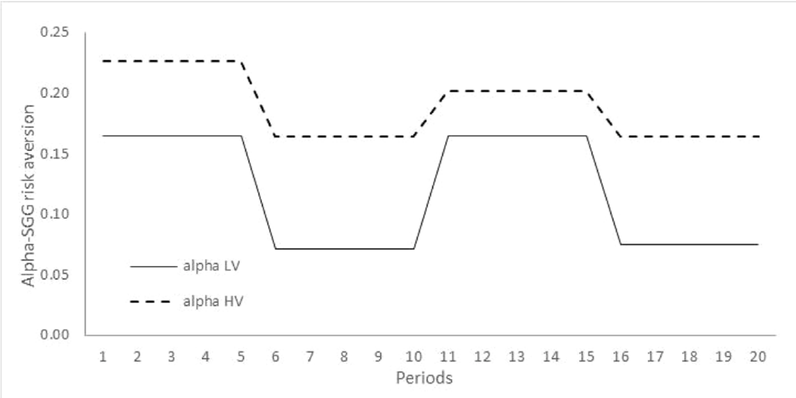

Fig. 3. Median risk aversion level for the SGG test, low vs. high volatility (LV vs. HV). This figure plots the median of the measure of risk aversion for traders who operate in a low-volatility state (in 2 of the 4 sessions) and different traders who operate, for the same periods, in high-volatility states (in the other 2 sessions) for each of the 20 periods of the experiment according to the scale of the SGG test (computed using alpha). The lower the risk aversion of the subjects is, the higher the value that this measure takes.

Results for Hypothesis 2: Market average risk aversion is significantly lower in the high-volatility regime compared to the low-volatility regime.

Support for Hypothesis 2: The evidence for this second hypothesis is obtained as follows. We identify every subject operating as a trader in the stock market at any point in time. We know the risk aversion of each subject of our experiment (from the lottery conducted in the first part and final part of each session), so we are able to associate each subject with a risk aversion level. We aggregate the risk aversion of all subjects operating as traders in each period of the experiment, and we further distinguish between periods corresponding to low- and high-volatility regimes. In this manner, we obtain a measure of the aggregated level of risk aversion in the market (in every period and for low- and high-volatility states) based on its participants.

Fig. 3 represents the value of the median of the SGG scale score for the traders (representing an aggregated risk aversion level) at every point in time. Clearly, the level of risk aversion during high-volatility states is lower than that during low-volatility states (a higher SGG score indicates lower risk aversion). Therefore, the level of risk aversion during high-volatility periods seems to decrease in the asset market. This result is robust for all periods and indicates a different risk tolerance of the subjects in the market during low- and high-volatility regimes. Subjects trading in high-volatility regimes are less risk-averse and continue trading even in an environment of higher uncertainty. However, subjects operating in a low-volatility state show an aggregated lower tolerance to risk.

To statistically test the significance of Hypothesis 2, in Table 5 we show a battery of tests for the equality of means and medians on the SGG risk aversion score during low- and high-volatility states. In all tests proposed, we reject the null of equality of medians (or means).

These two pieces of evidence support the idea of volatility changes affecting aggregated market risk aversion. During a regime with low volatility, the risk aversion observed in the market is significantly different from that in the market in a regime with high volatility. This result obtained in our experimental market is not different from the results obtained by Bliss and Panigirtzoglou (2004), Ghysels et al. (2014), Rossi and Timmermann (2010), and Salvador et al. (2014) using real market data. These authors also identify a state-dependent risk-return trade-off, which they associate with different levels of risk appetite/aversion in the market.

One important comment to make at this point is that the decrease of the market risk aversion level during these high-volatility periods may be due to a participation effect, to a change in the individual risk aversion levels or to a combination of both effects. To get a better understanding of the determinants of the variations in market risk aversion, we tested whether the individual risk aversion levels of the participants in our experiment are constant before (*SGGpre*) and after (*SGGpost*) the experimental financial market. Table 6 shows the results for several tests of equality of means (two-sided t-test and Kolmogorov–Smirnov) and equality of medians (Wilcoxon-rank test) for these two variables. None of the tests can reject the null of equality of means (medians) which

Table 5
Tests for equality of the means and medians for the level of risk aversion of the traders operating during high- and low-volatility states.

