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Working Papers in Economics and Statistics

2017-19

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The Role of Correlation in Two-Asset Games: Some Experimental Evidence*

Martin Geiger† Richard Hule‡

September 5, 2017

Abstract

In our experimental setting, participants face the decision to invest into two assets which are subject to correlated information. While fundamental states and signals about fundamental states are correlated, success and default of the investment projects is determined separately. Nevertheless, correlation of signals may give rise to spillovers through informational contagion since participants may overvalue correlated signals resulting from a double-counting problem in the updating process or may be prone to behavioral biases related to good and bad news. Quite strikingly, in our setting, the degree of correlation does not promote pronounced contagious effects. In particular, this is consistent with the theoretical two-dimensional global games solution of the underlying investment game. However, a heuristic of neglecting correlation and signals about the second asset has also merits to explain participants' investment behavior. In some treatments we can distinguish between participants' strategies being derived from the two-dimensional global game and from a heuristic being derived from a one-dimensional game. We cannot reject that people play the two-dimensional investment game as it would be two separate one-dimensional games and ignore correlation.

Keywords: global games, creditor coordination, experimental economics

JEL: C91, D82, G12

* Financial support through the Jubiläumsfonds (Project No. 15304) of the Oesterreichische Nationalbank is gratefully acknowledged.

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1. Introduction

How do people process correlated information? To contribute to this question, we carry out an experiment in which participants face the investment decision into two assets that are subject to correlated fundamental states. Participants receive public and idiosyncratic private information about the unobservable fundamental states of the two assets. Whether the investment yields a payout depends on the fundamental state of the respective asset and on the number of fellow participants that invest. In case participants do not invest, they receive a positive payout with certainty that is lower compared to the successful investment. We study to which extent the amount of correlation affects the way people take information about one asset into account when investing into another asset.

There is some evidence in the literature that the prevalence of correlated information biases people's behavior. E.g., Enke and Zimmermann (2017) identify a correlation neglect bias in the sense that people tend to treat correlated signals that are related to a common source to be independent.[1] They overvalue correlated signals and do not take adequately into account the resulting double-counting problem in the updating process when investing into the asset. As a result, people are excessively sensitive to related information and follow an overshooting pattern. In our experiment, however, we want to study a slightly different question. We want to assess whether correlation of fundamental states promotes contagion *across* assets in the spirit of such a correlation neglect bias. Such a channel of contagion might have been active e.g. in the context of government bonds during the recent European Sovereign Debt Crisis. The intuition of such a contagious channel is that news about e.g. the refinancing ability of Italy affects risk premia on Greek government bonds and vice versa. Empirical evidence shows that spreads of government bonds issued by Eurozone countries do not only depend on country-specific characteristics and an international risk factor, but also on news about foreign countries (De Santis, 2012, Metiu, 2012, Mink and de Haan, 2013).[2]

In this experiment we want to isolate one potential channel of informational contagion by studying the investment decision in assets with correlated fundamental states. Importantly, we rule out mutual spillovers in case of default of one asset to focus on informational contagion only due to the effects of correlation. While we change the amount of correlation of information about the fundamental states across treatments, the probability of success derived

[1] See also Kallir and Sonsino (2009) and Eyster and Weizsäcker (2011).

[2] Correlation of refinancing abilities in Currency Unions is conceivable due to various reasons (e.g. an increase in business cycle synchronisation, the common monetary policy, contingent liabilities, etc.). Contagion might therefore be particularly relevant in the Eurozone. Indeed, the introduction of the common currency has led to high degrees of convergence and co-movement of government bond yields.

from the theoretical solution of the investment game is comparable across treatments. This allows us to pin down the behavioral effects of correlation.

As a theoretical benchmark, we consider the continuous global game solution of the underlying investment game.[3] Under weak assumptions on the parameter space, global games can be solved uniquely. The model we refer to is introduced in a companion paper (Geiger and Hule 2016) and generalizes a model of debt rollover by Morris and Shin (2004) to a two-dimension game, where agents face the investment decision into two assets. While information about the two assets is correlated, there are no spillovers from one asset onto another in case of default. In other words, solvency conditions for each investment project do not depend on the realization of success or default of the other investment project. Contagion is solely transmitted through signals.

Global games have already been studied in the laboratory. Heinemann et al. (2004) examine the role of public and private information in affecting the coordination among participants. Heinemann et al. (2009) assess the predictive power of global games. Duffy and Ochs (2012) evaluate the global games refinement with other equilibrium selection principles. Trevino (2016) studies contagion in sequential global games and finds that, in some instances, contagion is reinforced even by uninformative foreign signals.

In our experiment, participants are exposed to settings where correlation of fundamental states and private signals are either low or high. Our findings indicate that the degree of correlation does not systematically affect the investment decision. Incidences of default are similar irrespective of the amount of correlation. Hence, the mere existence of correlation alone does not promote a behavioral bias that reinforces contagion among two assets. In particular, this is consistent with the theoretical prediction of the two-dimensional benchmark model which implies that contagious effects precipitated through correlation are very small.

However, the result that correlation does not have large effects may also be consistent with the notion that participants tend to play the two-asset game heuristically as if it would be two one-asset games regarding information about the two assets to be completely separate. Hence, we analyze whether the optimal strategy from the one-dimensional game or from the two-dimensional game better captures participants behavior. This is feasible because in the two-dimensional global game the individual decision is dependent on correlation while default of

[3] Global games were first studied by Carlsson and van Damme (1993) and further popularized by Morris and Shin (1998), who applied the global games refinement in a macroeconomic context. They can be applied to wide range of decision problems where coordination risk and incomplete information is involved. In such settings, the agents' payoffs depend on the actions of others as well as on an economic fundamental which is not perfectly observable.

the asset on the aggregate level is only to a small extent. It turns out that we cannot reject that participants play two separate one-dimensional games rather than one two-dimensional game.

Overall, the global games solution has some merits to forecast the behavior of participants in the laboratory. Although it appears that the coordination effect of good and bad information is stronger in the laboratory compared to the model, the behavior of participants responds to variations in the theoretical critical fundamental state in the direction predicted by the global games solution. This generalizes the findings from experimental evaluations of unidimensional models (see e.g. Heinemann et al. 2004).

2. The task

Participants take simultaneous investment decisions into two assets, Asset A and Asset B. In case they invest into the respective asset, they receive a payout of 10 Experimental Currency Units (ECU) in case of solvency of the investment project and 0 otherwise. The outside option is 4 ECU. Whether or not the investment yields a payout depends on the number of fellow participants who invest into the asset as well as on an unobservable fundamental, which we call θ_A for Asset A and θ_B for Asset B. In case the fundamental state is smaller than or equal to 0, there is no payout. In case the fundamental value is equal to or above 10, the asset pays out 10 ECU irrespective of the number of participants that invest. If the fundamental state is between 0 and 10, the realization of the payout is conditional on the number of investors. The investment project is successful if the fundamental state is large enough to sustain partial foreclosure, $\theta_A \geq nl_A$, where l_A is the fraction of participants who do not invest and n is the total number of participants for each investment, which is 10. Therefore, nl_A equals the number of participants that do not invest.

Upon investing, participants receive a public (i.e. visible to all participants) and a private signal about each asset, and are instructed on the amount of correlation of the fundamental states and the private signals. Also, they are instructed on the precision of signals.

Signals are determined as follows: As a first step, public signals are drawn. In the experiment, possible public signal realizations for both assets are either 0 (bad), 5 (intermediate), or 10 (good). Hence, we have nine possible combinations of the public signals which are uniformly distributed. Fundamental states of Asset A and Asset B are drawn from a bivariate normal distribution where the mean is the public signals about Assets A and B. Private signals about assets A and B are drawn from another bivariate normal density where the mean is the unobservable fundamental states of both assets.[4]

Participants take 100 investment decisions over 10 rounds of the experiment in which they have to indicate whether they invest into Asset A and whether they invest into Asset B. After each round, they learn how many ECU they receive from each investment. For each decision, groups are selected randomly. The sessions consist of 20 participants and we simultaneously formed two groups with constantly changing compositions. Participants were separated by blinds and they did know with whom they played they investment game.

The decision screen for one round is shown in Figure D. 1 in the appendix. For each investment decision, participants have to indicate whether they would like to invest or not by indicating "yes" or "no". To summarize the information, a graphical representation of the private and public signals can be displayed for each decision.

3. A Sketch of the Theoretical Model

As a theoretical benchmark we use a continuous, two-dimensional global games model, which we discuss in a companion paper (Geiger and Hule 2016). Under weak assumptions on the parameters space, the model allows us to determine success and default regions for assets A and B in the Nash Equilibrium. We do this by solving for equilibrium in switching strategies which are characterized by a critical boundary. At the boundary agents are indifferent between investing and not investing (i) and the investment project is on the verge of success and failure (ii). We can solve the model for the two assets separately. For ease of exposition, the equilibrium conditions are only shown for Asset A while they are analogous for Asset B.

Furthermore, please note that we define the model in the probability space. The total number of investors n acts as a scaling factor to scale the probability measures (i.e. the densities) in relation to the densities of the fundamental states and private signals in the experiment.

