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## Financial contagion and the wealth effect: An experimental study

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**Financial Contagion and the Wealth Effect:  
An Experimental Study**

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# Financial Contagion and the Wealth Effect: An Experimental Study\*

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## Abstract

We design a laboratory experiment to test the importance of wealth as a channel for financial contagion across markets with unrelated fundamentals. Specifically, in a sequential global game, we analyze the decisions of a group of investors that hold assets in two markets. We consider two treatments that vary the level of diversification of these assets across markets, which allows us to disentangle the wealth effect from other sources of financial contagion. We provide evidence of contagion due to a wealth effect when investors have completely diversified portfolios. In this treatment, for certain ranges of fundamentals, we show that a coordination failure in the first market reduces investors' wealth, which makes them more likely to withdraw their investments in the second market, thereby increasing the probability of a crisis.

**Keywords:** Financial contagion, financial crises, wealth, coordination games, global games.

**JEL Classification:** C72; C92; D8; G01; G11.

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# 1 Introduction

How do crises spread across countries, markets or asset classes? Episodes of contagion – defined as the spillover of disturbances across markets – are a frequent phenomenon.<sup>1</sup> However, the main drivers underlying these episodes of contagion are hard to pin down empirically. Contagion can occur in situations in which fundamentals are related (through trade or the financial sector) or unrelated (through the actions of investors). In this paper, we focus on the latter, as distinguishing between the various forms of investor behavior that trigger non-fundamental contagion is empirically more difficult. It is generally hard to identify whether such market co-movements are due to social imitation, wealth or liquidity problems. Therefore, in order to understand the importance of different channels of financial contagion, a laboratory experiment is a useful methodology that allows us to control for the information that investors have, the interdependencies between fundamentals, and the observability of feedback.

In this paper, we present an experiment that tests the role of investor wealth as an explanation of why a financial crisis spreads across markets with unrelated fundamentals (Kyle & Xiong 2001, Goldstein & Pauzner 2004, Yuan 2005). Our experimental design is based on Goldstein & Pauzner (2004), who model contagion as a sequential coordination game with incomplete information, i.e., a global game. In the model, the same group of investors holds a perfectly diversified portfolio of assets across two different markets, and decide on whether to withdraw or roll-over their investment in each market sequentially. This coordination game has a unique threshold equilibrium: for fundamentals that are below a threshold it is optimal to withdraw, while above it, it is optimal to roll-over. They show that the realization of a crisis in one market increases the probability of a crisis in the other market, even if the fundamentals of the two markets are uncorrelated. The mechanism through which this happens is a wealth effect. Specifically, risk-averse investors are less willing to bear risks in a second market after experiencing losses in the first market. This makes them less likely to coordinate on the high risk/high return outcome in the second market, which makes contagion more likely.

The experiment parametrizes the Goldstein & Pauzner (2004) model in two treatments that differ in the diversification of assets across the two markets. In a between-subjects design, participants are endowed with an initial wealth that is allocated across two markets. In the complete diversification treatment, wealth is invested evenly in both markets, while in the small diversification treatment, investors have 5% of their wealth invested in the first market and 95% in the second market. As the change in total wealth after the decision in the first market is much larger in the first treatment, we expect wealth effects to be important when portfolios are completely diversified and less so in

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<sup>1</sup>Well-known examples include the 1994 Mexican crisis that led investors to flee emerging markets in Asia and Latin America, the Thai currency crises of 1997 that spread to East Asia, Russia and Brazil. More recently, the 2008 Global Financial Crisis originated in the US and rapidly spread across emerging and advanced economies, as well as across different economic sectors, while the 2012 Sovereign debt crisis in Europe led to a spillover of sovereign yields spreads across a large number of advanced and emerging economies.

the small diversification treatment.

In each market, an investor can withdraw and obtain a safe payoff, or roll-over and obtain a risky payoff, which depends on the state of the economy and the behavior of others. Investors have asymmetric information about the underlying state of the economy and receive a precise noisy signal. The same group of five investors plays the simultaneous coordination game in each market sequentially. Each investor first takes a decision about his investment in market one, receives feedback about the outcome in this market, then he decide on the investment in market two. Subjects play for twenty rounds with random matching between rounds.

Our experimental framework best describes debt rollover crises, where two countries raise external debt from a common pool of creditors. This type of short-term financing is subject to re-financing risk that has its roots in the coordination problem faced by creditors when they make their rollover decisions. Debt roll-over crises such as these are a common phenomenon, in particular, among emerging markets which tend to finance themselves in the short-term (Broner et al. 2013). Understanding the role of investor wealth and portfolio diversification during such crises is therefore central to the design of policies aimed at limiting the spread of contagion.

We derive several testable hypotheses from the model's theoretical predictions and our parametrization. The first relates to the presence of contagion across the two markets. The main theoretical prediction is that contagion occurs for certain intermediate values of the state of the economy or fundamentals in the second market, where the decision to withdraw or roll-over is sensitive to the behavior in the first market. The second hypothesis is that changes in wealth drive this financial contagion across markets.

Our findings provide support for these hypotheses. We first show that, in both treatments and markets, the majority of subjects withdraw below a critical value of the fundamentals and roll-over above it. Their behavior is thus consistent with threshold strategies, in line with the experimental global games literature (Heinemann et al. 2004, 2009, Shurchkov 2013). In addition, our data shows that both treatments have a large proportion of withdrawals and runs (situations where all investors in a given market withdraw) in both markets. Furthermore, the actual change in total wealth after the decision in the first market is much larger in the complete diversification treatment compared to the small diversification treatment.

To uncover evidence of financial contagion, we test whether the decision to withdraw in the first market affects the investment decision in the second market. We find evidence of contagion for high levels of fundamentals in both treatments. However, we do not find that there are statistically significant differences between treatments.

We then examine whether this observed contagion is due to a wealth effect. We find that the changes in market one wealth have a statistically significant impact on the probability of withdrawing in market two in the complete diversification treatment for values of fundamentals above the theoretical threshold. However, in the small diversification treatment, this wealth effect is not sta-

tistically significant. Hence, we attribute financial contagion in the small diversification treatment to social imitation, i.e. that the previous decision of other investors influences an investor's subsequent decisions even if the fundamentals are unrelated. In the complete diversification treatment the main driver of financial contagion is a wealth effect even though there is possibly some degree of social imitation.

Moreover, we explore the determinants of the wealth effect in the complete diversification treatment. We find that the wealth effect depends non-linearly on the level of fundamentals. It is strongest for higher levels of fundamentals, where lower wealth or experiencing a loss in market one leads to a significant increase in the propensity to withdraw in market two. We can link this to the participant's level of risk aversion. Our finding that the wealth effect works for losses and not for gains is novel and not predicted by the extant theoretical literature. Thus, our results highlight the role of the wealth effect as a driver of financial contagion in situations where a common group of investors holds perfectly diversified portfolios across two markets.

There is a small but growing experimental literature on contagion. One type of experiments is related to fundamentals-based contagion in bank-run settings using a modified Diamond & Dybvig (1983) framework. Chakravarty et al. (2014) find that contagion can occur due to panics even when fundamentals are independent, while Brown et al. (2016) observe contagion of withdrawals across banks only when there are economic linkages between banks. In a one-bank setting, Kiss et al. (2018) find that panic-based runs can occur even in the absence of problems with fundamentals or problems with coordination failure among depositors. These can be attributed to unreasonable depositors' beliefs - depositors overestimate the likelihood that a bank run is occurring, and to depositors' loss-aversion. Finally, in a bank network experiment, Duffy et al. (2017) find evidence of contagion in bank networks where banks place cross-deposits with other banks. In contrast to this literature, we examine financial contagion in a setting where investors hold asset portfolios in markets with unrelated fundamentals. We find that the main reason for financial contagion is a wealth effect when investors have perfectly diversified portfolios, but we also observe some contagion due to social imitation when portfolios have a small degree of diversification.

A second type of experiment looks at contagion due to cross-market portfolio rebalancing. Cipriani et al. (2013) test the informational linkages channel modeled by Kodres & Pritsker (2002) in which a shock in one market transmits itself to others, as investors adjust their portfolio allocations. Contagion due to portfolio re-balancing occurs because subjects' payoffs depend not only on the return to their investment, but also on the composition of their portfolios. Cipriani et al. (2017) investigate experimental asset markets where financial contagion occurs when asset returns in two markets are correlated, but no contagion effect is present in markets with independent fundamentals. These models, however, describe a different nature of "crises", in which contagion is reflected in asset prices. Our setting best describes crises in which coordination plays a key role such as debt or currency crises.

Closer to our setting is Treviño (2019) who studies contagion in a global games framework and shows how contagion is driven by fundamentals and social learning channels. She finds that subjects in the experiment do not update information optimally: a base rate neglect bias makes agents underweight priors and weakens the fundamental channel, while an overreaction bias strengthens the social learning channel and makes subjects take into account the behavior of agents in the other country even when it is completely uninformative. Another related paper is Shurchkov (2013) who studies coordination and learning in a dynamic global game. She finds that beliefs about others' actions are crucial for understanding how the arrival of new information affects the attacking behavior of speculators. The experiment we propose shares the global games mechanism of these works, but focuses on a wealth channel that is absent from previous literature.

The remainder of the paper is organized as follows. Section 2 discusses the theoretical framework. Section 3 describes the experimental design and hypotheses. Section 4 presents our results and Section 5 concludes.

## 2 Financial contagion as a global game

Financial contagion across markets can be modeled as a global game - a coordination game of incomplete information where players receive private signals (Carlsson & Van Damme 1993, Morris & Shin 1998, 2004, Goldstein & Pauzner 2005). We base our experiment on the work of Goldstein & Pauzner (2004) (hereafter, GP) who focus on two countries that have independent fundamentals but share the same group of investors.<sup>2</sup> In the theoretical model, financial crises are self-fulfilling: investors withdraw their investment in a market because they believe others will also do so. Contagion from one market to another occurs because of a wealth effect: a crisis in the first market reduces investors' wealth, which makes them more risk averse, and therefore less likely to sustain their investments in the second market. This increases the probability of a crises in the second market.

GP consider a model with a continuum of risk-averse investors each holding a unit of wealth in a perfectly diversified portfolio of assets in two different markets, indexed by  $i = 1, 2$ , with independent fundamentals (denoted by  $\theta_i, i = 1, 2$ ). Investors have decreasing absolute risk aversion (DARA) utility functions, and choose between two actions in a sequential game: to withdraw or roll-over their investment in each market. First, given the private signal about market 1's fundamentals, each player decides whether to liquidate or roll-over his investment in market 1. If an investor decides to roll-over his investment in either market, then his payoff is  $R(\cdot)$ , which is increasing in fundamentals and decreasing in the number of investors who decide to withdraw, denoted by  $n_i$ , i.e.  $R(\theta_i, n_i)$ . If an investor withdraws in either market, he gets back his initial investment in that market. This implies investors' actions are strategic complements, as more investors withdrawing

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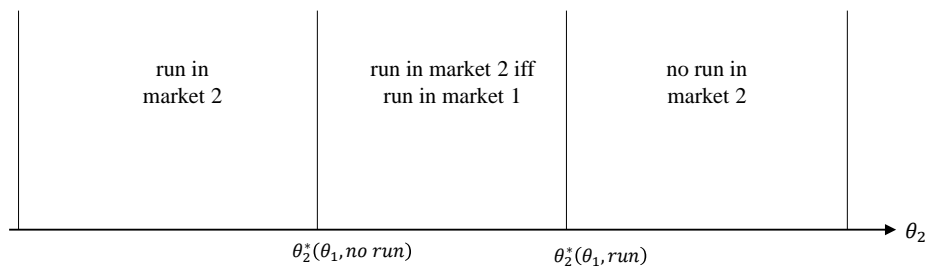
<sup>2</sup>While GP discuss contagion across countries, we frame our experiment in terms of markets rather than countries.

decreases the payoff of those rolling-over and, as such, increases the attractiveness of liquidating one's investment. Second, once the outcome of the coordination game in market 1 is realized and becomes known to all agents, an equivalent coordination game is played in market 2.