Periods	Wilcoxon rank test	t-test	Kolmogorov–Smirnov test
Last two blocks	−3.044***	−3.929***	0.500***
(periods 11–20)	*(0.002)*	*(0.009)*	*(0.011)*

The table displays the *t*-statistic and *p*-value (in parentheses) for the two-sided Wilcoxon rank-sum test (equality of median), the two-sided t-test (equality of means) and the Kolmogorov–Smirnov test (equality of distribution). We test the null hypothesis that the median (mean) of the alpha-adjusted SGG risk aversion level during low-volatility states and the median of the alpha-adjusted SGG risk aversion level in high-volatility states are samples from continuous distributions with equal medians (means and distribution) against the alternative that they are not. ***, **, and * represent rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively.

Table 6
Tests for equality of the means and medians for the level of individual risk aversion at the beginning (SGGpre) and the end (SGGpost) of experiment.

Null hypothesis	Wilcoxon rank test	t-test	Kolmogorov–Smirnov test
SGG pre = SGG post	0.028	1.93×10^{-7}	0.061
	(0.978)	*(1.000)*	*(0.880)*

The table displays the *t*-statistic and *p*-value (in parentheses) for the two-sided Wilcoxon rank-sum test (equality of median), the two-sided t-test (equality of means) and the Kolmogorov–Smirnov test (equality of distribution). We test the null hypothesis that the median (mean and distribution) of the alpha-adjusted SGGpre and SGGpost are samples form continuous distributions with equal median (mean) against the alternative that they are not. ***, **, and * represent rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively.

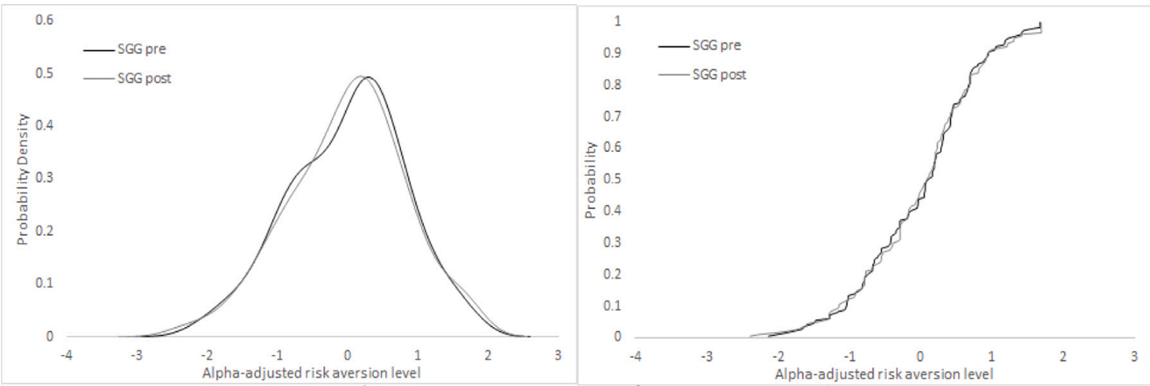

Fig. 4. Probability density function (PDF) and cumulative distribution function (CDF) for the individual risk aversion levels. The left figure plots the probability density function (PDF) for the individual risk aversion levels computed using the SGG measure before the experiment (black line) and after the experiment (gray line). The right figure plots the cumulative distribution function (CDF) for the individual risk aversion levels computed using the SGG measure before the experiment (black line) and after the experiment (gray line).

lead us to conclude that individual risk aversion levels before and after the market are generated from distributions with means and medians not statistically different. The same results can be observed clearly in Fig. 4 where the probability distribution function and the cumulative distribution functions of both variables (*SGGpre* and *SGGpost*) are plotted assuming a continuous approximation. Individual levels of risk aversion seem to follow the same distribution independently of whether they were measured before or after participating in the market.