In equilibrium, the underlying fundamental state of Asset A, θ_A, is such that the investment project is on the margin of success and failure when θ_A conditional on θ_B equals the fraction of foreclosers l_A. The higher the fundamental state, the more partial foreclosure it can sustain. We summarize these critical states by the function ${\theta_A}^{crit}(\theta_B)$. ${\theta_A}^{crit}(\theta_B)$ divides the fundamental state space into a success and a default region:

$$\forall\theta_B: {\theta_A}^{crit}(\theta_B) = l_A$$

[4] See Appendix A for the specifications of the densities.

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{x_A{}^{crit}(x_B)} f_x\big(x_A, x_B, \theta_A{}^{crit}(\theta_B), \theta_B\big) dx_A dx_B,$$

where f_x is the density of private signals with mean $(\theta_A{}^{crit}(\theta_B), \theta_B)$. The fraction of foreclosers is determined by the critical private signal function, $x_A{}^{crit}(x_B)$, which characterizes signals x_A conditional on x_B, where agents are indifferent between investing and not investing.

Agents are indifferent in case the value of the outside option λ_A equals the expected value of the investment.[5] The expected value of the investment is given by the density of the fundamental state given the critical private signal times the total number of investors:

$$\forall x_B : \lambda_A = \int_{-\infty}^{\infty} \int_{\theta_A{}^{crit}(\theta_B)}^{\infty} g_{\theta|x}\left(\theta_A, \theta_B, \zeta_A\big(x_A{}^{crit}(x_B), x_B\big), \zeta_B\big(x_A{}^{crit}(x_B), x_B\big)\right) \mathrm{d}\theta_A \mathrm{d}\theta_B,$$

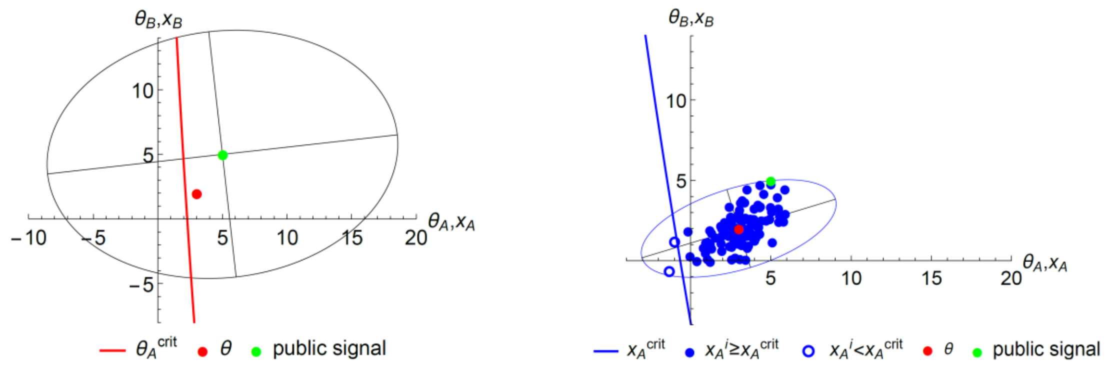
where the portion of the density above the critical fundamental state function is the expected value of the investment. The mean of the conditional distribution $g_{\theta|x}$, $\zeta = (\zeta_A\big(x_A{}^{crit}(x_B), x_B\big), \zeta_B\big(x_A{}^{crit}(x_B), x_B\big)$, is given by the convex combination of the critical signal x_A given x_B and the public signal (i.e. Bayes update). We solve the model for the two equilibrium functions in switching strategies which allows us to determine the probability of success of the investment project.

Figure 1 shows the critical functions for one possible parameterization. Also, we show one sample draw of the fundamental states to illustrate the game. The densities of the fundamental states and the private signals are illustrated by 99 percent confidence ellipses. Panel A illustrates the function $\theta_A{}^{crit}$, that divides the fundamental state space into a success and a default region, and one sample draw of the fundamental state. Realizations of θ to the right of $\theta_A{}^{crit}$ lead – according to the model – to a payout for the investment into asset A while relations to the left of $\theta_A{}^{crit}$ correspond to no payout (i.e. the investment project defaults). The sample draw is located in the success region since it is to the right of $\theta_A{}^{crit}$. Panel B shows the function $x_A{}^{crit}$, that divides the signal space into acceptance and denial regions, and 100 sample draws of private signals. In this case, only 2 out 100 draws of the private signal lie in the denial region. Hence, according to the model, for the respective draw of the fundamental states approximately 2 percent of investors foreclose.

[5] The scaling also applies to the outside option. In the experiment, participants receive 4 ECU. Hence, to solve for equilibrium, we parametrize λ_A to 0.4.

Figure 1: Illustration of the Game

Panel A: Solvency and Default Regions Panel B: Acceptance and Denial Regions



Notes: The density of θ, g_θ, is represented by the 99 percent confidence ellipse (black). The density of x, f_x, is represented by the 99 percent confidence ellipse (blue). Default and solvency regions are illustrated in Panel A. Realizations of θ to the right of ${\theta_A}^{crit}$ lead – according to the model – to a payout for the investment into asset A while relations to the left of ${\theta_A}^{crit}$ correspond to no payout. Panel B shows acceptance and denial regions. According to the model, agents with realizations of private signals x_i to the right of ${x_A}^{crit}$ rollover while agents signal to the left of ${x_A}^{crit}$ foreclose.

4. Treatments and Conjectures

We use a between-subject design. Since we are interested in how people process correlated information, we vary the amount of correlation of the fundamental states and the private signals across treatments. In the symmetric treatments, correlation of both, the fundamental states and the private signals is either low or high (see Table 1).

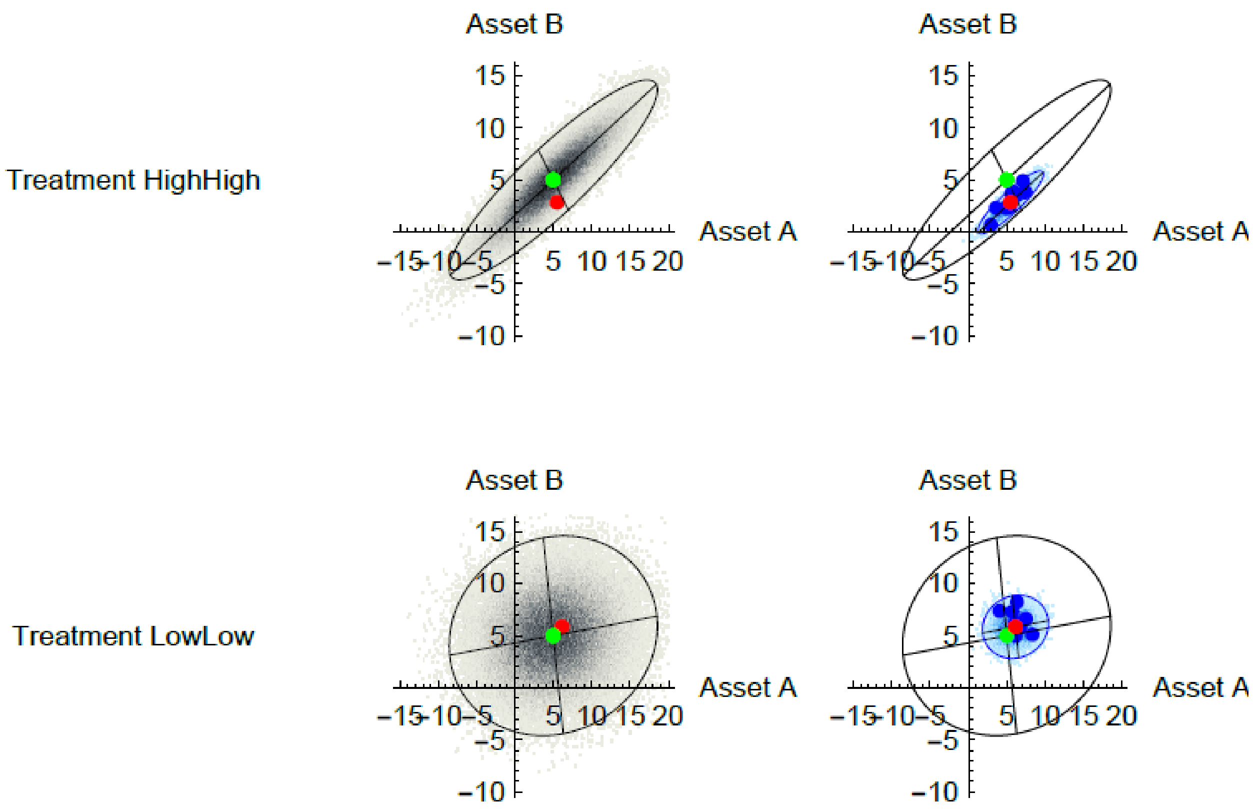
Table 1: Treatments

		Correlation of the private signals	
		0.1	0.9
Correlation of the fundamental states	0.1	LowLow	
	0.9		HighHigh

Figure 2 illustrates the densities of the fundamental states and private signals for the two treatments together with 99 percent confidence ellipses. The densities are represented by two-dimensional density plots where the shade of the colors gets darker towards the center according to the densities. The graphs in the middle column of Figure 2 illustrate the densities of the fundamental states. Note that for higher correlation of the fundamental states

(Treatment HighHigh), fundamental states have a tighter relationship resulting in narrower densities. The same applies to the densities of private signals (see the blue ellipses in the right column of Figure 2): higher correlation of private signals (Treatment) results in narrower densities.