The fundamentals in each market are independent and drawn from a uniform distribution over  $[0,1]$ . In the spirit of a global games equilibrium selection refinement, fundamentals are not observable and player  $j$  receives a noisy signal about the fundamentals in each market:  $\theta_i^j = \theta_i + \epsilon_i^j$ ; where the  $\epsilon_i$  are independent and uniformly distributed over  $[-\epsilon, \epsilon]$ .

Solving the game backwards and using a global game framework, GP show that there exists a threshold equilibrium in each market, where players withdraw when they observe signals below a threshold signal, and roll-over when signals are above a threshold. Since the game is sequential, the threshold of market 2 depends on the outcome in market 1, i.e. on whether a run occurred or not in market 1 (a run is a situation where all investors in a given market withdraw). This generates a ‘‘contagion’’ effect in markets with unrelated fundamentals. GP show that if the group of investors is wealthier (in distribution) after the investment in market 1, then crises in market 2 become less likely. The intuition is that an increase in wealth, as a result of the investment in market 1, makes investors more willing to bear risks in market 2 and more likely to choose the risky payoff, which is to roll-over the investment. This is the result of investors' diversified portfolios and their decreasing absolute risk aversion. Figure 1 exemplifies this contagion effect, by showing that the threshold in market 2 corresponding to when a run occurred in market 1,  $\theta_2^*(\theta_1, run)$ , is higher than the corresponding threshold when a run did not occur in market 1,  $\theta_2^*(\theta_1, no\ run)$ . The region where we expect contagion to occur is the intermediate region where there is a run in market 2 if and only if there has been a run in market 1.

Figure 1: Contagion of crises: the optimal decision in market 2



In the main analysis, GP assume investors have fully diversified portfolios and invest a unit of wealth in each of the two markets. They also explore how other levels of diversification affect the probability of runs and show that these are non-monotone. They suggest that the effects of diversification on the probability of runs depend on various factors such as proportion of wealth invested in each market, number of investors, and risk preferences.



In our experiment, we consider a simplified version of this game with a finite number of investors,  $N$ , who choose sequentially in markets 1 and 2 whether to withdraw or roll-over their investment. As such, in order to calculate the thresholds which determine whether an investor will withdraw or roll-over, we use a binomial distribution as in Heinemann et al. (2004). In addition, we assume that  $\theta_i$  are independent and uniformly distributed over  $[\underline{\theta}, \bar{\theta}]$ . Finally, in order to avoid any framing with the actions of withdrawing and rolling over, in the experiment, we ask subjects to choose between actions A and B, respectively. Action A has a safe payoff, while action B is a risky action since the payoff of action B depends on the fundamentals in the corresponding market and the number of investors that chose action A. In Appendix I, we detail how we compute the theoretical thresholds.

### 3 Experimental design and hypotheses

In this section, we describe the experimental design, parametrization and hypotheses.

#### 3.1 Experimental design

The experiment consists of two treatments using a between-subject design. We run six sessions with 20 participants in each treatment. Each session consists of two parts. In the first part, subjects play a coordination game for several rounds. Subjects are divided into groups of 5 (i.e.  $N = 5$ ).<sup>3</sup> In each round, the same group of participants are investors in the two markets: market 1 and market 2. There are 20 independent rounds, and in each round, participants in a given group change randomly from round to round.

In each round, each participant is initially endowed with 200 experimental currency points (EC) which are invested differently across two markets in each treatment. We consider two different treatments as follows. In the complete diversification treatment, hereafter CD, investors have 50% of their wealth in each market. In the small diversification treatment, hereafter SD, investors have 5% of their wealth in market 1 and 95% percent in market 2. The rationale for the two treatments is to compare two scenarios where the change in total wealth after investors' decision in market 1 is different: the potential change in total wealth after the decision in the first market in the CD treatment is much larger than in the SD treatment. Therefore, we expect wealth effects to be important in the CD treatment and less so in the SD treatment.

In each round there are two stages. In the first stage, each participant observes a private signal about market 1, takes a decision regarding market 1's investment, and receives feedback. In the second stage, each participant receives a private signal about market 2, takes a decision regarding market 2's investment and receives feedback. Then, a new round starts. Each round is independent from subsequent rounds.

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<sup>3</sup>Similar group sizes are employed in various experiments of coordination games, see, among others, Schotter & Yorulmazer (2009), Garratt & Keister (2009), Kiss et al. (2012), Peia & Vranceanu (2019).

The decision that each participant takes in each round and each market, and the corresponding payoffs are:

- Action A: The investor gets back the initial investment in the corresponding market.
- Action B: The investor receives the payoff  $R(\theta_i, n_i) = \frac{3\theta_i}{1+2n_i}$ , where  $\theta_i$  is the fundamentals in market  $i$ , and  $n_i$  is the number of investors in this market that choose to action A.

Thus, Action A is the safe action, but yields a zero return. Action B is risky due to two factors. The first is fundamental risk: a lower value of fundamentals implies lower returns. The second is strategic risk: the behavior of others since as more investors withdraw returns are lower.

In both treatments we choose the distribution of fundamentals and signals that allows us to numerically estimate the threshold equilibria in the GP model (we detail the steps of the numerical simulations in Appendix I). In the CD treatment, fundamentals in market  $i$ ,  $\theta_i$ , follow a uniform distribution in the interval  $[10, 150]$ , and fundamentals in each market are drawn independently from each other. Participants do not observe fundamentals before making their decisions, but each receives a private signal which is randomly selected from a uniform distribution in the interval  $[\theta_i - 10, \theta_i + 10]$ . Note that, as in GP, we have choose the signal precision in both treatments to be high in relation to the fundamentals in order to minimize the uncertainty level about fundamentals in a given market. This allows us to focus on the strategic risk. An example of a payoff table shown to participants is presented in Table 1.

In the SD treatment, the fundamentals in market 1,  $\theta_1$ , follow a uniform distribution over the interval  $[1, 10]$ , and private signals in market 1 are randomly selected from a uniform distribution in the interval  $[\theta_1 - 1, \theta_1 + 1]$  with 1 decimal. In market 2, fundamentals,  $\theta_2$ , follow a uniform distribution in the interval  $[20, 330]$ , and the private signals of market 2 are randomly chosen from a uniform distribution in the interval  $[\theta_2 - 20, \theta_2 + 20]$ .<sup>4</sup> Fundamentals in market 1 and 2 are drawn independently from each other. The independence of fundamentals across the two markets is carefully explained in the instructions to the participants such that this feature of the experiment is salient.<sup>5</sup>

In the second part of each experimental session, participants is asked to answer various individual incentivized tasks to elicit risk and loss aversion attitudes. As the wealth effect characterized in GP is the direct consequence of decreasing absolute risk aversion (DARA) preferences, it is important to assess the risk preferences of our subject pool. The risk aversion test is based on Eckel & Grossman (2008) and Dave et al. (2010). It consists of a choice between six lotteries each with a 50% probability of a low outcome and a 50% probability of a high outcome. The choice of a particular lottery corresponds to a range of relative risk aversion parameters.

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<sup>4</sup>The precision of signals in the SD treatment is chosen to match the relation between the signal precision to fundamentals in the CD treatment.

<sup>5</sup>The distribution of fundamentals was chosen with the goal of matching the theoretical probability of a run in the second market across the two treatments.

Table 1: Example of payoff table in complete diversification treatment

| Hypothetical number of other investors that choose A | Payoff if you choose A | Payoff if you choose B |             |             |             |              |              |              |
|--|------------------------|------------------------|-------------|-------------|-------------|--------------|--------------|--------------|
|  |                        | $\theta=0$             | $\theta=25$ | $\theta=50$ | $\theta=75$ | $\theta=100$ | $\theta=125$ | $\theta=150$ |
| 0  | 100                    | 0                      | 75          | 150         | 225         | 300          | 375          | 450          |
| 1  | 100                    | 0                      | 25          | 50          | 75          | 100          | 125          | 150          |
| 2  | 100                    | 0                      | 15          | 30          | 45          | 60           | 75           | 90           |
| 3  | 100                    | 0                      | 11          | 21          | 32          | 43           | 54           | 64           |
| 4  | 100                    | 0                      | 8           | 17          | 25          | 33           | 42           | 50           |

Furthermore, as our experiment entails the possibility of losses, we also conduct a loss aversion questionnaire adapted on the test in Gächter et al. (2007). The loss aversion tests asks subjects to choose how many lotteries they are willing to accept from a sample of six coin tosses where tails implies a fixed win, while heads an increasingly larger loss. The fewer the number of lotteries accepted, the larger the implied degree of loss aversion of the participant.<sup>6</sup>

Once the two main parts of the experiment are completed, participants also answer some additional questions regarding personal information.

With regards to incentives for the coordination game, we randomly choose one round of the 20 rounds, and participants are paid the earnings from this round according to the following formula: 100 EC are equivalent to 3 Euros. The Euros for this part are not shown to participants until the risk and loss aversion tasks and questionnaires are completed. With regards to incentives related to the risk and loss aversion parts, both tests are framed in experimental points to be gained/lost. We convert each 20 points to 1 Euro. Appendix II shows the instructions of all the parts of the experiment and Appendix III illustrates the screenshots of the coordination game.

Finally, participants were paid in private the total obtained during the first and second parts of the experiment. On average, participants received 18 Euros and sessions lasted 60 minutes.

The experiment had 240 participants, who were students of economics, business, finance and other related areas from Universitat Pompeu Fabra and ESADE Business School, both in Barcelona (Spain) using z-Tree (Fischbacher 2007).

### 3.2 Hypotheses

Given the parametrization described in the previous subsection, we derive the theoretical predictions of GP’s model of contagion. The first hypothesis concerns the relationship between a subject’s decision to withdraw and the realization of signals.

**Hypothesis 1** [Threshold strategies]: Subjects use threshold strategies, withdrawing their investment when the signal is below a threshold, and rolling-over when the signal is above it with at most

<sup>6</sup>As this test implies that subjects can incur losses, we parametrize the lotteries so that the maximum loss in the loss aversion test is equal to the minimum gain in the risk aversion questionnaire. This avoids participants ending up with overall losses from the experiment and receiving less than the participation fee.

one switching point.

We then derive the specific numerical thresholds corresponding to threshold strategies, above which it is optimal to roll-over and below which it is optimal to withdraw. These are presented in Table 2. The distributions of fundamentals and signals were chosen so that the probability of a run was similar across the two treatments. Thus, if subjects chose threshold strategies and withdrew below a certain threshold, then the probability of a run is the probability that the signal received is below the theoretical threshold. Given uniform distributions and the computed theoretical thresholds, these probabilities are displayed in the last column of Table 2. Notice that the threshold equilibrium values are around the third quartile of values of the fundamentals in both treatments, hence we expect a large proportion of withdrawals.