We now discuss further characteristics regarding traders' behavior in the following results.

Preliminary results for Hypothesis 3:

(a) In the asset market, a trader's net position depends on the volatility regime.

Given that we find a volatility effect on the market average risk aversion, we further explore whether, within the asset market, traders behave differently depending on the volatility state. We first provide an inference analysis of the trading activity in Table 7. As discussed in result 1, we observe a significantly higher number of traders during low volatility periods than during high volatility periods. As we expected, the traded price during high volatility periods shows a significantly higher value than the one traded during low volatility periods and both average prices follow closely the expected value of the payoffs (fundamentals). Also interestingly, the volatility of the traded prices (measured as the standard deviation of prices) during high volatility periods is significantly higher than the one observed during low volatility periods. This result allows us to establish a direct relationship between our definitions of high and low volatility regimes in terms of both fundamentals and prices. Finally, we observe that trading activity in the market is not significantly altered by the change in volatility. The average number of trades per agent in the market remains similar in both volatility states.

Table 7
Inferential analysis for the trading variables.

Variable	Obs. LV–HV	Low vol.	High vol.	Sign test p-value
Number traders per market	20–20	7.70	7.20	0.0193**
Number of trades (purchases + sales)	20–20	21.65	21.44	0.2517
Trade price	20–20	7.80	8.84	0.0577*
S.D. of Trade price per market	20–20	3.22	5.23	0.0203**

This table shows the means of the variables related to trading activity in the experimental markets during the last 10 periods of each market, allowing for learning in the previous periods. Prices are means of means per market. A one-sided sign test for matched pairs has been used to compare trading activity variables between low fundamental volatility and high fundamental volatility periods.

Table 8
Traders' net position depending on the volatility regime and risk aversion.

Model 1

$NP_{i,t} = \alpha_i + \beta_1\ SGG_{i,t} + \beta_2\ DHV_{i,t} \cdot SGG_{i,t} + \beta_3\ HV0_{i,t} + \varepsilon_{i,t}$

	α	β_1	β_2	β_3
Coeff.	0.678*	2.749***	−1.681***	0.663
(std. errors)	*(0.408)*	*(0.539)*	*(0.629)*	*(0.412)*
	Observations	Cluster	Wald statistic	(p-value)
	3600	180	49.460***	*(0.007)*

This table displays the estimates of the model in Eq. (4). We use a cross-sectional time-series FGLS regression to estimate the coefficients with standard errors adjusted for heteroscedasticity and cross-sectional correlation (assumed to be panel-specific AR(1)). We use a total of 3600 observations in 180 groups to estimate 16290 covariances and 180 autocorrelations, and we reject the Wald test for the true values of the parameters at the 1% level. ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively, and standard errors can be found in parentheses. The variable *NP* refers to the net position of traders (final stock minus initial stock). *DHV* takes the value of 1 for high-volatility periods and 0 otherwise. *SGG* is the risk aversion of the subjects: the higher SGG the lower the risk aversion. *HV0* is a dummy variable that takes the value of 1 when the session starts with a high-volatility state and 0 otherwise, and α is the constant of the model.

(b) More risk-averse traders reduce their holdings.

Besides this analysis of the trading activity, we also examine the number of assets (net position) held by traders at the end of each trading period.[24] We estimate the model in (4) below, including the volatility regime and risk aversion as explanatory variables, using random effects,[25] adjusting for heteroscedasticity and cross-sectional correlation.

$$NP_{i,t} = \alpha_i + \beta_1 SGG_{i,t} + \beta_2(DHV_{i,t} * SGG_{i,t}) + \beta_3 HV0_{i,t} + \varepsilon_{i,t} \tag{4}$$

where $NP_{i,t}$ represents the net position of each trader i at period t; $SGG_{i,t}$ refers to the risk aversion level of the subject i; $DHV_{i,t}$ takes the value of 1 for high-volatility periods and 0 otherwise; $HV0_{i,t}$ is a dummy variable that takes the value of 1 when the session starts with a high-volatility state and 0 otherwise; and α is the intercept of the model.