Figure 2: Illustration of the Informational Precision and Correlation (LowLow and HighHigh)



Notes: We indicate 99 percent confidence ellipses.

Participants were intensively instructed on how the signals are related to fundamental states and how their own private signals about Asset A and Asset B are related to the private signals of fellow participants. Instructions were read aloud.[6] Using graphs such as the ones shown in Figure 2, we instructed subjects on the densities to foster their intuition for the distributions from which fundamental states and private signals are drawn (of course, we provided them with larger graphs with a much higher resolution).[7] Moreover, before participants had to take investment decisions, they underwent sequences of interactive stages on the computer, where

[6] See Appendix C for the instructions.

[7] We also provided the variance-covariance matrices for the distributions of the fundamental states and the private signals in appendix to the instructions, but we did not expose them actively to the matrices.

they were exposed to sample draws of signals.[8] Also, there was one training round, where participants took ten investment decisions into each asset and had the opportunity to acquaint themselves with the devices on the decision screen.[9] The training round was not incentivized.

With the variation across the symmetric treatments we seek to investigate how people process different degrees of correlation and whether they become more susceptible to contagious effects vis-à-vis higher correlation. Ex ante, there are at least two possible conjectures how the treatment variation may affect participants' behavior. First, according to our theoretical benchmark, i.e. the global games Nash equilibrium prediction, the amount of correlation does not considerably affect the probability of default of the investment project. The intuition is that since there are no mutual effects between the two assets in case of default, the only channel of contagion is through information. In one-dimensional global games, given the outside option, the determinants of the probability of default are essentially the public signal and the precision parameters of the distributions of the fundamental states and the private signal. In the two-dimensional case, the agent additionally considers precision parameters from the second dimension (the other asset), the correlations of fundamental states and private signal as well as the public signal about the other asset. Although the agent considers the two-dimensional parameters, their effects on the probability of success are very small for precision parameters and correlation and are even zero for changes in the public signal about the other asset (see Geiger and Hule, 2016). A shift in the public signal about Asset B only results in a level shift of the probability of success of Asset B, while the probability of success of Asset A remains unchanged.[10]

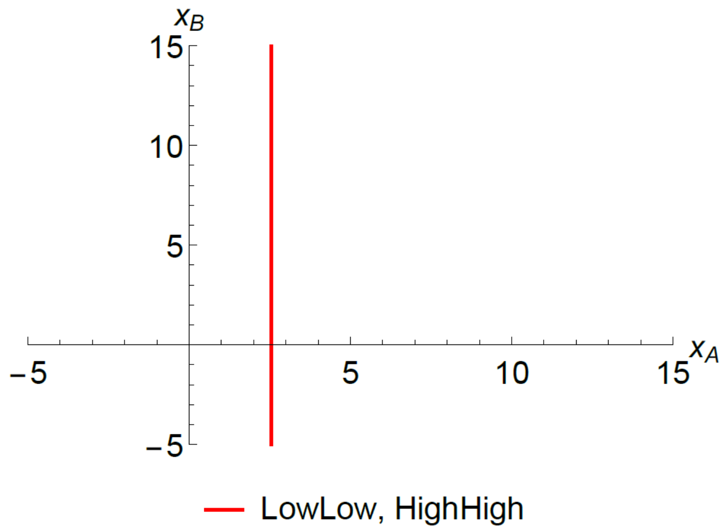
Hence, from the theoretical benchmark, in terms of the incidences and success and default of the investment project, we expect no differences across treatments. However, from a behavioral point of view, it is conceivable that participants react overly sensitively to information about one asset when investing into the other asset despite the fact that there are no fundamental linkages among the two assets. In this case, we would observe positive and negative contagion depending on the signals about the second asset.

[8] In the first stage, participants sequentially drew public signals, fundamental states and a sample of ten private signals. Realizations were illustrated graphically. Next, participants were exposed to the numerical values of a dummy sample of private signals to support participants' intuition on how private signals are related.

[9] For each investment decision, participants could access a graphical representation of their signal draws.

[10] A change in the public signal about Asset B shifts the density of the distribution of the fundamental states along the B-dimension. Ceteris paribus, this would result in a change of the probability of success of Asset A. But since ${\theta_A}^{crit}$ exactly shifts in the same direction and by the same amount, the probability of success of Asset A remains constant.

Figure 3: Cutoff functions ${x_A}^{crit}$ for Treatments LowLow and HighHigh



Notes: The figure shows theoretical cutoffs for each treatment dividing the signal space into a denial and an acceptance region.

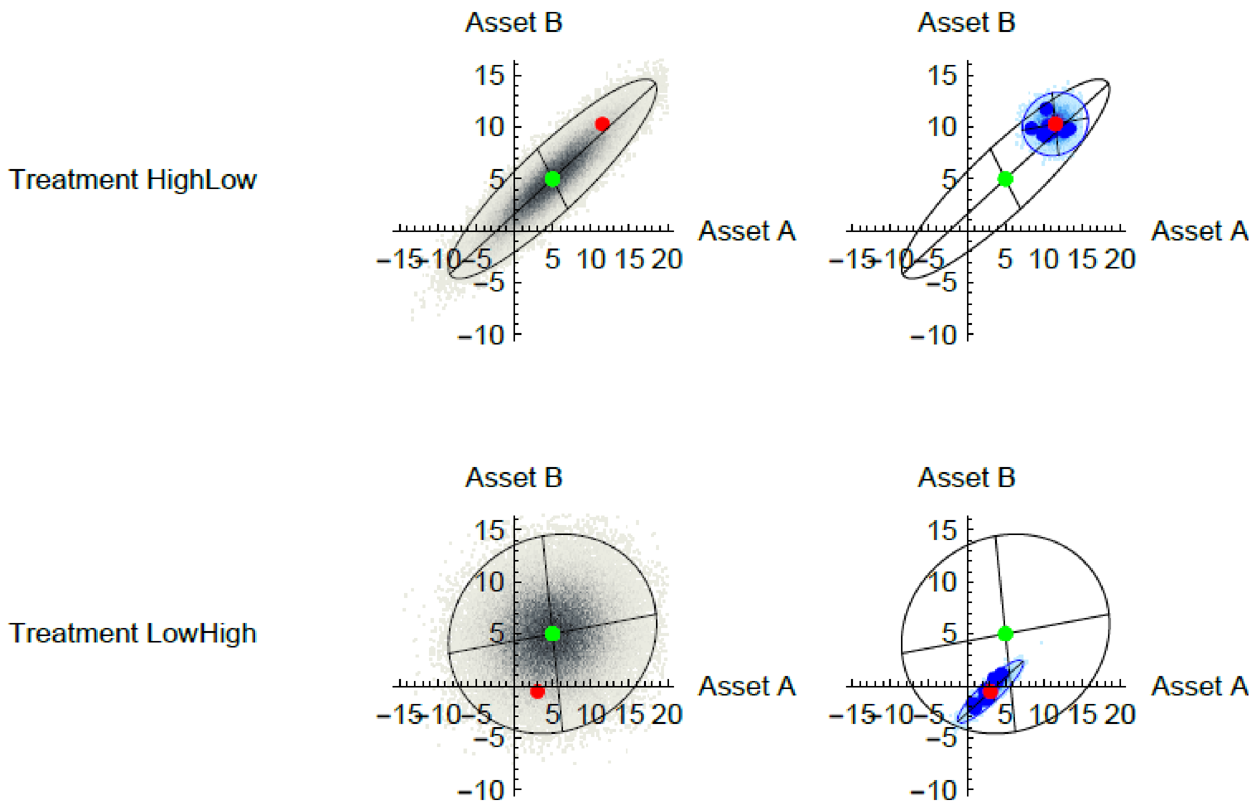
Theoretical cutoffs for the Treatments LowLow and HighHigh and the investment decision into Asset A are shown in Figure 3. The public signal is 5 for both assets in this example. Changes in the public signals lead to parallel shifts of the critical cutoff functions in the A and in the B-dimension respectively. Please note that for Treatments LowLow and HighHigh cutoffs are numerically identical and constant in the private signal about Asset B, x_B. Hence, from a theoretical point of view, participants should process signals the same way in Treatments LowLow and HighHigh. The reason why the cutoffs in case of Treatments LowLow and HighHigh are numerically identical is that in these cases the parametrization is akin to a special case where information about the second asset and correlation parameters cancels out from the equilibrium conditions (see Geiger and Hule 2016). In these cases the two-dimensional game boils down to the one-dimensional game discussed in Morris and Shin (2004). The special case is characterized by identical correlations of the fundamental states and private signals as well as identical precision parameters corresponding to the dimensions A and B for the densities of the fundamental states and the private signals. The parametrization used to draw signals in Treatments LowLow and HighHigh slightly differ from the special case because we have different precision parameters for information about Asset A and B. Nevertheless, since correlations of fundamental states and private signals are identical, numerically, the cutoffs are identical than for the special case.