Table 2: Numerical predictions for each treatment

| Market                         | Complete diversification |                    | Small diversification |                    |
|--------------------------------|--------------------------|--------------------|-----------------------|--------------------|
|                                | Threshold                | Probability of run | Threshold             | Probability of run |
| Market 1                       | 106                      | 75%                | 6.15                  | 68%                |
| Market 2 if run in Market 1    | 111                      | 79%                | 246                   | 79%                |
| Market 2 if no run in Market 1 | 99                       | 71%                | 241                   | 78%                |

While we analyze the general properties of the behavior in market 1, we aim to find differences between treatments in behavior of the second market. Table 2 shows that in the CD treatment, if there has been a run in market 1, the threshold value for the fundamentals in market 2 is equal to 111, while if there is no run in market 1, the threshold value for the fundamentals in market 2 is equal to 99. This means that we expect contagion due to a wealth effect since a run in market 1 increases the probability of a run in market 2. In fact, the difference in the probability of a run in market 2 depending on whether there has been a run in market 1 or not is equal to 8%.

In the SD treatment, we expect the outcome of market 1 to have a much smaller effect on market 2, since potential changes in wealth are very small. If there has been a run in market 1, the threshold value for the fundamentals in market 2 is equal to 246, while if there is no run in market 1, the threshold value for the fundamentals in market 2 is equal to 241. In fact, the difference in the probability of a run in market 2 depending on whether there has been a run in market 1 or not is close to 1%.

From these theoretical predictions, changes in wealth, together with investors' risk aversion is the only mechanism that can explain the correlation in the propensity to withdraw across the two markets. Recall that fundamentals in the two markets are uncorrelated in both treatments. However, empirically we can observe that contagion across the two markets is a result of social imitation, i.e., that the investors' behavior in the first market can affect investors' behavior in the second market. Hence, empirically we could observe contagion in both treatments. We can thus

formulate a second hypothesis regarding how the behavior in the first market affects that in the second.

**Hypothesis 2** [Contagion]. A higher proportion of withdrawals in the first market increases the proportion of withdrawals in the second market in markets with unrelated fundamentals.

Notice that we have formulated Hypothesis 2 in terms of withdrawals rather than runs. GP focus on runs, which require the full coordination of all the investors in a market. Given the usual experimental heterogeneity, we formulate the hypothesis in terms of withdrawals.

Contagion due to social imitation can be present in both treatments, however in the SD treatment, the change of overall wealth as a result of the investment in the market 1 is very small. Hence, we do not expect that this will play an important role in driving contagion in the SD treatment. As such, wealth effects will matter mainly in the CD treatment.

**Hypothesis 3** [The wealth effect]. The source of contagion in the second market is due to a change in participants' wealth in the first market. This contagion due to a wealth effect is mainly present in the CD treatment.

This is the main hypothesis of the paper.

## 4 Results

We start by presenting some simple statistics on the general features of the experimental data. We then briefly describe subjects' decisions in market 1. Next, we analyze participants' behavior in market 2. This focuses on understanding whether contagion exists, on the role of the wealth channel in explaining contagion, and on the importance of risk and loss aversion in driving our results. Finally, we discuss our results in the light of the channels that may be driving contagion in both markets.

### 4.1 General features of the experimental data

First, we check whether subjects behave in accordance with threshold strategies. Note that the signals about fundamentals received by participants were randomly drawn in each round and hence they were presented unordered.

Analyzing the data at the individual level across both treatments and markets, we find that, on average, 66% of subjects use monotone strategies and switch only once between the two possible actions (withdraw and roll-over) after the first five rounds.<sup>7</sup> This observed behavior is in accordance

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<sup>7</sup>Subjects that had chosen the same action for all signals were classified as using threshold strategies.

with the existing results in global games experiments (Heinemann et al. 2004, Shurchkov 2013, Szkup & Treviño 2017). This evidence provides support for Hypothesis 1.

**Result 1** [Threshold Strategies]: The majority of subjects employ threshold strategies after the first five rounds.

Next, table 3 presents some descriptive statistics on the average proportion of withdrawals and runs across our two treatments.

Table 3: Proportion of withdrawals and runs

|                             | Complete diversification | Small diversification |
|-----------------------------|--------------------------|-----------------------|
| Withdrawals in both markets | 63%                      | 71%                   |
| Runs in both markets        | 44%                      | 48%                   |
| Market 1 withdrawals        | 65%                      | 76%                   |
| Market 1 runs               | 45%                      | 52%                   |
| Market 2 withdrawals        | 62%                      | 68%                   |
| Market 2 runs               | 42%                      | 45%                   |

Table shows the proportion of withdrawals and runs in each treatment and market. There are 2400 observations in each treatment.

Overall, we observe that the average proportion of withdrawals is quite high and close to the levels suggested by the theoretical thresholds. The average probability of runs is slightly lower than the theoretical levels presented in Table 2, suggesting that we have more cases in which there are “partial runs”, i.e., not all of the five group members withdraw.

Finally, we present some statistics on the risk and loss preferences of participants collected in the second part of the experiment. The mechanism that explains the wealth effect in GP is a property of investors’ risk aversion. Even though GP do not analyze the effect of loss aversion on financial contagion, there is some experimental evidence that it matters (see, for example, Kiss et al. 2018).

Table 4 shows the distribution of participants along the two measures of risk and loss aversion assessed using the Dave et al. (2010) risk aversion test and Gächter et al. (2007) loss aversion questionnaire, respectively. Panel A shows the percentages of subjects accepting each lottery in the Dave et al. (2010) questionnaire eliciting risk preferences. The risk preference classification based on the lottery chosen is shown in the last column of Table 4. We find that 64% of participants chose gambles corresponding to risk aversion preferences. This is comparable to the proportion of risk averse participants (77%) in the original Dave et al. (2010) experiments. In our case, we observe a slightly higher number of subjects accepting the last lottery, which corresponds to a risk loving behavior (21% versus 11% in Dave et al.’s (2010) sample). This is most likely to be the result of the lower payoffs in our version of the questionnaire, which is in line with the experimental

literature on incentive and risk aversion (see Holt & Laury 2002). For our subsequent analysis, we construct a variable that captures risk attitudes as a scalar corresponding to the lottery chosen by the participant. The risk tolerance variable takes integer values from 1 to 6 with 1 being highly risk averse and 6 risk loving.

Similarly, in Panel B of Table 4, we report the implied degree of loss aversion across our sample of participants. Similar to Gächter et al. (2007), we find that around 64% of participants display moderate degrees of loss aversion, accepting from two to four of the gambles (compared to 60% in Gächter et al. (2007)). For the analysis which follows, we define a variable that captures the implied degree of loss aversion that makes an individual indifferent to the gains and losses in the lotteries chosen. The values of the loss aversion variable are displayed in the last column of Table 4, panel B (we cap the first and last value at 0 and 4, respectively).

Table 4: Distribution of subjects' preferences: risk and loss aversion

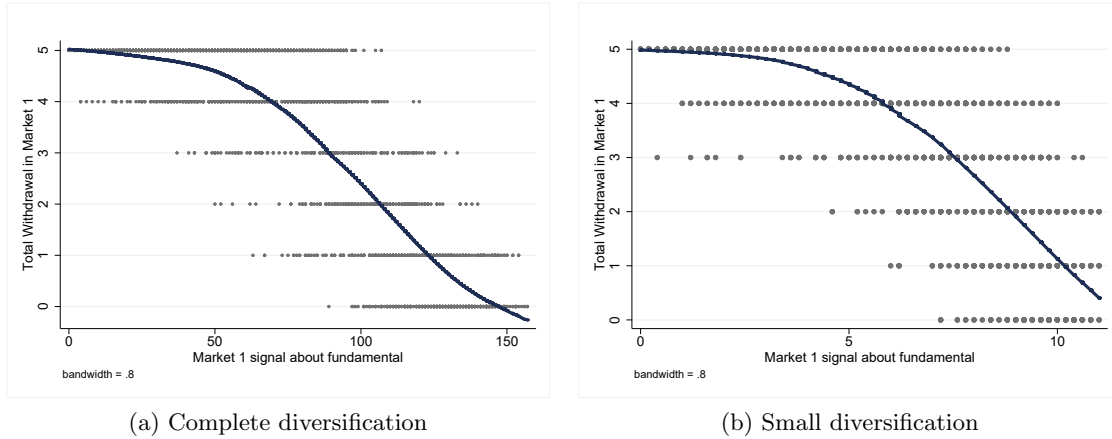
|   | CD  | SD  |                       |                |
|---|-----|-----|-----------------------|----------------|
| Panel A: Risk aversion test             |     |     | Implied risk aversion | Risk tolerance |
| Gamble 1                                | 8%  | 7%  | Highly risk averse    | 1              |
| Gamble 2                                | 13% | 11% | Very risk averse      | 2              |
| Gamble 3                                | 13% | 23% | Risk averse           | 3              |
| Gamble 4                                | 25% | 23% | Slightly risk averse  | 4              |
| Gamble 5                                | 27% | 15% | Risk neutral          | 5              |
| Gamble 6                                | 14% | 21% | Risk loving           | 6              |
| Panel B: Loss aversion test             |     |     | Implied loss aversion | Loss aversion  |
| Reject all lotteries                    | 6%  | 4%  | >3                    | 4              |
| Accept lottery 1, reject 2 to 6         | 14% | 17% | 3                     | 3              |
| Accept lotteries 1 and 2, reject 3 to 6 | 26% | 20% | 2                     | 2              |
| Accept lotteries 1 to 3, reject 4 to 6  | 20% | 21% | 1.5                   | 1.5            |
| Accept lotteries 1 to 4, reject 5 to 6  | 17% | 23% | 1.2                   | 1.2            |
| Accept lotteries 1 to 5, reject 6       | 11% | 11% | 1                     | 1              |
| Accept all lotteries                    | 2%  | 2%  | $\leq 0.87$           | 0              |

## 4.2 Behavior and outcomes in market 1

The main insight from analyzing market 1 behavior rests in understanding whether subjects behave in accordance to the prescriptions of the global games equilibrium selection criteria, i.e., they withdraw when values of the signal about market fundamentals are small and roll-over for high signals. Figure 2 shows a locally weighted scatterplot smoothing (lowess smoother) of the total number of withdrawals in Market 1 as a function of the signal about fundamentals received by participants. The graph clearly shows that in both treatments when signals are low, most participants withdraw, while if the signal is sufficiently high, most subjects do not withdraw. This evidence confirms that subjects' behavior is consistent with the theoretical prediction that coordination on rolling-over investments is more likely at higher values of the fundamentals.

It is also worth understanding the distribution of wealth after the decision in market 1. Table

Figure 2: Locally weighted scatterplot of the total number of withdrawals in market 1 as a function of signal



5 displays distribution of the decisions taken by subjects in each treatment (columns) by the total change in wealth after participants' decision in market 1 (rows).

We notice that, as expected by design, the variation in total wealth is much larger in the CD treatment (ranging from -40% to 169%) than in the SD treatment (ranging from -4.1% to 10%). A further analysis shows that in the CD treatment there are 10.5% of the observations with losses that are smaller than the smallest loss in the SD treatment (-4.7%), and 20.6% of the observations with gains that are larger than the largest gain in the SD treatment (10%). In addition, we observe that 69% of the observations in the CD treatment have a change of wealth which is of a similar range to the SD treatment, 65% of them correspond to withdrawals and 4% to roll-over decisions with a small return.

Table 5: Distribution of withdrawal and roll-over decisions by changes in wealth

| Change in total wealth after market 1 decision | CD Treatment |           | SD Treatment |           |
|--|--------------|-----------|--------------|-----------|
|  | Withdraw     | Roll-over | Withdraw     | Roll-over |
| <-5%   | 0%           | 11.04%    | 0%           | 0%        |
| [-5%, 10%]                                     | 64.92%       | 3.5%      | 75.63%       | 24.68%    |
| >10%   | 0%           | 20.54%    | 0%           | 0%        |

Table shows the proportion of withdrawals and roll-over decisions in each treatment by different levels of changes in total wealth after market 1 outcome. The change in wealth is computed as (market 1 wealth after the decision in market 1 + initial investment in market 2) divided by the total initial wealth invested in both markets.