The results in Table 8 suggest that the risk aversion level significantly correlates with the trading behavior in terms of net position. We observe a significant value of the β_1 parameter that is close to 3, which means that an increase of 1 point in the SGG score (a higher SGG score implies lower risk aversion) implies an increase in the net position held of 3 stocks. It is not surprising that net buyers are those who have a higher risk tolerance. However, this asset accumulation effect is marginally reduced when the volatility is high. The negative and significant value of the β_2 parameter of −1.68 implies that during high-volatility regimes, there is a reduction in the level of stock held in the portfolio, and this reduction is related to the level of risk aversion of the trader.

Giving an interpretation of the magnitude of this parameter is complex since it reflects the combined effect of high volatility and risk aversion on the net position. This evidence suggests that, during high-volatility periods, the total holding of stocks is reduced, pointing to a different type of behavior of the traders under higher uncertainty. The previous evidence in *result 2* shows that subjects who hold stocks in the market tend to be less risk-averse than sellers of stocks. Thus, we could be tempted to argue that during high-volatility periods, more risk-averse investors sell their holdings or directly do not enter the market. We provide further evidence concerning this last statement in the next result.

Results for Hypothesis 3: At the individual level, less risk-averse subjects are more likely to participate in the asset market when the volatility is high.

Support for Hypothesis 3: We construct a dummy variable that takes the value of 1 every time the subject acts as a trader in the experiment. We then estimate the model[26] in (5) below using this dummy variable as the dependent variable and the individual risk aversion level as explanatory variable. In this model, we estimate the coefficients using panel data, considering only the periods in

[24] The net position in each period was calculated as 10 units (initial endowment) plus any purchases minus any sales made in the same period.

[25] The equivalent model estimated using fixed-effects showed identification problems. Additionally, a battery of similar models with different control variables was estimated but, for the sake of brevity, was not included in the paper. The main conclusions hold for all of these models. The results are available upon request.

[26] We estimate a random-effect probit regression with clustered standard errors.

Table 9
Probability of becoming a trader depending on the volatility regime and risk aversion.

Model 2								
$Pr(Trader)_{i,t} = \alpha_i + \beta_1 SGG_{i,t} + \beta_2 HV0_{i,t} + \beta_3 DT_6 + \beta_4 DT_{11} + \beta_5 DT_{16} + \varepsilon_{i,t}$								
		α	β_1	β_2	β_3	β_4	β_5	
Model 2	Coeff.	0.918***	0.319***	0.088	−0.252	0.227	0.397***	
	(p-value)	*(0.000)*	*(0.001)*	*(0.630)*	*(0.144)*	*(0.161)*	*(0.027)*	
Number of observations		720	Cluster	20	Wald statistic *(p-value)*		25.210*** *(0.006)*	
Model 2.1								
$Pr(Trader)_{i,t} = \alpha_i + \beta_1(DLV_{i,t} \cdot SGG_{i,t}) + \beta_2(DHV_{i,t} \cdot SGG_{i,t}) + \beta_3 HV0_{i,t} + \beta_4 DT_6 + \beta_5 DT_{11} + \beta_6 DT_{16} + \varepsilon_{i,t}$								
		α	β_1	β_2	β_3	β_4	β_5	β_6
Model 2.1	Coeff.	0.942***	0.143	0.507***	0.095	−0.287*	0.234	0.362***
	(p-value)	*(0.000)*	*(0.290)*	*(0.002)*	*(0.603)*	*(0.089)*	*(0.165)*	*(0.038)*
Number of observations		720	Cluster	20	Wald statistic *(p-value)*		25.340*** *(0.000)*	