Therefore, for Treatments LowLow and HighHigh we cannot plausibly distinguish whether the one-asset or two-asset game and the respective solutions better capture the participants' behavior. To scrutinize whether people simply disregard one asset when investing into the other asset (i.e. play the one-dimensional game), we consider two additional treatments for which theoretical solutions are not constant in the private signal about Asset B, x_B. Cutoffs are not constant when the parametrization differ from the special case also in respect to the correlations of fundamental states and private signals. Hence, we look at Treatments in which these correlations differ (see Table 2).

Table 2: Treatments

		Correlation of the private signals	
		0.1	0.9
Correlation of the fundamental states	0.1		LowHigh
	0.9	HighLow	

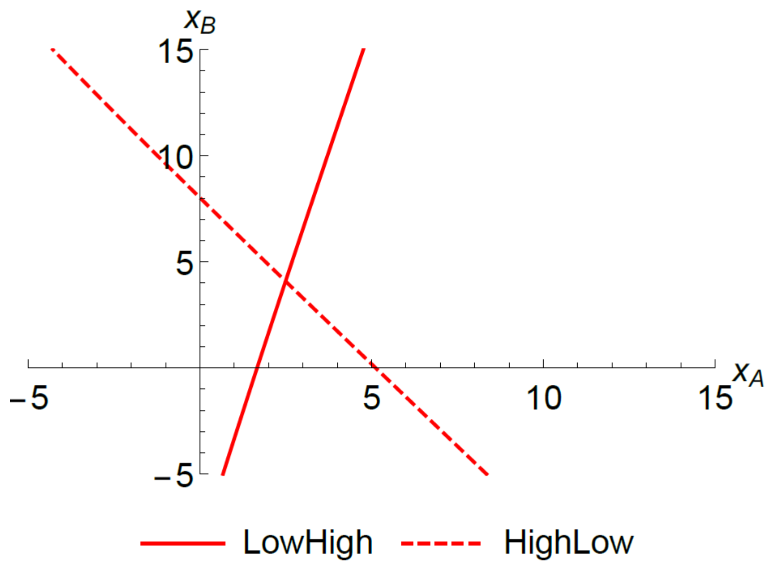
Figure 4: Illustration of the Informational Precision and Correlation (HighLow and LowHigh)



Notes: We indicate 99 percent confidence ellipses.

Densities for fundamental states and private signals for Treatments HighLow and LowHigh are shown in Figure 4. In these Treatments, cutoffs are not constant in x_B (see Figure 5). The critical private signal about Asset A ${x_A}^{crit}$ is increasing in the private signal about Asset B in Treatment LowHigh and decreasing in Treatment HighLow. We are going to exploit this variation in the slopes of the critical functions below when we evaluate whether participants rather use a cutoff which is constant in the private signal x_B or a cutoff that depends on x_B. Specifically, we evaluate whether investment behavior is rather captured by the constant cutoff or the conditional cutoff which is dependent on x_B.

Figure 5: Cutoff functions ${x_A}^{crit}$ for Treatments LowHigh and HighLow



Notes: The figure shows theoretical cutoffs for each treatment dividing the signal space into a denial and an acceptance region.

5. Results

For each treatment we have 40 participants in two sessions per treatment. In each session two groups traded 100 assets of type A and type B. Hence, in total, 400 (=2*2*100) assets of type A and B are traded in each treatment. Since there are 3x3 different combinations of public signals (bad, medium and good public signals), we have approximately 44.4 observations for market outcomes for each combination of public signals. Table 3 shows the fractions of successful investment projects for each combination of public signals and for each treatment. The fractions of successful investment projects for Asset B are shown in Table B. 1 in Appendix B. To avoid going back and forth between the two investment decisions into Asset A and Asset B when discussing the results, we only consider Asset A in the discussion of the results, but our findings similar for Asset B. Results for Asset B are relegated to the Appendix and only briefly commented in the main text.

Since we draw the combinations of public signals randomly from a uniform distribution, observations across markets vary. We have a minimum of 26 markets and a maximum of 62 markets for each parametrization. As a reference, we also indicate the theoretical predictions from the continuous model in parenthesis. Please recall that from the theoretical predictions we do not expect (i) pronounced differences across treatments and (ii) effects of the public signal about one asset onto the other. For changes in the public signal (i.e. ii), from the theoretical benchmark we even expect a zero effect. Hence, since the probability of success of Asset A is identical across realizations of the public signal about Asset B, we indicate the theoretical probability of success only in the last column in parenthesis.

Table 3: Fraction of successful investments into asset A in %

	Public Signal Asset A	**Public Signals Asset B**			
		0	**5**	**10**	**Average**
LowLow	**0**	7.9	4	3.8	5.3 (38)
	5	66	50	67.6	60.3 (53.2)
	10	88.6	94	85.7	89.3 (68)
Average		56.8	49.3	62.1	55.5
HighHigh	**0**	14.3	10.5	11.7	12.3 (38)
	5	61.9	54.5	44.1	54.2 (53.2)
	10	95.2	81.3	94.2	91.3 (68)
Average		52.9	47.4	48.6	49.8
LowHigh	**0**	13	5.3	16.7	11.7 (38)
	5	62.5	53.2	30	50.6 (53.2)
	10	90.9	92.9	91.7	91.8 (67.9)
Average		55.5	52.1	45.5	51.5
HighLow	**0**	9.5	4.2	4.8	6.1 (38.1)
	5	66.7	50	59.1	59.3 (53.1)
	10	76.5	85.7	96.7	88 (67.7)
Average		49.2	48.5	58.9	52.5

Notes: Predictions from the continuous global game in parenthesis.

Across treatments we find success rates of similar orders of magnitude conditional on the public information about Asset A. The fractions are already indicative about two important findings: First, public signals about Asset B do not considerably affect participant's investment into Asset A, which is exactly what we would expect from the theoretical benchmark. Second, differences across treatments are not very large and not particularly systematic. In none of the treatments, success rates are particularly high or low across the three steps of the quality of the public signal of Asset A. Moreover, qualitatively, realized success rates are consistent with the global games prediction for the continuous game. Nevertheless, while for public signals with medium quality (i.e. the public signal about Asset A equals 5) the global games prediction is also quantitatively remarkably accurate, this is clearly not the case for bad and good public signals. In case of bad public signals, participants tend to shy away from investing compared to the theoretical prediction leading to relatively low success rates. In case of good public signals, people are more likely to invest compared to the global games prediction leading to relatively high success rates. Hence, we conclude that coordination effects of good and bad information are stronger in the laboratory compared to the model. Nevertheless, the behavior of participants clearly responds to variations in the theoretical critical fundamental state in the direction predicted by the global games solution. This finding is consistent with behavior observed in one-dimensional global games (e.g. Heinemann et al. 2004). Pooled over all treatments and all public signals about Asset B, we observe approximately 9% of all markets to yield successful investment projects given the public signal about Asset A is 0. For a public signal of 5, the average success rate is 55.8%. In case of a public signal of 10, we observe 90% of all markets to yield a positive payout for investing participants.

To investigate further what drives participants' behavior on the individual level, we study the determinants of the investment decision. Specifically, we further scrutinize the effects of different amounts of correlation (i.e. Treatments) and the effects of signals about Asset B on the investment decision into Asset A. Table 4 reports marginal effects evaluated at means for probit regressions, where we regress the individual investment decision on public signals about asset A and B, the deviation between private and public signals which we interpret as the additional information of the private signals which is distinct from the public signals. In addition to the signals, we control for the Treatments as well as the periods capturing potential learning effects (Broseta 2000), the time people take to make the decisions for each stage[11] and the amount of ECU earned (one ECU is worth 1 Eurocent). In the last column we allow for interaction effects for the treatments and public and private signals to account for the

[11] Each decision stage in each period consists of 10 investment decisions into both assets.

possibility that subjects process the signals differently depending on the treatment. Results for the investment decision into Asset B are shown in Table B. 2.

From the regressions we get a clear indication that participants tend to predominately consider signals about Asset A when they invest into this asset. Since the public signals vary only in three steps, we introduce dummy variables for qualities of public signals of 0, 5 and 10. Receiving better public signals about Asset A increases the likelihood to invest by approximately 40 and 70 percentage points, respectively. A change of the additional private information about Asset A, which we define as the difference between the private and the public signal, by one unit, increases the probability of a participant investing into Asset A by approximately 5 percentage points. Further independent variables introduced in the second regression do basically not affect participant's investment decision. Only the amount of tokens earned has a significant, albeit small influence on participants' propensity to invest. Participants, who earned one Euro more compared to the average, are approximately 4 percentage points more likely to invest.

We allow for interaction effects in the third regression. This does not reveal very pronounced and systematic differences in the way how participants process signals across treatments. Nevertheless, it is noteworthy that participants tend to react less strongly to signals in Treatment LowHigh. In particular they react less strongly to public signals about Asset A. In sum, the unique effect of the Treatment LowHigh is slightly negative and weakly significant (the unique effect has a p-value of 0.073). Unique effects for the other Treatments are not significant.