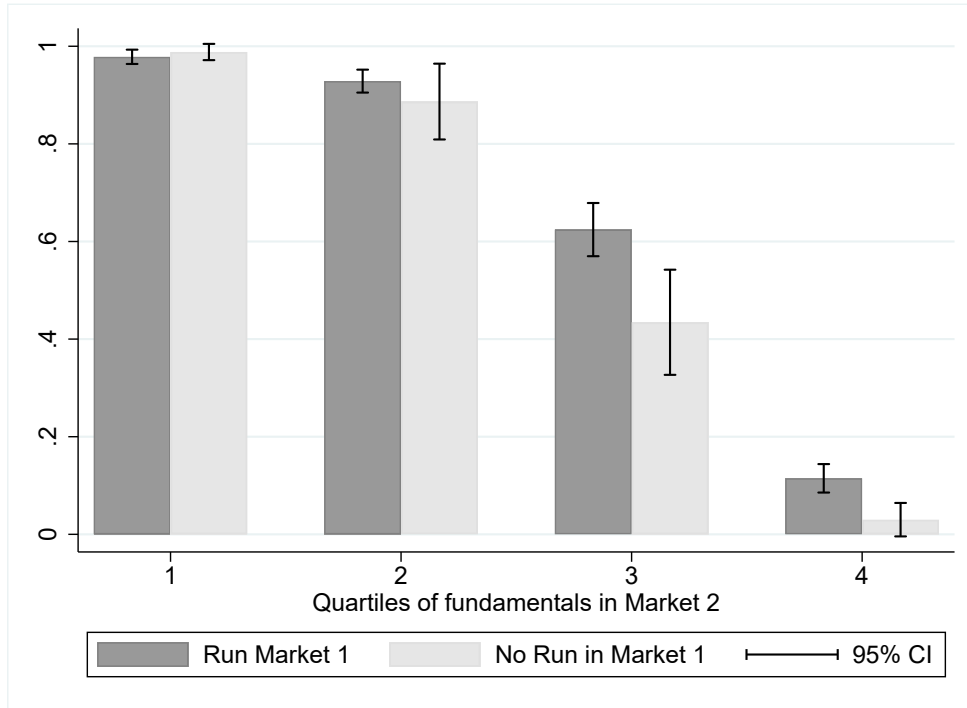
### 4.3 Behavior and outcomes in market 2

We now turn to analyzing the behavior of market 2 and focus on understanding how the outcomes of market 1 affect the proportion of withdrawals in market 2. Recall that prior to observing their signal in market 2, subjects learn the outcome of the coordination game (the behavior of other investors) and their wealth from their investment in market 1.



We first examine whether the outcome of market 1 affects the proportion of withdrawals in market 2. Figure 3 displays the average proportion of withdrawals in market 2 in both treatments as a function of the fundamentals in market 2 and whether a run occurred in market 1. We sort the fundamentals into the corresponding quartiles in each treatment.

Figure 3: Contagion across the two markets



Similar to the analysis in market 1 in the previous section and as predicted by the theory, Figure 3 shows that overall there is a higher proportion of withdrawals for lower values of the fundamentals. Moreover, in the first two quartiles, there are no significant differences in the proportion of withdrawals depending on whether there has been a run in market 1 or not. In other words, when market 2 fundamentals are low, subjects are likely to withdraw their investment, regardless of the outcome in market 1. However, for higher values of market 2 fundamentals (in the third and fourth quartiles), we observe that the proportion of withdrawals differs substantially as a function of the outcome in market 1. Specifically, in these two last quartiles, we find a statistically significant higher number of withdrawals if there has been a run in market 1 compared to when a run did not occur (t-test of equality of means is  $t=3.12$  for the 3rd quartile and  $t=2.23$  for the 4th quartile, respectively). Thus, the figure suggests that there is contagion from market 1 to market 2 in both treatments, particularly for higher values of fundamentals. Moreover, contagion appears stronger in the third quartile, where the proportion of withdrawals in market 2 is 18% higher in rounds when a run occurred in market 1 as opposed to those in which it did not. This quartile corresponds to values of the fundamentals close to the theoretical thresholds characterized in the previous section.

Additionally, Table 6 reports market-level regressions for each treatment separately where the

Table 6: Contagion at the market level

| Dependent variable:                     | Complete diversification |                      | Small diversification |                      |
|---|--------------------------|----------------------|-----------------------|----------------------|
|   | (1)                      | (2)                  | (4)                   | (5)                  |
| M1 withdrawals                          | -0.049<br>(0.180)        | -0.276<br>(0.204)    | 0.471**<br>(0.198)    | 0.319<br>(0.211)     |
| M1 withdrawals $\times$ $Y \in 3^{rd}Q$ |                          | 0.394**<br>(0.162)   |                       | 0.373**<br>(0.182)   |
| Y                                       | -0.075***<br>(0.004)     | -0.075***<br>(0.004) | -0.024***<br>(0.001)  | -0.023***<br>(0.001) |
| Period                                  | 0.073***<br>(0.012)      | 0.071***<br>(0.012)  | 0.038***<br>(0.013)   | 0.041***<br>(0.014)  |
| Constant                                | 6.467***<br>(0.354)      | 6.546***<br>(0.347)  | 4.247***<br>(0.286)   | 4.181***<br>(0.277)  |
| Observations                            | 480                      | 480                  | 480                   | 480                  |

Table presents GLM estimations where the dependent variables is the proportion of withdrawals in market 2. M1 withdrawals is the proportion of withdrawals in market 1. M1 withdrawals  $\times$   $Y \in 3^{rd}Q$  is an interaction term between the proportion of market 1 withdrawals and a dummy variable that takes the value 1 if Y is in the 3<sup>rd</sup> quartile of the distribution. Y is the fundamentals in market 2. Period is a scalar from 1 to 20. Robust standard error in parenthesis. \*\*\*, \*\* and \* denotes significance at the 1%, 5% and 10% levels.

dependent variable is the proportion of withdrawals in market 2 in each period. Since the dependent variable is a proportion, we estimate the models in Table 6 using a generalized linear model that assumes the dependent variable follows a binomial distribution.<sup>8</sup>

Columns (1) and (2) in Table 6 pertain to the CD treatment, while (3) and (4) to the SD treatment. The baseline regression in each treatment (columns (1) and (3)) control for: the proportion of withdrawals in market 1 (M1 withdrawals), the market 2 fundamentals (Y), and a period variable (Period) to account for learning effects across periods. In this first specification, we find that the proportion of withdrawals in market 1 is statistically significant only in the SD treatment. Moreover, as expected, the market 2 fundamentals have a strong impact on the proportion of withdrawals, with the proportion of withdrawals decreasing for higher values of the fundamentals. In addition, when looking at the regression coefficient, we notice that withdrawals tend to be more sensitive to fundamentals in the CD treatment than in the SD treatment, which would explain the low statistical power of the withdrawals in market 1 in this treatment.

At the same time, the descriptive statistics in Figure 3 suggests that contagion across markets only occurs for some ranges of fundamentals in market 2 and not for others. Recall that the theoretical contagion region occurs in the third quartile of fundamentals of market 2. To explore this possibility, in columns (2) and (4) of Table 6 we add an interaction term between market 1 proportion of withdrawal and a dummy variable equal to 1 if the value of the market 2 fundamentals

<sup>8</sup>See Baum (2008) for a discussion on how this method is appropriate for handling bounded data such as proportions.

is in the third quartile ( $M1 \text{ withdrawals} \times Y \in 3^{rd}Q$ ).

The results in columns (2) and (4) show that, in both treatments, market 1 withdrawals only matter when fundamentals of market 2 are in the third quartile. The regression coefficient of the interaction term is positive and statistically significant in both treatments, indicating that there is contagion from the outcome of market 1 to the proportion of withdrawals in market 2 if fundamentals are in the third quartile.

Finally, across all specifications in Table 6, the period scalar is significant suggesting that the proportion of withdrawals increases over time. Consequently, we control for learning effects in all subsequent tests.

Overall, the analysis in Table 6 provides evidence of contagion effects from market 1 to market 2 for some levels of fundamentals in market 2. These findings can be summarized as follows.

**Result 2** [Contagion at the market level]: A higher proportion of withdrawals in market 1 increases the proportion of withdrawals in market 2 for high levels of fundamentals in market 2 in both treatments.

The fact that there is contagion from market 1 to market 2 for some levels of fundamentals in market 2 supports Hypothesis 2. However, the fact that there is no statistically significant difference between the two treatments could be the result of different mechanisms. In the next section, we attempt to isolate the role of wealth as a driver of this observed contagion across the two markets, and explore the role of other potential channels of financial contagion.

#### 4.4 Contagion due to the wealth effect

We provide several tests that aim to isolate the role that changes in wealth play in explaining the contagion documented in the previous section. We expect market 1 wealth to be significant in the CD treatment where subjects hold perfectly diversified portfolios in both markets, but matter less in the SD treatment, where the investment in market 1 represents only 5% of the total investment.

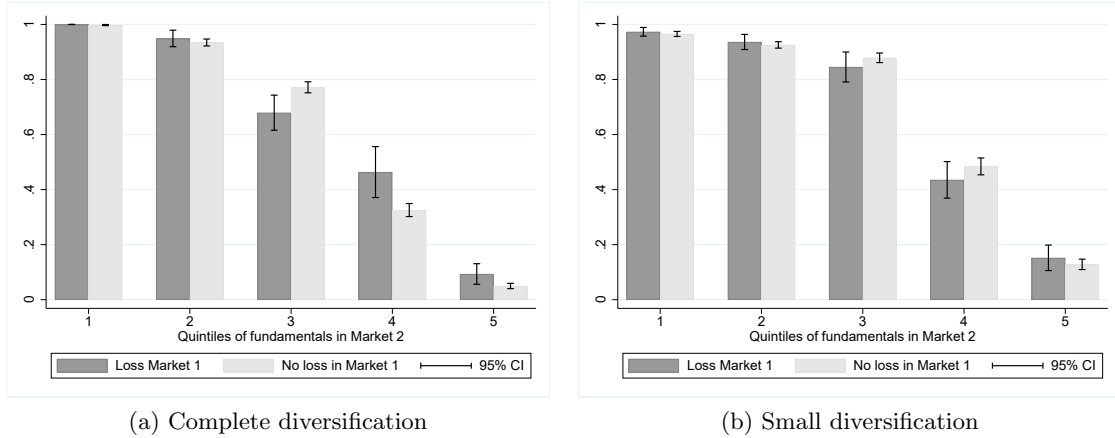
The analysis in the previous section suggested that the level of the fundamentals plays an important role in the strength of contagion across the two markets. Consequently, we start by plotting the average proportion of withdrawals across different quintiles of the market 2 fundamentals ( $Y$ ) in Figure 4. We split the sample of fundamentals in quintiles and then look at the average withdrawals in market 2 in cases where the subject experienced a loss in market 1 and no loss, separately.<sup>9</sup> Figure 4 shows the distribution of outcomes in the CD treatment (Panel a) and SD treatment (Panel b).

Similar to the results in the previous section, the outcome in market 1 affects market 2 behavior for some ranges of fundamentals and not others. In particular, in the CD treatment in Figure 4 panel

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<sup>9</sup>The equivalent graphs for gains show no statistically significant differences.