This table displays the estimates of models 2 and model 2.1 for the data of the experiment (periods 1, 6, 11 and 16). We use a random-effect probit regression to estimate the coefficients with standard errors adjusted for 20 clusters in MarketID. We use a total of 720 observations in 180 groups, and the ML function is optimized for a total of 12 integration points using the integration of the Gauss–Hermite Quadrature. We reject the Wald test for no joint significance of the parameters at the 1% level. ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively, and standard errors can be found in parentheses. *DHV* takes the value of 1 for high-volatility periods and 0 otherwise. *SGG* is the risk aversion of the subjects: the higher SGG the lower the risk aversion. *HV0* is a dummy variable that takes the value of 1 when the session starts with a high-volatility state and 0 otherwise and α is the constant of the model. The *DT6*, *DT11* and *DT16* variables are dummy variables that take the value of 1 if the observation refers to period 6, 11 and 16, respectively, and 0 otherwise.

which there is a regime shift in volatility. The purpose of this model is to eliminate potential noise generated by the data collected between these changes since the chosen role remains fixed every five periods. We further control the estimates for situations in which changes in the probability of being a trader are more relevant during a specific period of a volatility shift. Therefore, we introduce the dummy variables DT_6, which takes the value of 1 for period 6 and 0 otherwise, DT_{11}, which takes the value of 1 for period 11 and 0 otherwise, and DT_{16}, which takes the value of 1 for period 16 and 0 otherwise.

$$Pr(Trader)_{i,t} = \alpha_i + \beta_1 SGG_{i,t} + \beta_2 HV0_{i,t} + \beta_3 DT_6 + \beta_4 DT_{11} + \beta_5 DT_{11} + \varepsilon_{i,t} \tag{5}$$

where $Pr(Trader)_{i,t}$ represents the probability of subject i acting as a trader in period t; $SGG_{i,t}$ refers to the risk aversion level of the subject i; $HV0_{i,t}$ is a dummy variable that takes the value of 1 when the session starts with a high-volatility state and 0 otherwise; and α_i is the intercept of the model.

In order to determine if the probability of becoming a trader is different depending on the volatility regime, we also estimate the model in (6) below. We introduce the dummy variables $DLV_{i,t}$ which takes the value of 1 for low-volatility periods and 0 otherwise and $DHV_{i,t}$ which takes the value of 1 for high-volatility periods and 0 otherwise.

$$\begin{aligned} Pr(Trader)_{i,t} \ = \ & \alpha_i + \beta_1(DLV_{i,t} SGG_{i,t}) + \beta_2(DHV_{i,t} SGG_{i,t}) \\ & + \beta_3 HV0_{i,t} + \beta_4 DT_6 + \beta_5 DT_{11} + \beta_6 DT_{11} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

where all the other variables are defined as above.

Table 9 displays the results for the previous models. According to the estimates of the model in (5), a lower risk aversion (β_1) significantly increases the probability of choosing to be a trader. The value of the β_1 parameter is positive and significant, showing that subjects with a higher SGG score (less risk aversion) are more likely to become traders. The probability of becoming a trader decreases in period *6* and increases in periods *11* and *16*. We believe that this unexpected result in *DT6* may be explained by a "curiosity effect" since a participant who acts as a trader during the first 5 periods may want to try both possibilities.

The results of the model in (6) show that the relationship between risk aversion and an increase in the probability of becoming a trader is not linear. Only during high volatility periods (β_2) we can observe a significant result but we fail to find any evidence for this relationship in low volatility periods (β_1). The conclusions for the other variables of the model barely change regarding the model in (5).

These results suggest that individuals with lower levels of risk aversion choose the market much more often, particularly when there is high volatility. Since the subjects know the expected payoffs at any point in time, this entry of subjects is not due to individual changes in future expected returns. Instead, it is due to the different levels of risk aversion of the subjects. At the market level, this effect of risk aversion on individual subjects translates into differences in the aggregated market risk aversion, as shown in *result 2*. The interpretation that we give to this finding is that, during high-volatility periods, risk-averse investors do not enter the market (act as *accountants*) and only less risk-averse investors trade in the risky asset. When we aggregate the risk profile of these less risk-averse subjects, we find the aforementioned lower aggregated risk aversion during high-volatility periods.