Table 4: Determinants of the Investment Decision

	Investment	Investment	Investment
PubSignalA==5	0.439***	0.436***	0.429***
	(0.000)	(0.000)	(0.000)
PubSignalA==10	0.711***	0.709***	0.727***
	(0.000)	(0.000)	(0.000)
PubSignalB==5	-0.000400	-0.00430	0.0311
	(0.973)	(0.725)	(0.210)
PubSignalB==10	-0.00298	-0.00570	0.0290
	(0.832)	(0.680)	(0.290)
PrivPubDevA	0.0554***	0.0559***	0.0547***
	(0.000)	(0.000)	(0.000)
PrivPubDevB	0.00173	0.00226	0.00186
	(0.433)	(0.302)	(0.575)
Treatment HighHigh		0.0414	0.0870
		(0.384)	(0.378)
Treatment LowHigh		-0.0286	0.103
		(0.545)	(0.305)
Treatment HighLow		0.0388	0.0108
		(0.394)	(0.924)
Period		0.0000359	-0.00103
		(0.991)	(0.742)
Time		-0.000118	-0.000127
		(0.794)	(0.778)
Total Profit		0.000444***	0.000440***
		(0.000)	(0.000)
HighHigh*PubSignalA==5			0.0247
			(0.779)
HighHigh*PubSignalA==10			-0.00885
			(0.954)
LowHigh*PubSignalA==5			-0.117
			(0.195)
LowHigh*PubSignalA==10			-0.258*
			(0.058)
HighLow*PubSignalA==5			0.118
			(0.216)
HighLow*PubSignalA==10			0.111
			(0.538)
HighHigh*PubSignalB==5			-0.0775**
			(0.014)
HighHigh*PubSignalB==10			-0.0816**
			(0.043)
LowHigh*PubSignalB==5			0.0223
			(0.500)
LowHigh*PubSignalB==10			-0.0357
			(0.333)
HighLow*PubSignalB==5			-0.0944***
			(0.008)
HighLow*PubSignalB==10			-0.0466
			(0.192)
HighHigh* PrivPubDevA			0.00602
			(0.637)
LowHigh* PrivPubDevA			-0.00365
			(0.739)
HighLow* PrivPubDevA			0.00472
			(0.725)
HighHigh* PrivPubDevB			-0.000369
			(0.962)
LowHigh* PrivPubDevB			-0.00769*
			(0.070)
HighLow* PrivPubDevB			0.00574
			(0.318)
	16000	16000	16000

Notes: Probit regression reporting marginal effects evaluated at means. Standard error adjusted for subject-clusters; p-values in parentheses (* p<0.1, ** p<0.05, *** p<0.01).

Overall, from the evaluation of treatment effects and the effects of information directly related to Asset B, we confirm the intuition from the descriptive statistics presented in Table 3: The amount of correlation between fundamental states as well as the amount of correlation between private signals has no systematic effect on participants' propensity to invest. Hence, in our setting, correlation does not appear to be a prominent transmitter of contagion across assets. In line with this evidence, we do not find that participants take signals about Asset B into account when they take the investment decision into Asset A.

In a next step of the analysis, we evaluate accuracy of the global games prediction in our setting. Table 5 shows the shares of participants investing consistently with the theoretical benchmark (Table B. 3 shows the results for Asset B). An investment decision qualifies to be consistent with theory, if someone whose signal is located in the acceptance region of the signal space, invests, and if someone whose signal is located in the denial region of the signal space, does not invest.

Across Treatments, approximately 80.5 percent of the participants invest in line with the continuous model. The shares vary slightly across Treatments, but are of similar orders of magnitude. Interestingly, we observe the highest share of theory-consistent investment decisions for good public signals which might be related to the fact that investment are less risky and hence, risk aversion might play a less dominant role.

Table 5: Shares of Participants investing into Asset A consistent with the theoretical prediction (in percent)

	LowLow	**HighHigh**	**HighLow**	**LowHigh**
PubSignalA==0	76.5	79.4	83.1	75.6
PubSignalA==5	74	76.9	78.6	73.2
PubSignalA==10	89	87.7	88	81.6

To have a closer look at what drives the consistency with the theoretical prediction, we assess the determinants of theory-consistent investment decisions. Table 6 shows results from a probit regressions (Table B. 4 shows the results for the theory-consistency of investment decisions into Asset B). In the first regression we control for discrete changes in the public signals and for the deviation between the public and private signals (i.e. the additional information provided by the private signal). Moreover we control for treatment effects, for the distance of private signals to the critical border, the number of periods played, the time participants take to finish the stage where they take 10 investment decisions and the payout.

The distance between the critical border ${x_A}^{crit}(x_B)$ and the private signal is measured as the Euclidean norm. We consider this measure capturing that people may be more uncertain about investing or not the closer they are to the theoretical threshold. If the theoretical benchmark is relevant to explain investment behavior, we would intuitively expect higher uncertainty around the critical border: the closer the signals are to the critical border, the more difficult it is to assess the chances for default. A significant and positive marginal effect would indicate that distance from the critical border is associated with higher propensity to invest in a way consistent with theory. Evaluating the theory-consistency of investments, this is our main variable of interest.

Table 6: Determinants of theory-consistent Investment Decisions

	investment consistent with theory	investment consistent with theory
PubSignalA==5	-0.0465***	-0.0722*
	(0.006)	(0.081)
PubSignalA==10	-0.0998***	-0.117
	(0.001)	(0.128)
PubSignalB==5	0.00421	0.0270*
	(0.591)	(0.096)
PubSignalB==10	-0.00338	0.0145
	(0.704)	(0.481)
PrivPubDevA	-0.0180***	-0.0209***
	(0.000)	(0.000)
PrivPubDevB	0.00619***	0.00136
	(0.000)	(0.431)
Treatment Highhigh	0.0158	0.0452*
	(0.252)	(0.088)
Treatment LowHigh	0.0277**	0.0654**
	(0.032)	(0.018)
Treatment HighLow	-0.0179	0.0137
	(0.166)	(0.682)
Distance to Border	0.0366***	0.0420***
	(0.000)	(0.000)
Period	0.00633***	0.00644***
	(0.000)	(0.000)
Time	-0.000238	-0.000214
	(0.113)	(0.132)
Total Profit	0.000679***	0.000676***
	(0.000)	(0.000)
HighHigh*PubSignalA==5		0.0447
		(0.238)
HighHigh*PubSignalA==10		0.0467
		(0.463)
LowHigh*PubSignalA==5		0.00940
		(0.845)
LowHigh*PubSignalA==10		-0.0552
		(0.611)
HighLow*PubSignalA==5		0.0266
		(0.512)
HighLow*PubSignalA==10		0.0432
		(0.488)
HighHigh*PubSignalB==5		-0.0536*
		(0.062)
HighHigh*PubSignalB==10		-0.0922**
		(0.012)
LowHigh*PubSignalB==5		-0.0308
		(0.217)
LowHigh*PubSignalB==10		-0.00451
		(0.859)
HighLow*PubSignalB==5		-0.0420*
		(0.096)
HighLow*PubSignalB==10		-0.00334
		(0.895)
HighHigh* PrivPubDevA		0.00944
		(0.223)
LowHigh* PrivPubDevA		-0.00407
		(0.596)
HighLow* PrivPubDevA		0.0168**
		(0.012)
HighHigh* PrivPubDevB		-0.00214
		(0.553)
LowHigh* PrivPubDevB		0.0101***
		(0.001)
HighLow* PrivPubDevB		-0.00560
		(0.196)
HighHigh* Distance to Border		-0.00493
		(0.598)
LowHigh* Distance to Border		-0.00409
		(0.680)
HighLow* Distance to Border		-0.00870
		(0.332)
Observations	16000	16000

Notes: Probit regression reporting marginal effects and standard error adjusted for subject-clusters. Marginal effects evaluated at means; p-values in parentheses (* p<0.1, ** p<0.05, *** p<0.01)

Turning now to the first regression, we first evaluate whether the variation in theory-consistency of investments depend on whether participants receive good or bad signals. Interestingly, the higher shares of participants investing theory-consistently for good public signals shown in Table 5 is apparently not related to a general tendency of participants investing in a more theory-consistent manner vis-à-vis good public signals.[12]

Treatment effects are not very systematic. Though, in one case, Treatment LowHigh, the dummy is significant and positive, the magnitude of the effect is rather modest. Interestingly, regarding Asset B, we observe a significant treatment effect for Treatment HighLow (see Table B. 4). Overall, the treatment effects are not very systematic making it difficult to interpret.

The effect of the distance to optimum appears to be very distinct. Receiving a private signal which is one unit farther away from the critical border ${x_A}^{crit}(x_B)$, increases the propensity to invest in a theory-consistent way by approximately 4 percentage points. The large and significant effect of the distance to the critical border reemphasizes the fact the theoretical benchmark has some merit in explaining participants behavior in the laboratory.

Moreover, the number of periods is positively related to the likelihood of theory-consistent investments. Hence, we observe some degree of convergence to the global games prediction. Also, those participants with higher payouts from the experiment tend to invest in theory-consistent manner to a larger extent. Taking more time to take the investment decision is not related to theory consistency of investments. In contrast to that, time, albeit only weakly significant, has a negative marginal effect.

In the second regression we allow for interaction effects to take account for treatment differences transmitted through the processing of information and through different effects of the distance to the border. While some of the marginal interaction effects are significant, we cannot infer a systematic and distinct pattern for interactions with the treatments. Hence, summarizing the results concerning the theory-consistency of the investment decisions, we conclude that Treatment effects are rather modest and the theoretical cutoff ${x_A}^{crit}(x_B)$ has some merit in capturing participants' investment decisions.