Figure 4: Proportion of withdrawals in market 2 for different returns in market 1



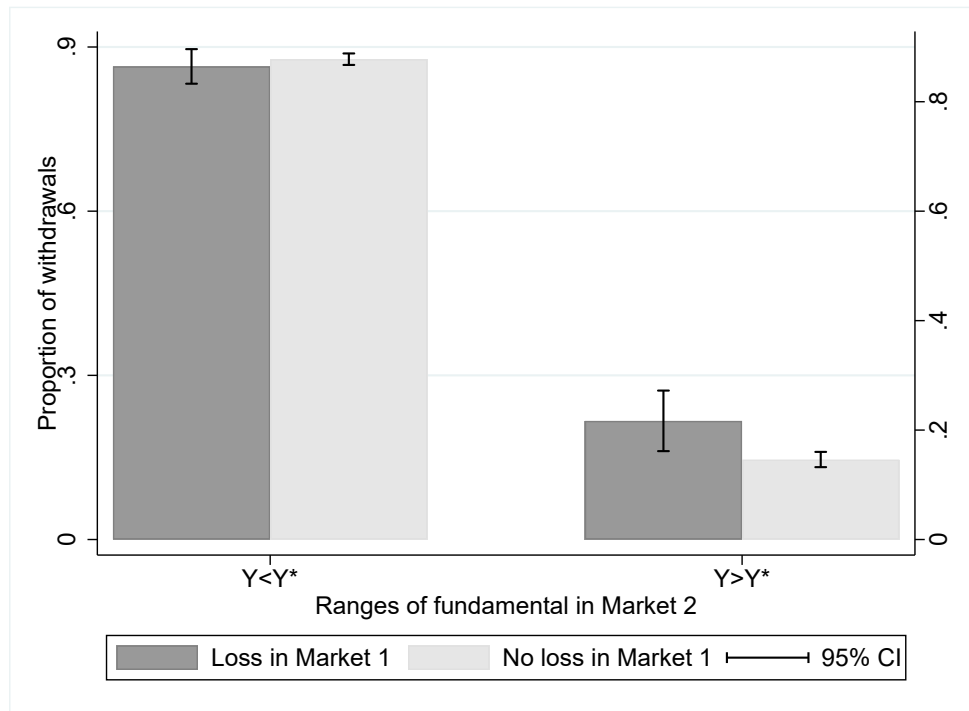
(a), we observe that for the first three quintiles of fundamentals there is no statistically significant difference in the average proportion of withdrawals in market 2 between subjects that experienced a loss or no loss in market 1 (95% confidence intervals for the means in each group are shown on the graphs). However, for the remaining two quintiles of fundamentals (starting at  $Y = 83$ ), we find that the proportion of withdrawals is significantly higher when subjects experienced a loss in market 1 compared to when there was no loss (t-test of equality of means is  $t=3.38$  for the 4<sup>th</sup> quintile and  $t=2.97$  for the 5<sup>th</sup> quintile, respectively, both tests being rejected at the 1% level). However, this difference is only observed in the CD treatment (panel a), whereas in the SD treatment, (panel b) there is no statistically significant difference in the proportion of withdrawals for a change in wealth in market 1 across the quintiles of fundamentals considered. Notice also that experiencing a loss in the first market does not correspond to a run in the first market, as the latter implies all subjects recover their initial investment. So the contagion illustrated in this figure is more likely to be driven by losses, than by the behavior of others, as depicted in Figure 3.

The patterns observed in Figure 4 suggest that, in the CD treatment, the change in wealth after the decision in market 1 (in particular if there is a loss) does have a significant effect on the proportion of withdrawals in market 2, but only for higher values of the fundamentals. In particular, this effect appears significant around the theoretical threshold level computed in Section 3.2. To investigate if this is the case, Figure 5 splits the sample at the corresponding theoretical threshold,  $Y^* = 99$ . We find that, whenever subjects experience a loss in market 1, there is a significantly higher proportion of withdrawals in market 2 for values of  $Y$  above the theoretical threshold ( $t=3.16$ ), but not below it.<sup>10</sup>

Moreover, a closer analysis presented in Appendix IV (Figure 13) suggests that this effect is mainly driven by strong differences in the proportion of withdrawals in the region of fundamentals [99-111] for which the theoretical framework in section 3.2 suggested contagion.

<sup>10</sup>We do not observe such differences in the SD treatment.

Figure 5: Market 2 withdrawals for different returns in market 1 in the Complete diversification treatment



These descriptive statistics suggest that wealth does matter, but only for intermediate values of the market fundamentals for which the optimal decision to roll-over is sensitive to whether a loss was experienced in market 1. For values of fundamentals below the theoretical threshold, the optimal decision to withdraw is not affected by the level of wealth from market 1. This suggests that, unlike the theoretical framework in GP, contagion due to a wealth effect is asymmetric: losses make withdrawals more likely, but gains do not make them less likely.

In Table 7, we provide a more robust investigation of this wealth effect. We present a series of probit regressions where the dependent variable is a dummy variable equal to 1 if a participant withdrew his/her investment in market 2, and 0 otherwise. We investigate the determinants of the individual probability of withdrawing for the CD treatment (columns (1)-(2)) and SD treatment (columns (3)-(4)) separately. Our main independent variables are two proxies for the wealth effect: (i) the percentage change in the first market's wealth (Wealth M1) and (ii) interactions between Wealth M1 and the fundamentals, given the non-linear dynamics suggested by the descriptive statistics above. Across all specifications, we control for the level of the fundamentals in market 2 ( $Y$ ), a variable for the period (Period) to capture any learning effects across the 20 periods, and individual controls for risk tolerance and loss aversion. We cluster errors at the individual level to account for any correlation across the 20 decisions of each individual.

Columns (1) and (3) in Table 7 present our baseline estimations for each treatment, where we include the change of wealth in market 1 and its interaction with market 2 fundamentals. We find

evidence that wealth matters in the CD treatment, but does not in the SD treatment. Moreover, this wealth effect is non-linear. Figure 6 shows that for low values of the fundamentals, a higher wealth in market 1 makes participants more likely to withdraw, although this effect is generally not statistically significant. However, for larger values of the fundamentals, higher wealth has a statistically significant negative effect on the propensity to withdraw. Again this effect appears significant for values of fundamentals above the theoretical threshold. This is confirmed in column (2) of Table 7, where we interact wealth with a dummy taking the value 1 whenever the fundamentals is above the equilibrium cut-off ( $\text{Wealth Market 1} \times Y > Y^*$ ). In this specification only the interaction term is robustly estimated. This suggests that, for values of the fundamentals where the optimal strategy is to roll-over, market 1 wealth lowers the propensity of withdrawing in market 2.<sup>11</sup>

Table 7: Wealth effects in the individual probability of withdrawing

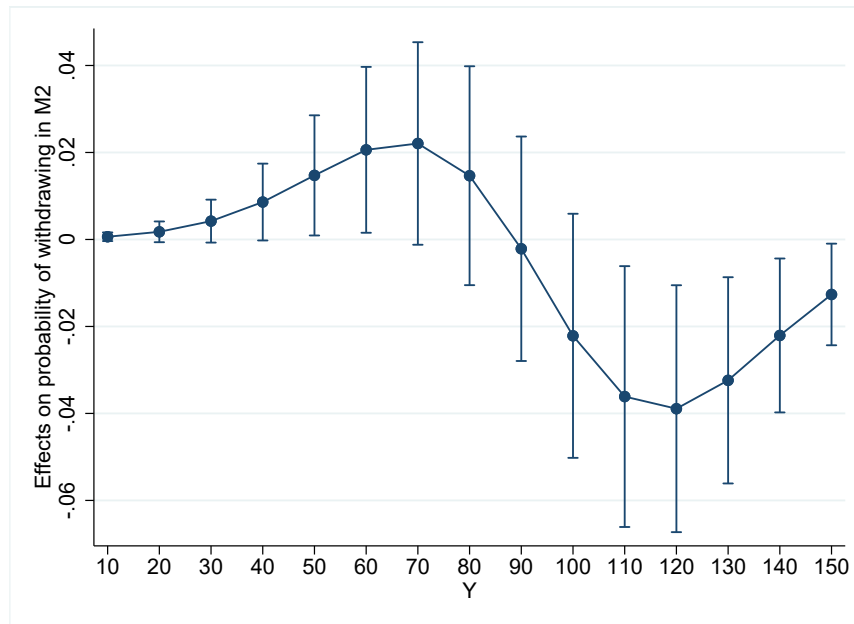
|                                  | Complete diversification |                      | Small diversification |                      |
|----------------------------------|--------------------------|----------------------|-----------------------|----------------------|
|                                  | (1)                      | (2)                  | (3)                   | (4)                  |
| Wealth M1                        | 0.529***<br>(0.194)      | 0.068<br>(0.050)     | 0.315<br>(0.259)      | -0.041<br>(0.070)    |
| $Y \times \text{Wealth M1}$      | -0.006***<br>(0.002)     |                      | -0.002<br>(0.001)     |                      |
| Wealth Market 1 $\times Y > Y^*$ |                          | -0.200***<br>(0.074) |                       | -0.099<br>(0.186)    |
| Y                                | -0.045***<br>(0.003)     | -0.045***<br>(0.003) | -0.016***<br>(0.001)  | -0.016***<br>(0.001) |
| Period                           | 0.045***<br>(0.009)      | 0.044***<br>(0.009)  | 0.029***<br>(0.008)   | 0.030***<br>(0.008)  |
| Risk tolerance                   | -0.085*<br>(0.047)       | -0.085*<br>(0.046)   | -0.071<br>(0.059)     | -0.070<br>(0.059)    |
| Loss aversion                    | 0.041<br>(0.075)         | 0.040<br>(0.074)     | -0.161*<br>(0.096)    | -0.163*<br>(0.096)   |
| Constant                         | 4.117***<br>(0.356)      | 4.150***<br>(0.353)  | 3.571***<br>(0.418)   | 3.567***<br>(0.416)  |
| Observations                     | 2,400                    | 2,400                | 2,400                 | 2,400                |
| Number of subjects               | 120                      | 120                  | 120                   | 120                  |

The table presents panel probit estimations where the dependent variable is a dummy variable equal 1 if an individual withdrew in Market 2.  $Y$  is the fundamentals in Market 2.  $Y > Y^*$  is a dummy variable equal to 1 for values of the fundamentals above the theoretical threshold ( $Y^* = 99$  in the Complete diversification treatment and  $Y^* = 241$ ). Period is a scalar for the 20 experimental rounds. Risk tolerance is a scalar from 1 to 6 with 1 being highly risk averse and 6 risk loving. Loss aversion is a scalar taking value from 0 to 4, with higher numbers indicating a higher degree of loss aversion. Standard errors are clustered at the individual level. \*\*\*, \*\* and \* denotes significance at the 1%, 5% and 10% levels.

<sup>11</sup>These results are robust to different specifications of changes in wealth, such as replacing the change in wealth in market 1 by the total change in wealth of an investor's portfolio. We present the results of the change in wealth in market 1 since these are more conservative and equivalent in the two treatments.

Additionally, we also find some evidence that higher risk aversion (lower values of the risk tolerance measure reported in Table 7) is associated with a higher probability of withdrawing, although the risk aversion coefficient is only significant in the CD treatment. Loss aversion is statistically significant only in the SD treatment and with the opposite expected sign.<sup>12</sup>

Figure 6: Average marginal effects of wealth in market 1 on market 2 withdrawals for the complete diversification treatment



The marginal effects graph corresponds to columns (1) and (3) in Table 7. 95% confidence intervals are shown.