This finding represents a plausible explanation for the empirical results found by Ghysels et al. (2014) and Salvador et al. (2014), among others. The pro-cyclical market risk aversion found in their studies can be explained by this individual behavior of the more risk-averse traders who do not participate in the market during periods of higher uncertainty. During these high-volatility periods, only traders who tolerate such levels of risk are operating. This result is also in line with the observations of the literature on the Flight-to-Safety/Quality (Baele et al., 2018) occurring mainly during high volatility periods. A defining feature of flight-to-safety is insufficient risk-taking by investors, which we corroborate in terms of participation.

The risk-return trade-off observed during high-volatility periods also shows different patterns from that identified during low-volatility periods. According to our results, the reason for these differential patterns emerges from the fact that the aggregated market behavior is generated by subjects with different types of behavior. However, the relationship between risk aversion and the probability of becoming a trader is not linear, which shows the difficulties in identifying the fundamental linear risk-return trade-off proposed by classical finance theory even in our simplified experimental setting. Relaxing the strong linear assumption between return and risk and the constant aggregated risk aversion proposed in some asset pricing models represents an interesting opportunity to develop new models that can accommodate financial theory with empirical evidence. Our results also highlight that taking into account the participation effect seems relevant to understand the variations in the aggregate market risk/aversion.

5. Conclusion

To the best of our knowledge, this paper is the first attempt to provide experimental evidence aimed at understanding the dynamics between aggregated risk aversion and volatility regimes. By conducting an experiment in which we exogenously control the volatility level of the fundamentals, we analyze the individual behavior of the investor and, at the aggregate level, the average risk aversion level in the market.

In the experiment, we estimate the individual risk aversion level for every subject both before and after the experimental asset market. In the main task, the subject can participate as a trader in a risky market or as an accountant in an alternative task. We design the experiment to test several hypotheses regarding (i) the evolution of the number of traders in each volatility regime, (ii) the average risk aversion level of the market during each volatility state and (iii) the behavior of the individual agents during periods of calm and uncertainty (expressed as the net position in stock holdings or their probability of becoming an accountant).

Our results show significant differences in the subjects' behavior across regimes. The number of subjects acting as traders increases in low-volatility regimes, and the average market risk aversion increases during these low-volatility periods. Our evidence also shows that during low-volatility periods, more risk-averse investors enter the market (while mostly the less risk-averse agents were doing the trading in high-volatility periods), which leads to an increase in the average risk aversion level of the market. The individual risk aversion of the participants remains pretty stable across time (before and after the experimental market) which leads us to conclude that the changes in the aggregated market risk aversion are due to a participation effect. A possible future extension of our work could consist in a replication of the study using a battery of different risk-attitude elicitation methods to check for the robustness of our results.

CRediT authorship contribution statement

V. Aragó: Term, Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Funding Acquisition. **I. Barreda-Tarrazona:** Conceptualization, Methodology, Formal analysis, Software, Data curation, Writing Original, Writing – review & editing, Validation, Funding Acquisition. **A. Breaban:** Methodology, Software, Validation, Data curation, Writing – original draft, Writing – review & editing. **J.C. Matallín:** Data curation, Validation, Funding Acquisition, Writing – review & editing, Data curation. **E. Salvador:** Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Data curation.

Appendix A. General instructions

Welcome to this experiment. The instructions are simple, and if you follow them carefully, you can earn a considerable amount of money. Your final earnings will be communicated to you individually and will be paid to you in cash at the end of the experiment. Your personal details are confidential and will not be used for purposes other than this study. Your name will never be publicly associated with your decisions.

Communication with other participants is not allowed during the experiment, and breaking this rule will mean that you can no longer participate in the experiment.

The experiment consists of 3 parts:

1st: One lottery in which you will have to choose the preferred option.

2nd: An asset market or an arithmetic sum activity, depending on your own choice.

3rd: One lottery in which you will have to choose the preferred option.

Your final earnings will be the sum of the earnings that you can obtain in the second part of the experiment plus the earnings of one randomly chosen lottery (by casting a 4-sided die) out of the two lotteries in parts 1 and 3.