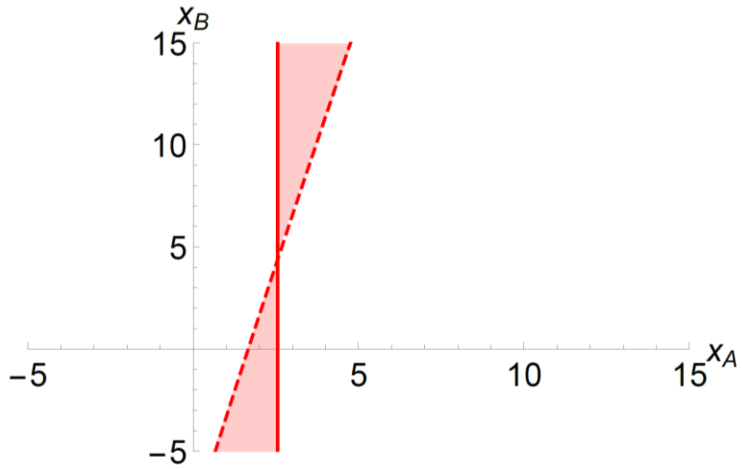
To further study which role the theoretical cutoff plays, and whether participants, on average, take the slope of ${x_A}^{crit}(x_B)$ into account when investing into the Asset A, we evaluate

[12] Since high public signals about Asset A make it more likely to receive signals farther away from the critical border (the density of the distribution of the fundamental states shifts to the right), it is rather the distance of private signals to the critical border that facilitate higher shares of theory-consistent investments vis-à-vis good public signals.

whether participants tend to use different cutoffs depending on the Treatment. Please recall that in Treatments LowLow and HighHigh cutoffs are constant while they have a positive slope in case of Teatment LowHigh and a negative slope in Treatment HighLow. We evaluate on a descriptive level whether participants' investment decisions are rather captured by a constant cutoff (ignoring correlations and private signals about Asset B) or by a cutoff that is conditional on private signals about Asset B. Specifically, we evaluate for Treatments LowHigh and HighLow, whether the respective theoretical cutoffs, which are conditional on the private signal x_B, or constant cutoffs are more likely to correctly predict investment behavior. As constant benchmark cutoffs we use the cutoffs derived from Treatments LowLow and HighHigh given public signals about Asset A and Asset B. As mentioned above, due to parametrization that is akin to the special case discussed above, these cutoffs are as for a one-dimensional game where agents only invest in one asset and do not take information about the other asset into account.

We look at cases in Treatments LowHigh and HighLow where, given private signals about Assets A and B, the investment behavior is predicted differently depending on whether one would use a constant or non-constant cutoff. Figure 6 illustrates how we identify these cases. For signals which are to the left of both functions, participants do not invest no matter which cutoff they use. For signals which are to the right of both functions, participants invest in any case. We consider investment decisions of participants who received private signals located in the red shaded area.

Figure 6: Cutoff conditional on x_B vs. constant cutoff



Notes: The figure illustrates acceptance and denial regions for constant and non-constant cutoffs.

Table 7 shows actual investment decisions split into four cases. In the left panel we classify the observations for participants who did not invest, in the right panel we classify participants who invested. The four cases classify whether the actual investment decisions are consistent with according to the constant cutoff and consistent with the conditional, non-constant cutoff (2*2 cases). Considering the left Panel of Table 7 we see that the majority of investment decisions are consistent with predictions using either of the cutoffs (2511 out of 3807 observations). Considering the right Panel this share is even higher (3724 out of 4193 observations). For the cases printed in bold, the two cutoffs predict different investment decisions. The number of cases where investment decisions are consistent with predictions based on the non-constant, actual global games cutoff, is 148+22=170. The number of cases where investment decisions are consistent with predictions based on the constant cutoff is lower amounting to 41+74=115. Though, if we redo the same exercise using investment decisions into Asset B (also in case of Asset B cutoffs are non-constant in Treatments LowHigh and HighLow while they are constant in the other treatments), we get the opposite results (consider Table 8). For cases where the two predictions differ, clearly more participants invest consistent with the constant cutoff (236 vs. 954 cases).[13] Hence, we cannot reject that participants use constant cutoffs (i.e. play the game as it would be one-dimensional game) in their investment strategies.

Table 7: Investment decisions into Asset A

No Investment (no. of obs.: 3807)				Investment (no. of obs.: 4193)			
		non-constant cutoff				non-constant cutoff	
		not inv.	invest			not inv.	invest
constant cutoff	not inv.	2511	**41**	constant cutoff	not inv.	373	**22**
	invest	**148**	1107		invest	**74**	3724

Notes: The table shows consistency of the actual investment decisions with the constant and non-constant (two-dimensional global games) cutoff

[13] Due to different precision parameters for the two assets, critical functions differ across assets. In case of Asset B, a larger portion the density of the private signals is located in the region, where predictions from the cutoffs derived from the two-dimensional global game and from the constant cutoff differ.

Table 8: Investment decisions into Asset B

No Investment (no. of obs.: 3591)				Investment (no. of obs.: 4409)			
		non-constant cutoff				non-constant cutoff	
		not inv.	invest			not inv.	invest
constant	not inv.	2039	**513**	constant	not inv.	392	**99**
cutoff	invest	**137**	902	cutoff	invest	**441**	3477

Notes: The table shows consistency of the actual investment decisions with the constant and non-constant (two-dimensional global games) cutoff

6. Conclusion

In this paper we assess whether correlation of fundamental states promotes contagion across assets. Such a channel of contagion might have been active e.g. in the context of government bonds during the recent European Sovereign Debt Crisis. In the laboratory we can isolate the effects of contagion due to correlation by studying a two-asset investment game by varying the amount of correlation across treatments.

Our findings indicate that the degree of correlation does not necessarily lead to a behavioral bias giving rise to contagion. In our setting, participants do not overvalue signals from one asset when taking the investment decision into the other asset. As a benchmark to evaluate participants' behavior we use the global games solution to the underlying investment game. According to the theoretical benchmark, contagious effects of correlation are very small and this is also what we find in the laboratory. Overall, the global games solution has some merit to predict the behavior of participants in the laboratory. Although it appears that the coordination effect of good and bad information is stronger in the laboratory compared to the model, the behavior of participants responds to variations in the theoretical critical fundamental state in the direction predicted by the global games solution.

While we do not want to overextend the external validity of our results, given the stylized nature of laboratory experiments, our analysis shows a rather cautious picture that in case of the recent European Government Debt Crisis it is rather unlikely that contagion was predominately due to pure informational contagion precipitated by correlated fundamental states.

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Appendix A

All agents know the distribution of the fundamental states θ and the distribution of the private signals x_i. We assume a the bivariate normal distribution for the distribution of the fundamental state and private signals, because they are conjugate, incorporate correlation, and are intuitively appealing to model the case of informational dispersion. Hence, we assume that agents know that θ is normally distributed with known mean, which is the public signals y, and known covariance matrix Σ_{public}:

$$\theta = \begin{pmatrix} \theta_A \\ \theta_B \end{pmatrix} \sim N\left(y, \Sigma_{public}\right)$$

where

$$\Sigma_{public} = \begin{pmatrix} \frac{1}{\alpha_A} & \frac{\rho_{public}}{\sqrt{\alpha_A}\sqrt{\alpha_B}} \\ \frac{\rho_{public}}{\sqrt{\alpha_A}\sqrt{\alpha_B}} & \frac{1}{\alpha_B} \end{pmatrix} = \begin{pmatrix} \frac{1}{0.5} & \frac{\rho_{public}}{2} \\ \frac{\rho_{public}}{2} & \frac{1}{1} \end{pmatrix}$$

and

$$x_i = \begin{pmatrix} {x^i}_A \\ {x^i}_B \end{pmatrix} \sim N\left(\theta\, , \Sigma_{private}\right)$$

where

$$\Sigma_{\text{private}} = \begin{pmatrix} \frac{1}{\beta_A} & \frac{\rho_{\text{private}}}{\sqrt{\beta_A}\sqrt{\beta_B}} \\ \frac{\rho_{\text{private}}}{\sqrt{\beta_A}\sqrt{\beta_B}} & \frac{1}{\beta_B} \end{pmatrix} = \begin{pmatrix} \frac{1}{5} & \frac{\rho_{\text{private}}}{50} \\ \frac{\rho_{\text{private}}}{50} & \frac{1}{10} \end{pmatrix}.$$

The correlation of the fundamental state is denoted ρ_{public} and the correlation of private signals is denoted $\rho_{private}$.