We summarize these findings as follows.

**Result 3** [Comparison of the wealth effect in the two treatments]: In the complete diversification treatment, the change in market 1’s wealth has a statistically significant impact on the probability of withdrawing the investment in market 2 for values of fundamentals above the theoretical threshold. However, the wealth effect is not statistically significant in the small diversification treatment.

This result provides support for Hypothesis 3 that the wealth effect is an important driver of contagion in the CD treatment where changes in wealth are large by construction.

We now examine the determinants of the wealth effect. Given the evidence of Figure 4, we repeat the previous empirical exercise by analyzing losses in Table 8. We replace the change of wealth in market 1 with a dummy variable which is equal to 1 if a loss was experienced in market 1, and 0 otherwise. Again, we find that having experienced a loss overall decreases the propensity to withdraw, but this effect turns positive for larger values of fundamentals in the CD treatment. Specifically, when fundamentals are above the theoretical threshold, experiencing a loss in the first

<sup>12</sup>In unreported results, we also control for the gender of the participant. Surprisingly, we find that women are less likely to withdraw in both treatments.

market increases the probability of withdrawing in the second. Again, none of these effects are present in the SD treatment. In addition, we notice that the wealth effect does not work for gains in either treatment. The determinants of the wealth effect in the CD treatment can be summarized as follows:

**Result 4** [Determinants of the wealth effect]: In the complete diversification treatment, the wealth effect depends non-linearly on the level of fundamentals. It is strongest for higher levels of fundamentals, where experiencing a loss in market 1 leads to a significant increase in the propensity to withdraw in market 2. Risk aversion increases the propensity to withdraw in market 2.

Our result goes in line with the predictions of GP that financial contagion only occurs for some regions of fundamentals in the third quartile. However, our finding that the wealth effect works for losses and not for gains is novel and not predicted by the extant literature.

Table 8: Market 1 losses and the individual probability of withdrawing in Market 2

|                                  | Complete diversification |                      | Small diversification |                      |
|----------------------------------|--------------------------|----------------------|-----------------------|----------------------|
|                                  | (1)                      | (2)                  | (3)                   | (4)                  |
| Loss M1                          | -1.029***<br>(0.396)     | -0.160<br>(0.157)    | -0.187<br>(0.301)     | -0.234**<br>(0.118)  |
| Loss M1 $\times$ Y               | 0.012***<br>(0.004)      |                      | -0.000<br>(0.002)     |                      |
| Loss Market 1 $\times$ $Y > Y^*$ |                          | 0.458*<br>(0.241)    |                       | -0.064<br>(0.261)    |
| Y                                | -0.048***<br>(0.003)     | -0.047***<br>(0.003) | -0.016***<br>(0.001)  | -0.016***<br>(0.001) |
| Period                           | 0.046***<br>(0.009)      | 0.044***<br>(0.009)  | 0.028***<br>(0.008)   | 0.028***<br>(0.008)  |
| Risk tolerance                   | -0.082*<br>(0.046)       | -0.082*<br>(0.046)   | -0.066<br>(0.058)     | -0.066<br>(0.058)    |
| Loss aversion                    | 0.039<br>(0.073)         | 0.037<br>(0.073)     | -0.163*<br>(0.094)    | -0.164*<br>(0.094)   |
| Constant                         | 4.394***<br>(0.394)      | 4.315***<br>(0.377)  | 3.576***<br>(0.413)   | 3.582***<br>(0.411)  |
| Observations                     | 2,400                    | 2,400                | 2,400                 | 2,400                |
| Number of subjects               | 120                      | 120                  | 120                   | 120                  |

The table presents panel probit estimations where the dependent variable is a dummy variable equal to 1 if an individual withdrew in Market 2. Loss M1 is a dummy equal to 1 if an individual experienced a loss in market 1. Y is the fundamentals in Market 2.  $Y > Y^*$  is a dummy variable equal to 1 for values of the fundamentals above the theoretical threshold ( $Y^* = 99$  in the Complete diversification treatment and  $Y^* = 241$ ). Period is a scalar for the 20 experimental rounds. Risk tolerance is a scalar from 1 to 6 with 1 being highly risk averse and 6 risk loving. Loss aversion is a scalar taking value from 0 to 4, with higher numbers indicating a higher degree of loss aversion. Standard errors are clustered at the individual level. \*\*\*, \*\* and \* denotes significance at the 1%, 5% and 10% levels.



Our experimental results show that contagion can occur in markets with unrelated fundamentals due to investors' actions. In Section 4.3 we showed that in some regions of fundamentals, the behavior of investors in market 1 affects the outcome in market 2, and that these spillover effects are present in both treatments. In line with theoretical predictions, contagion occurs for intermediate values of the fundamentals in the second market, where the decision to withdraw or roll-over is sensitive to the propensity to coordinate in the first market. Subjects place more weight on the value of fundamentals in their decision for very low or high levels of fundamentals.

Moreover, in the region where financial contagion exists, we have shown in Section 4.4 that, in the CD treatment returns in the first market impact the propensity to run in the second, while in the SD treatment this effect is not statistically significant. Hence, contagion in the SD treatment is likely to be due to social imitation, i.e. that the previous decision of the group of investors influences an investor's subsequent decision, thus generating financial contagion. It is possible that this channel also partially explains financial contagion in the CD treatment, however our results clearly show that changes in wealth, and losses in particular, are an important channel through which the outcome of market 1 influences the outcome of market 2 even if fundamentals in the two markets are unrelated.

## 5 Conclusions

Our experiment is the first to analyze the importance of the wealth effect as a channel for financial contagion in a controlled laboratory setting. Specifically, we analyze the sequential decisions of the same group of investors in two markets that have independent fundamentals. Investors have incomplete information about fundamentals in each market and receive private signals. We use the global games solution of Goldstein & Pauzner (2004) as the benchmark, which highlights that a coordination failure in one market can be the result of a coordination failure in another market. This is due to a wealth effect: a crisis in one market reduces investors' wealth, making them more averse to the risk in the other market. This increases their incentive to withdraw their investment in the second market, which increases the probability of a crisis in the second market. In addition, our design allows us to disentangle the effects of social imitation (observability of what others have done in the previous period) from the wealth channel.

We find evidence of financial contagion across markets in both treatments when fundamentals are high, but not when they are low. Our results indicate that this observed financial contagion is due to a wealth effect when investors have completely diversified portfolios and not when there is a small degree of diversification. In addition, the wealth effect when investors have perfectly diversified portfolios depends non-linearly on fundamentals since it is stronger for higher levels of fundamentals, where subjects experienced a loss in the first market. We also find that risk

averse investors are more likely to withdraw. Given our experimental design, when there is small diversification, the channel which best explains financial contagion is social imitation.

Our results highlight the wealth effect as an important driver of financial contagion in situations where a common group of investors holds diversified portfolios across two markets. Understanding the main source of financial contagion is crucial in designing policies to limit the effects of these episodes on the wider economy. Take for example, the case of government debt crises. If contagion happens only because of herding behaviour among government debt holders, then policy can address this through increased market transparency. However, if wealth effects play an important role in portfolio decisions, then understanding the nature of the balance sheet constraints of government debt holders is crucial in understanding how contagion will spread.

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## Appendix I: Calculation of equilibrium numerical thresholds

We compute the numerical thresholds implied by the game described in Section 2 and our experimental design in Section 3.1. We illustrate the calculation for the structure and parameters of the CD treatment, while an analogous derivation may be obtained for the SD treatment.

Each market is indexed by  $i = 1, 2$ , with independent fundamentals (denoted by  $\theta_i, i = 1, 2$ ). We assume that for a given level of wealth,  $\omega$ , agents have a DARA utility function as in GP given by:  $u(\omega) = \log(\omega)$ , where  $\log$  is the natural logarithm. Denote the agent's initial wealth in each market as  $\omega_{0i}$ , for  $i = 1, 2$ .

As in GP, the coordination game is solved backwards. First, we compute the threshold in market 2, for a given equilibrium outcome in market 1. We then compute the expected wealth from the market 2's investment, which depends on the computed threshold in market 2 and the realization of market 2's fundamentals. Next, the threshold in market 1 is found, which depends on market 1 fundamentals, but also the expected wealth in market 2.

The model of GP is modified to account for the finite number of players. In addition we assume that  $\theta_i$  are independent and uniformly distributed over  $[\underline{\theta}, \bar{\theta}]$ . Following the global games approach, players withdraw their investment if their signal,  $\theta_i^j$ , is below a threshold signal, denoted by  $\theta_2^*$ . The probability that a single player gets a signal below  $\theta_2^*$  for a random state  $\theta_2$  is:  $p(\theta_2) = Prob[\theta_i^j < \theta_2^* | \theta_2] = \frac{\theta_2^* - \theta_2 + \epsilon_2^i}{2\epsilon_2^i}$ , given  $\theta_2^i \sim [\theta_2 - \epsilon_2^i, \theta_2 + \epsilon_2^i]$ . A player's payoff then depends on the probability that none, one, two, three or four of the other players withdraws their investment. This can be represented by the binomial distribution:  $Bin(n_2, 4, p(\theta_2))$ , where  $Bin$  is the probability that  $n_2$  of the other 4 players withdraw, when each player withdraws with a probability  $p(\theta_2)$ . Then the expected utility from rolling over ones' investment in market 2 for any  $\theta_2 \sim [\theta_2^i - \epsilon_2^i, \theta_2^i + \epsilon_2^i]$  is simply:

$$EU_{\text{WAIT}}(\theta_i^j) = \sum_{n_2=0}^4 \left[ \frac{1}{2\epsilon} \int_{\theta_2=\theta_2^i-\epsilon}^{\theta_2^i+\epsilon} B(n_2, 4, p(\theta_2)) u(R_2(\theta_2, n_2) + \omega_1) d\theta_2 \right], \quad (1)$$

while the payoff from withdrawing is:

$$EU_{\text{WITHDRAW}}(\theta_i^j) = u(\omega_{02} + \omega_1), \quad (2)$$

where  $\omega_1$  is the wealth resulting from market 1's investment. An agent receiving a signal equal to the threshold  $\theta_2^*$  is indifferent between withdrawing and rolling over. We can thus compute the threshold signal  $\theta_2^*(\omega_1)$ , by solving the indifference condition:

$$EU_{\text{WAIT}}(\theta_2^*(\omega_1)) = EU_{\text{WITHDRAW}}(\theta_2^*(\omega_1)) \quad (3)$$

Given this threshold, we can compute the expected wealth from market 2's investment.

Following GP, we assume that when the noise in the signals is low, players' behavior can be

approximated as follows: all players run when fundamentals are below the threshold signal and do not run above. In the first case, each player has a wealth of  $\omega_{02}$ , while in the second, each has  $R(\theta_2, n_2 = 0)$ . This means that the expected wealth from market 2 investment for a given threshold  $\theta_2^*(\omega_1)$  is:

$$E[\omega_2(\theta_2^*(\omega_1))] = Prob[\theta_2 < \theta_2^*(\omega_1)] \times \omega_{02} + Prob[\theta_2 \geq \theta_2^*(\omega_1)] \times \frac{1}{2\epsilon} \int_{\theta_2=\theta_2^*(\omega_1)}^{\bar{\theta}} R(\theta_2, 0) d\theta_2 \quad (4)$$

Note that the threshold signal  $\theta_2^*(\omega_1)$  and  $E[\omega_2]$  depend on  $\omega_1$ , and thus on fundamentals and number of withdrawals in market 1, i.e.,  $\theta_1$  and  $n_1$ , respectively.