Instructions for part 2

This part of the experiment will consist of 20 periods of 2 min each.

In period 1, you have to decide whether you want to form part of an asset market or whether you prefer to make money by doing an arithmetic sums task. Nevertheless, you can change this decision every 5 periods. That is, at the beginning of period 1, period 6, period 11 and period 16, you can choose the task that you want to perform for the next 5 periods. In this manner, if in period 1 you decide to participate in the asset market, you will have to continue in the asset market for 5 periods until, in period 6, you will have the chance to choose again between the two options. At all times, you will not know the identity of the participants in your market or other markets. Your earnings for this part of the experiment will be the sum of all the earnings in each of the 20 periods, regardless of the number of times that you participated in the asset market or in the arithmetic sums task.

The currency used in the experiment is the Experimental Currency Unit (ECU), such that prices, earnings, dividends, etc., are all expressed in terms of ECUs. At the end of the experiment, the total amount of ECU that you accumulated will be converted into euros based on the following exchange rate: 100 ECUs = 1 euro. Remember that the more ECUs you gain, the more euros you will receive at the end of the experiment.

The asset market

At the beginning of each of the 20 periods, your initial portfolio will consist of 10 assets and 340 ECUs. All participants are endowed with the same initial portfolio. All assets in the market are identical and pay the same dividend.

The market will be open for two minutes each period. During these two minutes, you can buy and sell assets. At the end of each period, each asset that you hold in your inventory will yield a dividend that will be added to your earnings.

The dividends that the asset can potentially pay off will change every 5 periods. More precisely, in regime A, the possible dividends will be 17 ECUs or 0 ECUs, with a 50–50 chance, for each asset that you hold in your inventory. On the other hand, in regime B, the dividend will be either 25 ECUs or −2 ECUs, with a 50–50 chance. The experiment will start with regime B and will change every 5 periods.

At the end of each period, the computer will randomly select the dividend that the asset will pay: 17 ECUs or 0 ECUs for regime A and 25 ECUs or −2 ECUs for regime B. The exact dividend will be announced at the end of each period.

If you are trading in the asset market, you will only be able to switch to the arithmetic sum activity in the periods corresponding to a regime shift, that is, in periods 6, 11, and 16.

In each period, you can buy and sell as many assets as you wish provided that you have enough cash and assets to do so. Any offer to sell or offer to buy that is accepted in the market will translate into a transaction for one unit. The rest of the offers that you have made for the same price will then be eliminated automatically when you manage to trade one unit, and you will be able to post new offers in the market if you wish to do so.

Your earnings at the end of each period are equal to:

+ ECUs you receive for the assets that you sold

− ECUs paid for the assets that you bought

+ the dividend announced at the end of the period multiplied by the number of assets that you hold at the end of that period

Note that the initial cash endowment is not part of your earnings.

At the beginning of each period, you will have a new portfolio available with 10 assets and 340 ECUs, regardless of the purchases and sales you may have made in the previous period. Therefore, your total earnings in the asset market, in terms of ECUs, will be equal to the sum of your earnings in each of the periods. This information will be shown to you on your screen as accumulated earnings at the end of each period. You will also receive aggregated information about the mean earnings by the agents participating in the asset markets in each period and the mean earnings of the participants doing sums.

The arithmetic sum activity

The earnings in this part of the experiment will depend on the number of correct arithmetic sums that you are capable of doing in periods of two minutes each. These sums will consist of adding five two-digit numbers. For each correct answer, you will receive 5 ECUs.

You will only be able to switch to the asset market in the periods corresponding to a regime shift, that is, in periods 6, 11 and 16.

Therefore, your total earnings in this task, in terms of ECUs, will be equal to the number of correct sums that you did multiplied by 5 ECUs. This information will be shown to you on your screen as accumulated earnings at the end of each period. You will also receive aggregated information about the mean earnings by the participants performing sums in the session in each period and the mean earnings of the participants in the asset market.

If you have any questions or concerns, please ask the experimenter. Bear in mind that it is important that you fully understand how the interaction in the market occurs since your earnings will depend on your decisions and the decisions of the other participants in the same market.