Appendix B

Table B. 1: Fraction of successful investments into Asset B in %

	Public Signal Asset B	Public Signals Asset A 0	5	10	Average
LowLow	**0**	0	4	2.3	2.3 (32.6)
	5	44	46.2	70	53.3 (54.8)
	10	100.0	94.1	96.4	96.6 (75.3)
Average		42.1	42.6	60	49
HighHigh	**0**	7.1	11.9	4.8	7.9 (32.6)
	5	44.7	47.7	53.1	48.2 (54.8)
	10	91.7	94.1	100	95.2 (75.3)
Average		49.4	48.3	56.3	51.3
LowHigh	**0**	4.3	3.6	11.4	6.2 (32.7)
	5	65.8	66.1	59.5	64.1 (54.6)
	10	100	100	94.4	98.2 (74.9)
Average		52.5	52.5	52.5	52.5
HighLow	**0**	0	11.9	0	4.2 (32.9)
	5	66.7	59.4	51.8	58.8 (54.6)
	10	95.2	100	100	98.6 (75.1)
Average	**0**	0	11.9	0	53.9

Notes: Predictions from the continuous global game in parenthesis.

Table B. 2: Determinants of the Investment Decision

	Investment	Investment	Investment
PubSignalA==5	-0.00869	-0.00658	-0.0165
	(0.427)	(0.542)	(0.291)
PubSignalA==10	-0.0151	-0.0169	0.0200
	(0.255)	(0.216)	(0.460)
PubSignalB==5	0.452***	0.449***	0.466***
	(0.000)	(0.000)	(0.000)
PubSignalB==10	0.701***	0.699***	0.728***
	(0.000)	(0.000)	(0.000)
PrivPubDevA	0.00172	0.00175	0.00115
	(0.299)	(0.293)	(0.505)
PrivPubDevB	0.0575***	0.0582***	0.0626***
	(0.000)	(0.000)	(0.000)
Treatment HighHigh		0.0161	0.0603
		(0.766)	(0.564)
Treatment LowHigh		-0.0138	0.113
		(0.806)	(0.250)
Treatment HighLow		0.0338	-0.0281
		(0.480)	(0.806)
Period		-0.0000537	0.00147
		(0.988)	(0.673)
Time		0.000349	0.000349
		(0.509)	(0.501)
Total Profit		0.000148	0.000138
		(0.297)	(0.320)
HighHigh*PubSignalA==5			0.00658
			(0.811)
HighHigh*PubSignalA==10			-0.0570
			(0.135)
LowHigh*PubSignalA==5			0.0317
			(0.187)
LowHigh*PubSignalA==10			-0.0360
			(0.341)
HighLow*PubSignalA==5			0.00912
			(0.745)
HighLow*PubSignalA==10			-0.0760**
			(0.038)
HighHigh*PubSignalA==5			-0.0583
			(0.545)
HighHigh*PubSignalA==10			-0.0209
			(0.902)
LowHigh*PubSignalA==5			-0.119
			(0.189)
LowHigh*PubSignalA==10			-0.320**
			(0.021)
HighLow*PubSignalA==5			0.124
			(0.206)
HighLow*PubSignalA==10			0.102
			(0.590)
HighHigh* PrivPubDevA			0.00451
			(0.368)
LowHigh* PrivPubDevA			-0.00186
			(0.491)
HighLow* PrivPubDevA			-0.00588
			(0.110)
HighHigh* PrivPubDevB			-0.00617
			(0.681)
LowHigh* PrivPubDevB			-0.0143
			(0.267)
HighLow* PrivPubDevB			0.0141
			(0.365)
Observations	16000	16000	16000

Notes: Probit regression reporting marginal effects evaluated at means. Standard error adjusted for subject-clusters; p-values in parentheses (* p<0.1, ** p<0.05, *** p<0.01)

Table B. 3: Shares of Participants investing into Asset B consistent with the theoretical prediction (in percent)

	LowLow	**HighHigh**	**HighLow**	**LowHigh**
PubSignalB==0	67	73.6	59.4	76.6
PubSignalB==5	72.3	66.4	61.2	71.8
PubSignalB==10	90.9	91.3	78.9	82.8

Table B. 4: Determinants of theory-consistent Investment Decisions

	investment consistent with theory	investment consistentwith theory
PubSignalA==5	-0.00858	-0.0765***
	(0.488)	(0.002)
PubSignalA==10	-0.0832***	-0.133***
	(0.000)	(0.003)
PubSignalB==5	-0.0150	-0.0646
	(0.347)	(0.141)
PubSignalB==10	0.0697***	-0.0760
	(0.000)	(0.384)
PrivPubDevA	0.000658	-0.00173
	(0.531)	(0.289)
PrivPubDevB	-0.0138***	-0.0326***
	(0.000)	(0.000)
Treatment Highhigh	0.00849	-0.000164
	(0.621)	(0.997)
Treatment LowHigh	0.0173	0.0544
	(0.351)	(0.146)
Treatment HighLow	-0.208***	-0.220***
	(0.000)	(0.000)
Distance to Border	0.0347***	0.0643***
	(0.000)	(0.000)
Period	0.00402**	0.00344**
	(0.019)	(0.043)
Time	0.0000950	0.000106
	(0.639)	(0.595)
Total Profit	0.000672***	0.000665***
	(0.000)	(0.000)
HighHigh*PubSignalA==5		0.0472*
		(0.094)
HighHigh*PubSignalA==10		0.0216
		(0.652)
LowHigh*PubSignalA==5		0.0236
		(0.341)
LowHigh*PubSignalA==10		0.0463
		(0.238)
HighLow*PubSignalA==5		0.138***
		(0.000)
HighLow*PubSignalA==10		0.105***
		(0.002)
HighHigh*PubSignalB==5		-0.0271
		(0.664)
HighHigh*PubSignalB==10		0.0428
		(0.640)
LowHigh*PubSignalB==5		0.0360
		(0.504)
LowHigh*PubSignalB==10		-0.0409
		(0.720)
HighLow*PubSignalB==5		0.0896***
		(0.008)
HighLow*PubSignalB==10		0.172***
		(0.000)
HighHigh* PrivPubDevA		0.00182
		(0.637)
LowHigh* PrivPubDevA		0.00360
		(0.129)
HighLow* PrivPubDevA		-0.00238
		(0.360)
HighHigh* PrivPubDevB		0.0134
		(0.252)
LowHigh* PrivPubDevB		0.0100
		(0.322)
HighLow* PrivPubDevB		0.0380***
		(0.000)
HighHigh* Distance to Border		-0.00789
		(0.569)
LowHigh* Distance to Border		-0.0227*
		(0.069)
HighLow* Distance to Border		-0.0459***
		(0.332)
Observations	16000	16000

Appendix C

Instructions (translated from German)

Welcome to the experiment. Please do not speak to other participants and use only applications on the computer that are required for the experiment. Please remove all personal items from your desk and switch off your mobile phone and similar electronic devices. Please note that activities which are not related to the experiment such as playing computer games, surfing on the internet or reading non-experiment related material leads to an expulsion from the experiment. In this case you do not receive a payout. Thank you for your understanding.

The goal of this experiment is to study decision-making behavior. You can earn real money. Your payout depends only on your decisions and the decisions of other participants according to the rules of the experiment explained in the instructions at hand.

Data from the experiment is anonymized and cannot be traced back to participants. Neither the other participants nor the experimenters know which decisions you have taken and how much you have earned.

Overview

This experiment is about fictitious investment decisions. Every period you have to take a couple of decisions at the same time.

Upon each decision you receive information about the true state of two financial assets and you have to decide whether you invest into the assets.

In case the investment is successful you receive 10 tokens. In case it is not successful since not enough participants have invested into the asset, you receive no payout. In case you do not invest, you receive a fixed payout of 4 tokens.

The true state of the financial asset

The underlying value of the financial asset – we call it the true state of the asset – is unknown to participants throughout the experiment. You neither learn the true state during nor after the experiment.

In principle it applies that the higher the true value, the higher are the chances for a successful investment. However, whether an investment is successful does not only depend on the true state but also on the number of participants who invest.

You take every investment decision with 9 fellow participants. Overall, 10 participants are involved in the investment decision. Each group consisting of 10 participants is separately and randomly assembled. The true state of the asset, which is unknown, but you will receive hints about it, determines how many participants have to invest **at least**, such that the investment is successful.

In case the true state is **lower than 0**, an investment **never yields a payout**; in case the true state is **larger than 10**, an investment **always yields a payout**. If the true state is between 0 and 10, the number of participants who invest determines whether an investment is successful. **The lower the true state, the more participants have to invest such that the investment yields a payout. How this relationships looks like and under which circumstances the investment will be successful is shown in the following table:**

The true state	Payout
Larger than 10	Always yields a Payout
Between 9 and 10	Payout, if at least 1 participant invests
Between 8 and 9	Payout, if at least 2 participants invest
Between 7 and 8	Payout, if at least 3 participants invest
Between 6 and 7	Payout, if at least 4 participants invest
Between 5 and 6	Payout, if at least 5 participants invest
Between 4 and 5	Payout, if at least 6 participants invest
Between 3 and 4	Payout, if at least 7 participants invest
Between 2 and 3	Payout, if at least 8 participants invest
Between 1 and 2	Payout, if at least 9 participants invest
Between 0 and 1	Payout, if all participants invest
Smaller than 0	Never yields a payout

Example: *Given the unknown true state is 3.53, the investment yields a payout if at least 7 participants invest. There is no payout if fewer participants invest.*

Information about the true state

Upon investing, you get two different kinds of hints about the true states of two assets in which you invest:

- **Mean (expected value) of the true states:** This kind of information is identical for everybody.
- **Private hints:** This kind of hints is individual. This means that every participant get her own hints. Hints may be similar across participants, but they are not identical.