Turning to the equilibrium in market 1, the behavior of players can be approximately described as follows: All agents run in market 1 when the fundamentals in market 1 are below  $\theta_1^*$ ; whereas none of the agents withdraws when fundamentals in market 1 are above  $\theta_1^*$ . In the first case, all players possess wealth of  $\omega_{01}$ ; while in the second each has wealth  $R(\theta_1, 0)$ . By the results of Theorem 1 in GP, in the first case agents will run in market 2 when the fundamentals are below the threshold  $\theta_{2,run}^*(\omega_1 = \omega_{01})$ , which is higher than the threshold  $\theta_{2,no\ run}^*(\omega_1 = R(\theta_1, 0))$  corresponding to the second case.

If none of the agents run in market 1,  $n_1 = 0$ , the expected wealth from market 1 investment depends on the realization of  $\theta_1$  and the threshold signal in market 1,  $\theta_1^*$ . The threshold equilibrium in market 1, however, now depends on the signals and expectations of agents that withdraw in market 1, but also, on the expected wealth in market 2, in Eq. (4). As such, the indifference condition that determines this equilibrium condition in market 1 is:

$$U_{WAIT}^1 - U_{WITHDRAW}^1 = \sum_{n_1=0}^4 \left[ \frac{1}{2\epsilon} \int_{\theta_1=\theta_1^*-\epsilon}^{\theta_1^*+\epsilon} B(n_1, 4, p(\theta_1)) u(R_1(\theta_1, n_1) + E[\omega_2(\theta_2^*)]) d\theta_1 \right] - \sum_{n_1=0}^4 \left[ \frac{1}{2\epsilon} \int_{\theta_1=\theta_1^*-\epsilon}^{\theta_1^*+\epsilon} B(n_1, 4, p(\theta_1)) u(\omega_{01} + E[\omega_2(\theta_2^*)]) d\theta_1 \right], \quad (5)$$

where  $E[\omega_2(\theta_2^*)]$  is given by Eq. (4). The equilibrium thresholds are the solutions to the system of equations: (3), (4), and (5). Using our parametrization, we find the equilibrium thresholds presented in Table 2 using this approach.

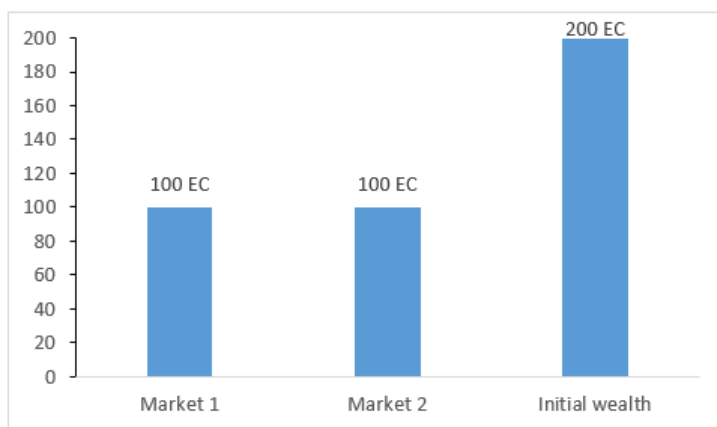
## Appendix II: Instructions- Complete diversification treatment

### Part I: Game

You are about to participate in an economic experiment where you will be asked to make decisions under uncertainty and have the chance to earn some money. Please read the instructions carefully. If you have any questions during the experiment, please raise your hand and wait for an experimenter to come to you. Please do not talk or communicate with other participants. The use of mobile phones is not allowed. The rules are the same for all the participants. The experiment consists of two parts: In part I, you will play a game with other participants, while in part II, you will be asked to fill out several individual questionnaires. Your final payoff will be the sum of your gains in both parts of the experiment to which a 5 Euros participation fee is added.

### Part I

**Background:** In this experiment, your role is to be an investor. There are 20 rounds and you will be asked to take 2 decisions in each round. Each round is independent of the others. There are 20 participants in the experiment, which will be divided into groups of 5. In each round, the same group of 5 participants are investors in two markets: market 1 and market 2. Investors in your group will change randomly from round to round. You will not know which of the other participants belong to your group in a given round. In each round, you and the other participants in your group have an initial wealth of **200 Experimental Currency (EC)**, which is invested in the two markets in the following way: **100 EC in market 1 and 100 EC in market 2**. Graphically, your wealth is distributed in the following way:



In each round, there are two stages:

- In the first stage, you have to decide regarding your investment in market 1 and you will then be provided with feedback about the outcome of this investment.



- In the second stage, you are asked to take a decision about your investment in market 2, and feedback is provided about the outcome of your investment in both markets.

**Decisions:** In each round and for each market, you will choose between Action A and Action B:

- Action A. You get back your initial investment.
- Action B. You receive a payoff that depends on an unknown state of the economy in a market (*State of the economy*) and on the decision of the other investors in your group. The higher the state of the economy, the higher your payoff. The higher the number of investors that select A, the lower your payoff. Specifically, if you choose B the payoff for your investment in market  $i$ , where  $i = 1, 2$  is:

$$\frac{3 \times (\text{State of the economy in market } i)}{1 + 2 \times (\text{Number of investors that choose action A in your group in market } i)}$$

We illustrate the potential payoffs with an example later in the instructions.

### **Features of markets 1 and 2:**

In each market, the state of the economy is randomly selected **from the interval 10 to 150**. Each state in the interval has the same probability of being drawn and is the same for all the investors in your group. When you make your decision, you do **not** know the exact value of the state of the economy.

However, in each market, each member of your group receives a hint about the unknown state of the economy. The hint number is randomly selected from the interval:

$$[\text{State in market } i-10, \text{State in market } i+10],$$

where  $i = 1, 2$ .

All numbers in the interval have the same probability to be drawn. Hint numbers of different participants are drawn independently from the same interval. Note that each of the investors in your group receives a different hint, which is only known by the participant who receives it.

**IMPORTANT: The state of the economy in market 1 and 2 are drawn independently from each other. This means that the state of the economy in market 1 does not convey any information about the state of the economy in market 2. Specifically, receiving information about the state of the economy in market 1 does not tell you anything about the state of the economy in market 2.**

Recall that, in each round, the same group of 5 participants invest in both market 1 and market 2. However, investors in your group will change randomly from round to round.

**Feedback:** After all participants in market 1 take their decisions, you will receive the following feedback: state of the economy in market 1; the number of investors that choose A and your own payoff from market 1. After all participants in market 2 take their decisions, you will receive the following feedback: state of the economy in market 2; the number of investors that choose A; your own payoff from market 2; and your total EC at the end of this round, which adds up your earnings from investing in markets 1 and 2.

**Example of potential payoffs:** We provide an example of potential payoffs in market 1 in the table below (in EC).

| Hypothetical number of other investors that choose A | Payoff if you choose A | Payoff if you choose B |          |          |          |           |           |           |
|--|------------------------|------------------------|----------|----------|----------|-----------|-----------|-----------|
|  |                        | State=10               | State=25 | State=50 | State=75 | State=100 | State=125 | State=150 |
| 0  | 100.0                  | 30.0                   | 75.0     | 150.0    | 225.0    | 300.0     | 375.0     | 450.0     |
| 1  | 100.0                  | 10.0                   | 25.0     | 50.0     | 75.0     | 100.0     | 125.0     | 150.0     |
| 2  | 100.0                  | 6.0                    | 15.0     | 30.0     | 45.0     | 60.0      | 75.0      | 90.0      |
| 3  | 100.0                  | 4.3                    | 10.7     | 21.4     | 32.1     | 42.9      | 53.6      | 64.3      |
| 4  | 100.0                  | 3.3                    | 8.3      | 16.7     | 25.0     | 33.3      | 41.7      | 50.0      |

We provide an example of potential payoffs in market 2 in the table below (in EC).

| Hypothetical number of other investors that choose A | Payoff if you choose A | Payoff if you choose B |          |          |          |           |           |           |
|--|------------------------|------------------------|----------|----------|----------|-----------|-----------|-----------|
|  |                        | State=10               | State=25 | State=50 | State=75 | State=100 | State=125 | State=150 |
| 0  | 100.0                  | 30.0                   | 75.0     | 150.0    | 225.0    | 300.0     | 375.0     | 450.0     |
| 1  | 100.0                  | 10.0                   | 25.0     | 50.0     | 75.0     | 100.0     | 125.0     | 150.0     |
| 2  | 100.0                  | 6.0                    | 15.0     | 30.0     | 45.0     | 60.0      | 75.0      | 90.0      |
| 3  | 100.0                  | 4.3                    | 10.7     | 21.4     | 32.1     | 42.9      | 53.6      | 64.3      |
| 4  | 100.0                  | 3.3                    | 8.3      | 16.7     | 25.0     | 33.3      | 41.7      | 50.0      |

Incentives:

At the end of Part I, one of the 20 rounds will be randomly selected, and you will be paid your earnings from this round according to the formula: 100 Experimental Currency (EC) are equivalent to 3 Euros. These will not be shown to you until the end of Part II of the experiment.

**Example:** Market 1

The state of the economy for market 1 is drawn and it is equal to 36. The hints for the 5 investors are in the range [26, 46] and are equal to: 39, 46, 35, 37, 33. The participant who receives hint 39 knows that the state of the economy in market 1 must be between 29 and 49. The participant who receives hint 46 knows that the state of the economy in market 1 must be between 36 and 56 etc. The table below illustrates the payoff from choosing A and B depending on the hypothetical number of other investors that choose A.

In order to show how the payoffs for B are calculated, suppose that if 3 other investors choose A and I choose B. Then, my payoff is 15.4 EC since:  $\frac{3 \times 36}{1 + 2 \times 3} = \frac{108}{7} = 15.4$  EC.

Market 2

The state of the economy for market 2 is drawn and it is equal to 127. The hints for the 5 participants are in the range [117, 137] as follows: 129, 135, 130, 128, 126. The participant who

| Hypothetical number of<br>other<br>investors that choose A | Payoff if you choose A | Payoff if you choose B<br>State=36 |
|--|------------------------|------------------------------------|
| 0  | 100.0                  | 108.0                              |
| 1  | 100.0                  | 36.0                               |
| 2  | 100.0                  | 21.6                               |
| 3  | 100.0                  | 15.4                               |
| 4  | 100.0                  | 12.0                               |

receives hint 129 knows that the state of the economy in market 2 must be between 119 and 139. The participant who receives hint 135 knows that the state of the economy in market 2 must be between 125 and 145 etc. The table below illustrates the payoff from choosing A and B depending on the hypothetical number of other investors that choose A.

| Hypothetical number of<br>other<br>investors that choose A | Payoff if you choose A | Payoff if you choose B<br>State=127 |
|--|------------------------|-------------------------------------|
| 0  | 100.0                  | 381.0                               |
| 1  | 100.0                  | 127.0                               |
| 2  | 100.0                  | 76.2                                |
| 3  | 100.0                  | 54.4                                |
| 4  | 100.0                  | 42.3                                |

In order to show how the payoffs for B are calculated, suppose that 1 other investor chooses A and I choose B. Then, my payoff is 127 EC since:  $\frac{3 \times 127}{1 + 2 \times 1} = \frac{381}{3} = 127.0$  EC.

**Part II** You will be asked to make several other decisions, which are answered individually and do not depend on the choices of other participants. You will see 2 screens where you will choose among different gambles. The gambles in the two screens are independent from each other. You will be able to gain or lose money depending on your choice and outcome of the gamble. When we reach this part, the instructions will be found in the computer screen. This part is also incentivized - the computer screens will show how ECs are converted to Euros.