The experimenter will now demonstrate how the asset market works. You will first learn how to buy and sell assets using the software interface.

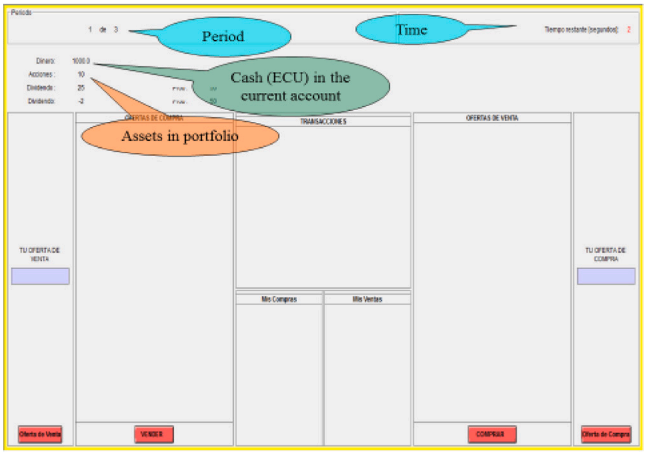

Fig. B.1. Interface of the stock market (user's position information).

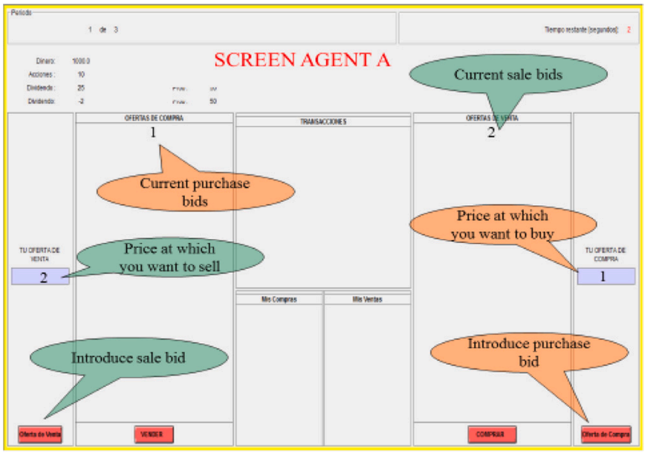

Fig. B.2. Interface of the stock market (introducing orders).

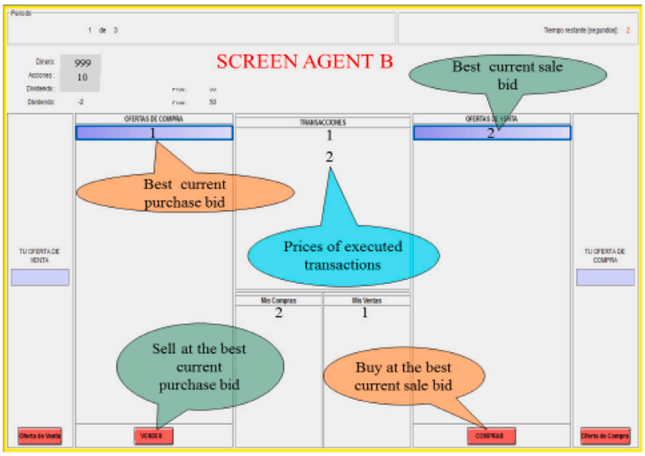

Fig. B.3. Interface of the stock market (trading information).

Appendix B. User's interface

This appendix shows three figures representing the interface used in the experiment.

The first figure displays the interface before the trading is initiated. The places where the participant can find information about her monetary balance in ECUs, the number of assets in her portfolio, the time remaining until the market is closed and the period of the experiment are highlighted. (See Fig. B.1.)

The second figure highlights the information related to the manner in which purchase or sale orders in the market are introduced. (See Fig. B.2.)

The last figure represents the user's interface once there is some trading activity in the market. It shows where the information related to the current orders and executed transactions is displayed. (See Fig. B.3.)

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