The structure of information

We call the financial assets in which you can invest, A and B. To illustrate the relationship between Asset A and Asset B as well as the relationship between the private hints about Asset and Asset B, we show a graphical representation (Supplement 1). The correlation, that captures the mutual relationship, remains constant throughout the experiment.

The means of the true states

In both graphics in Supplement 1, means of the true states of Asset A and Asset B have value of 5. The mean for Asset A relates to the x-axis, the mean for Asset B relates to the y-axis. Together, the means of the true states of Asset A and Asset B make up a point the coordinate system which is depicted by a green dot.

True states for Asset A and Asset B are illustrated with a red dot. The location of the true states is unknown and randomly determined in the experiment. This means that for each investment decision you take, is related to a different true state. The distribution of the true states is a two-dimensional normal distribution centered around the means of the true states.

Graphic 1 in Supplement 1 shows how the true states are determined and how they are distributed. The distribution of the true states is represented by the shades of the area: 99% of the true states are located within the ellipsis. The darker the shading, the higher the probability, that a true state will be located there.

Private hints

Private hints are an additional source of information. Please note that private hints are individual – other participants may receive similar but not identical hints.

Private hints about Asset A relate to the x-axis, private hints about asset B to the y-axis.

Graphic 2 in Supplement 1 show how private hints are determined and how they are distributed. Similar than for true states – in respect to the relation of the shading of the area and the probability, the same rules apply – private hints are more likely to be located in the center of the ellipsis, which is centered around the true state. 99% of private hints are located within the blue ellipsis. The distribution is also a two-dimensional normal distribution.

Hints in the experiment

In the experiment, the medians of the true states vary. In the graphics, such a variation shifts the green dot, but the distributions, i.e. the ellipses around the means of Asset A and Asset B and the ellipsis around the true states of Asset and Asset B, remain unchanged. A change in the mean of Asset B shifts the green dot along the x-axis, a change in the mean of Asset B shifts the green dot along the y-axis.

You can review a graphical representation of the hints for each decision. This utility can be tested in the training round.

Summary – the investment decision

In respect to each investment decision, you receive 4 hints: the means of Asset A and Asset B, and private hints about Assets A and B. Moreover, you can infer the distribution of true the true states as well as the distribution of the private hints from the graphics shown in Supplement 1. The ellipses that represent the distributions remain constant throughout the experiment.

The true states are drawn from the distributions around the means of Asset A and Asset B, i.e. they are selected randomly. In turn, the private hints are drawn around the unknown true states.

On the grounds of this information you decide whether you want to invest. In case you do not invest, you receive a fixed payout of 4 tokens. In case you invest, you receive 10 tokens in case the investment is successful. You receive nothing in case the investment is not successful – i.e., given the value of the true state, not enough participants have invested.

The decision screen is shown on Supplement 2. You take 10 decisions in each round of the experiment. In total, there are 10 rounds (periods).

Payout

The total payout depends on the sum of tokens you earn over the course of the experiment from your investment decisions. The exchange rate from tokens to Euro is as follows:

1 token = 1 Eurocent

Additionally, you receive 4 Euros independently of your investment decisions for coming to the experiment.

Appendix to the instructions[14]

The distribution of the true states is a two-dimensional normal distribution. The means of the true states are displayed for every decision. The covariance matrix is constant and is illustrated by the ellipses. Formally, the covariance can be represented by the following covariance matrix:

$$\begin{pmatrix} 20 & \sqrt{20} * \sqrt{10} * correlation\ of\ true\ states \\ \sqrt{20} * \sqrt{10} * correlation\ of\ true\ states & 10 \end{pmatrix}$$

The variances are shown on the main diagonal (for Asset A and for Asset B) and the covariances are shown on the off diagonal.

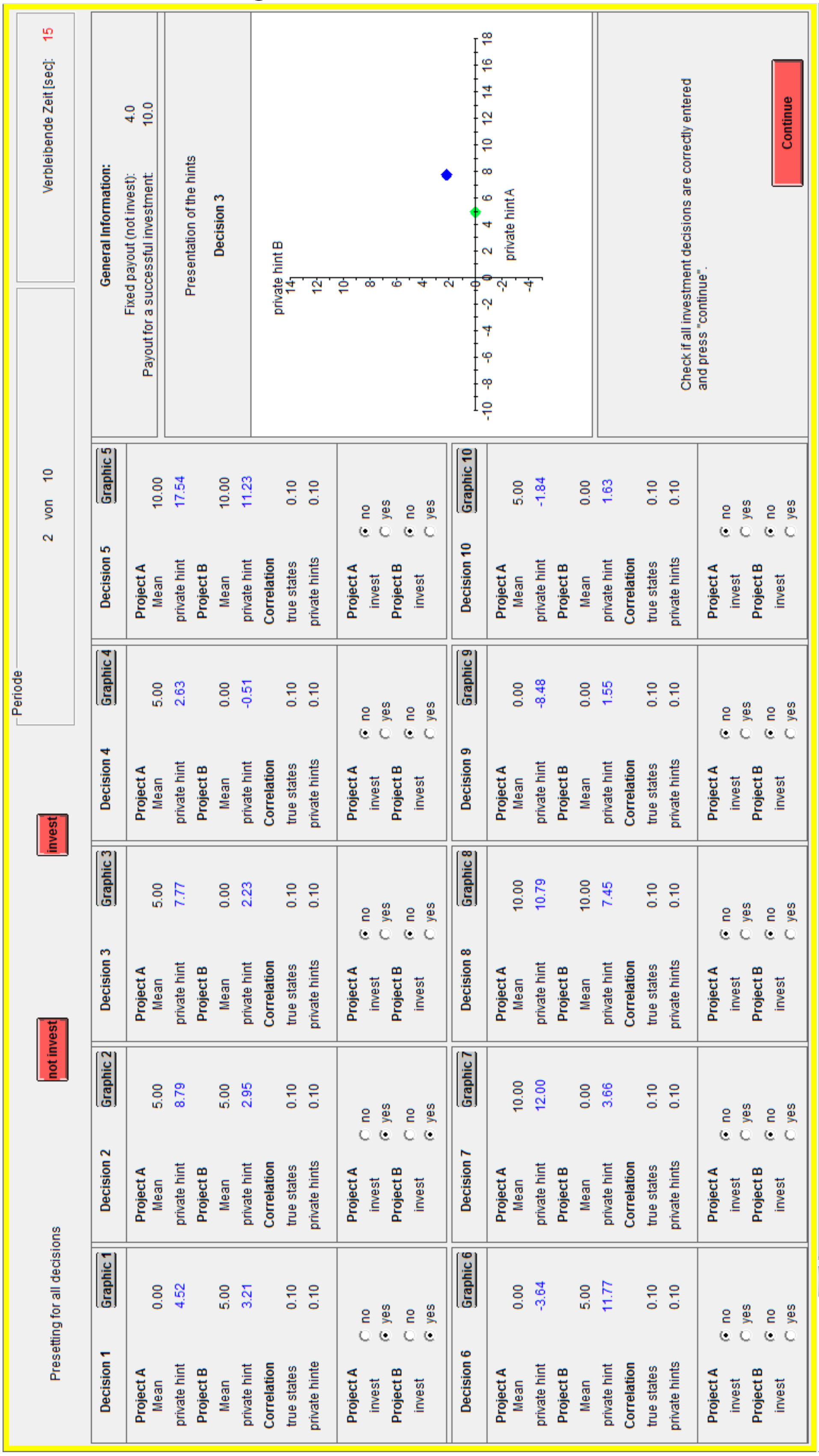
For the private hints, the distribution is centered around the unknown true states (mean of the distribution of the private hints). The covariance matrix is:

$$\begin{pmatrix} 2 & \sqrt{2} * \sqrt{1} * correlation\ of\ private\ hints \\ \sqrt{2} * \sqrt{1} * Korrelation\ private\ hints & 1 \end{pmatrix}$$

[14] The appendix is on an extra page and is not read aloud. Though, to be very transparent to participants, we at provide them with the determinants of the covariance-matrix.

Appendix D

Figure D. 1: The decision screen



Notes: The Figure shows the decision screen. Participants have to take ten investment decisions into each asset per period.

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Martin Geiger, Richard Hule

The role of correlation in two-asset games: Some experimental evidence

Abstract
In our experimental setting, participants face the decision to invest into two assets which are subject to correlated information. While fundamental states and signals about fundamental states are correlated, success and default of the investment projects is determined separately. Nevertheless, correlation of signals may give rise to spillovers through informational contagion since participants may overvalue correlated signals resulting from a double-counting problem in the updating process or may be prone to behavioral biases related to good and bad news. Quite strikingly, in our setting, the degree of correlation does not promote pronounced contagious effects. In particular, this is consistent with the theoretical two-dimensional global games solution of the underlying investment game. However, a heuristic of neglecting correlation and signals about the second asset has also merits to explain participants' investment behavior. In some treatments we can distinguish between participants' strategies being derived from the two- dimensional global game and from a heuristic being derived from a one- dimensional game. We cannot reject that people play the two-dimensional investment game as it would be two separate one-dimensional games and ignore correlation.

ISSN 1993-4378 (Print)
ISSN 1993-6885 (Online)