At the end of Part II of the experiment, we will display on the screen your total payoffs for the experiment, which includes the participation fee and the payoffs for Parts I and II of the experiment in Euros.

**Questionnaire** Subsequently, we will ask you some personal information. The data will be treated confidentially and will be used only for research purposes.

## Part II: Risk and Loss aversion tests

### Risk aversion

You have to select ONE gamble that you would like to play from the gambles below. Each gamble has two possible outcomes (Event A or Event B), each with 50% chance of occurring. For example, if you select gamble 4 and Event A occurs, you will gain 21 points. If event B occurs, you will get 57 points. Your gains in points will be converted into Euros according to the conversion rate: 20 points are equivalent to 1 Euro.

Figure 7: Risk aversion test

| Gamble | Event | Payoff in Points | Probabilities |
|--------|-------|------------------|---------------|
| 1      | A     | 33               | 50%           |
|        | B     | 33               | 50%           |
| 2      | A     | 29               | 50%           |
|        | B     | 41               | 50%           |
| 3      | A     | 25               | 50%           |
|        | B     | 49               | 50%           |
| 4      | A     | 21               | 50%           |
|        | B     | 57               | 50%           |
| 5      | A     | 17               | 50%           |
|        | B     | 65               | 50%           |
| 6      | A     | 7                | 50%           |
|        | B     | 75               | 50%           |

### Loss aversion

For EACH gamble below, you have to choose whether you want to Accept it or Reject it. If you reject a gamble, your payoff is zero. Each gamble has two possible outcomes (Event A or Event B), each with a 50% of occurring. After you have made your choice, one of the gambles you accepted will be picked at random and you will be paid the outcome of that gamble. Your gains in points will be converted into Euros according to the conversion rate: 20 points are equivalent to 1 Euro. See Figure 8.

Figure 8: Loss aversion test

| Gamble | Event | Payoff in Points | Probabilities |
|--------|-------|------------------|---------------|
| 1      | A     | 6                | 50%           |
|        | B     | -2               | 50%           |
|        |       |                  |               |
| 2      | A     | 6                | 50%           |
|        | B     | -3               | 50%           |
|        |       |                  |               |
| 3      | A     | 6                | 50%           |
|        | B     | -4               | 50%           |
|        |       |                  |               |
| 4      | A     | 6                | 50%           |
|        | B     | -5               | 50%           |
|        |       |                  |               |
| 5      | A     | 6                | 50%           |
|        | B     | -6               | 50%           |
|        |       |                  |               |
| 6      | A     | 6                | 50%           |
|        | B     | -7               | 50%           |

### Part III: Personal Information

At the end of the two parts, we asked participats some demographic information: gender, age, and degree studied.

# Appendix III: Screenshots for the coordination game (Small diversification treatment)

Figure 9: Screen 1

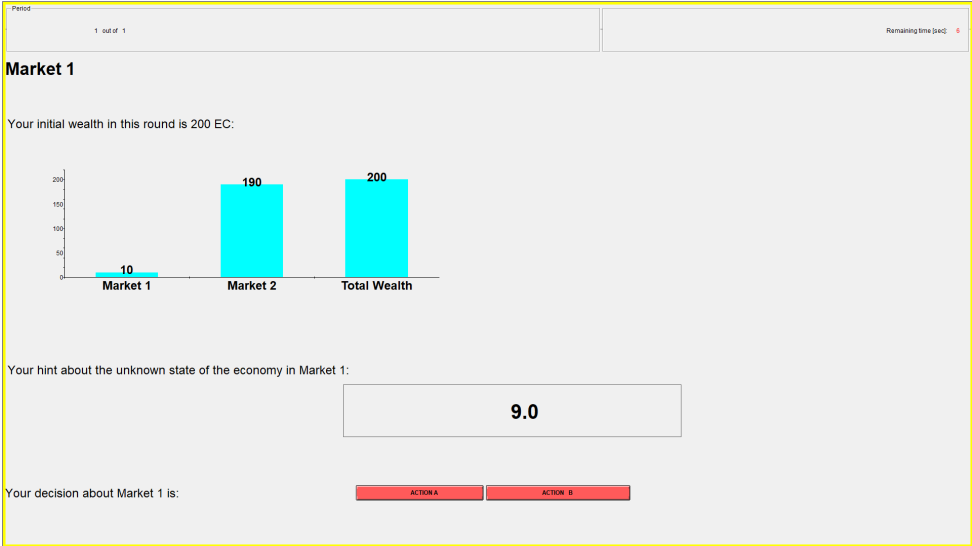


Figure 10: Screen 2

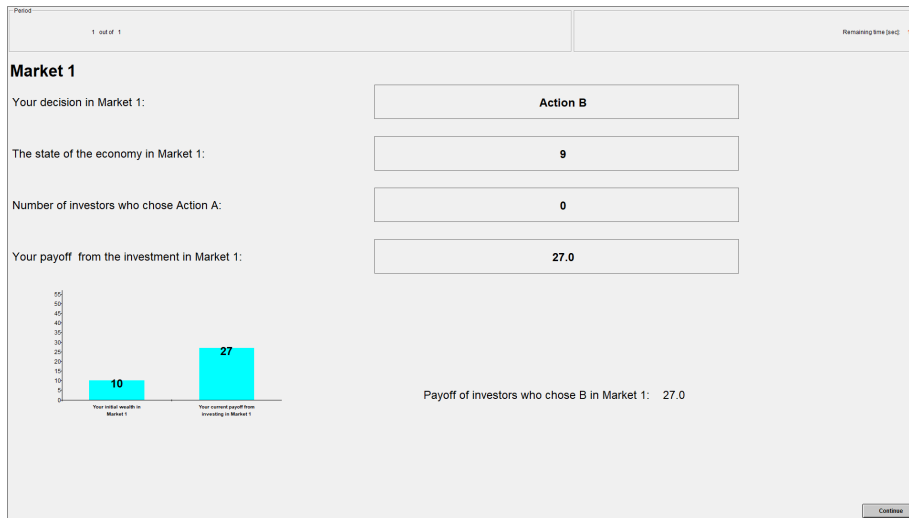


Figure 11: Screen 3

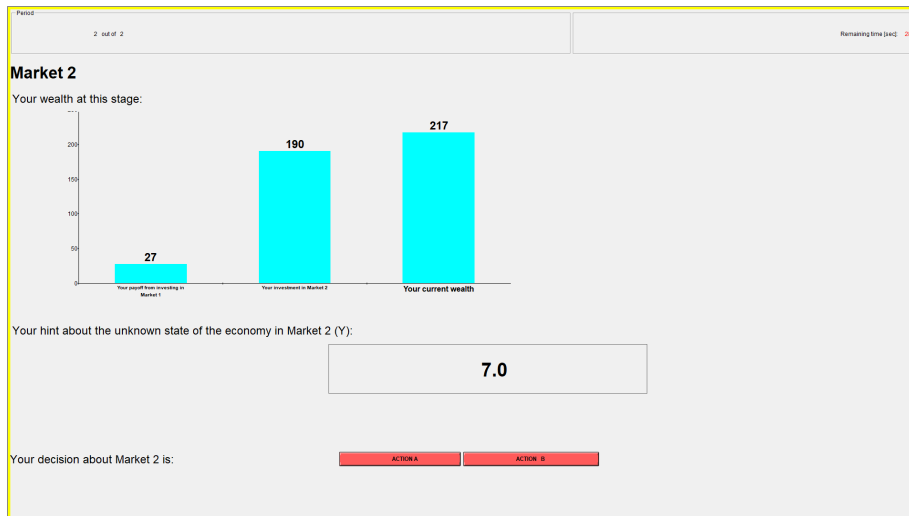
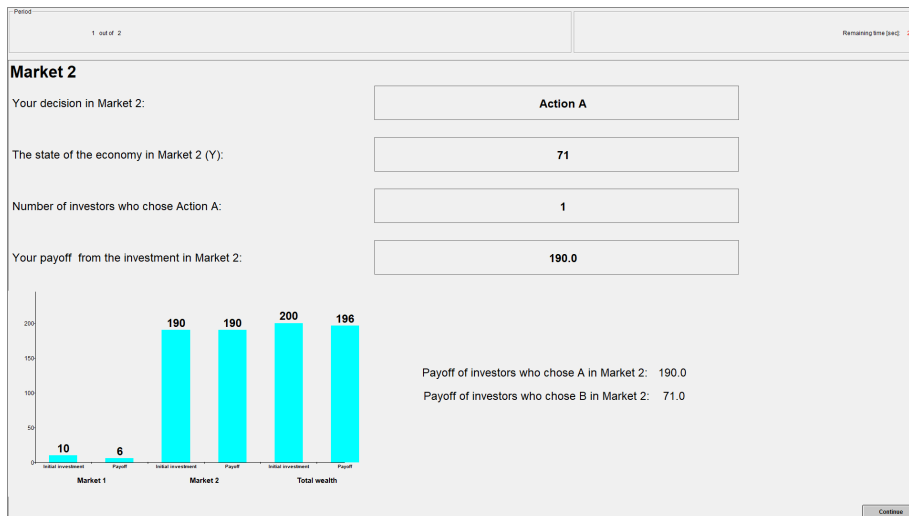
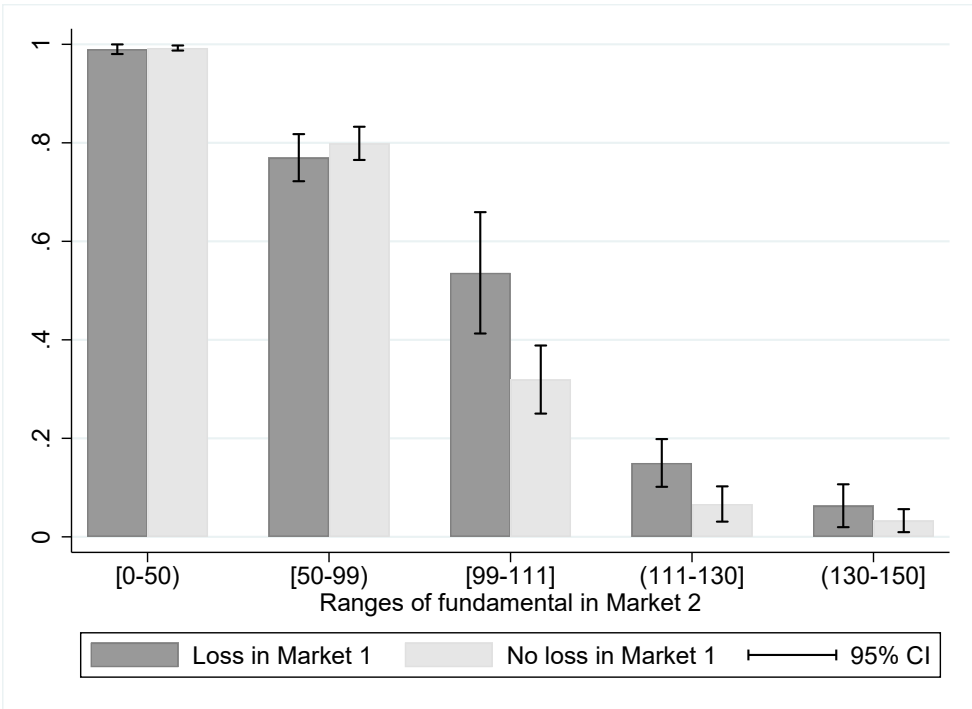


Figure 12: Screen 4



# Appendix IV: Robustness tests

Figure 13: Complete diversification treatment





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