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## Synchronization in human decision-making

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### Abstract

**Just as soldiers crossing a bridge in sync can produce a catastrophic structural failure, we use experiment, theory, and simulation to show how synchronization in human decision-making can lead to extreme outcomes. *Individual* decision-making and risk-taking are well known to be gender dependent. However, much less is known about the impact of gender on the generation of *collective* risk through aggregate decision-making, where the decision of one individual can affect the decision-making of other individuals, leading eventually to synchronization of behavior. To study the formation of collective risk as generated by synchronization in human decision-making, we have devised a**

**series of experiments that can be analyzed and understood within a game-theoretical framework. Experiments involve groups of either men or women, and each individual decides to buy or sell a financial asset using information that contains previous price trends and economic news. Risk can be generated collectively through coordination in the aggregate decision-making, which leads to a price formation far from the fundamental value of the asset. Here we show that collective risk can be generated in groups of either gender, but also that the way it is generated happens through a different type of individual risk-taking for groups composed of men and groups composed of women.**

## **1.0 Introduction**

At the very height of the international credit crisis and during the near collapse of the Icelandic banking system from the end of 2008 through to the beginning 2009, the Icelandic politician Johanna Sigurdardottir attracted voters by promising to “end the era of testosterone”. In 2008, the businessman of the year in Iceland was a woman, and after Sigurdardottir became prime minister in February 2009, half of her new ministers were women. Furthermore, the CEOs in two of the three largest banks were replaced by women. If anything, this Icelandic tale shows that, both inside and outside of politics , there is a common preconception that risky behaviour is an attribute deeply rooted in male decision-making, especially during crisis situations, and could be avoided by including more women in the decision-making process. Politically as well as economically, it is therefore important to have some reliable research results telling us whether there is any truth in this viewpoint. The specific purpose of this paper is thus to introduce tools for understanding the origins of

excessive risk-taking as generated through synchronization in collective decision-making, but taking into account the gender issue.

Recent research on cognitive and behavioural effects has demonstrated the important role of the endocrine system in individual decision-making<sup>[1-8]</sup>. For example, it has been shown how the testosterone levels of traders in the City of London could be used to predict their gains, while cortisol levels of traders would rise with increasing uncertainty in those gains<sup>[7]</sup>. However, later studies showed that larger gains were only obtained by taking greater risk<sup>[8]</sup>. These studies explain how individuals react and make their decisions in isolation, but they do not probe the way risk is created in collective decision-making, where decisions made by one individual can influence subsequent decisions by other individuals. The study we describe in the following can thus be viewed as an example of social epistemology, where the collective achievement is knowledge of a number, viz., the proper price of an asset<sup>[9-13]</sup>. More generally, this paper addresses how one can understand and identify cognitive biases documented in behavioural economics, (for another interesting study see e.g. [14-15] which uses the decoy effect to identify shifts in people's preferences).

## **2.0 Performance of a series of experiments.**

To investigate how risk at the level of a system can be created collectively we performed a series of trading experiments involving students. The experiments were carried out at the Laboratory of Experimental Economics in Paris (LEEP). The experiments ran over 60 periods. In each period, the students received general economic news and could decide whether to buy or sell an asset or simply do nothing. At the end of the 60 periods, the students were paid pro rata according to their performance (for more details about the way the experiments were set up, see "Methods").

At the beginning of the experiment the students were told that the asset was, at this initial stage, properly priced according to rational expectations<sup>[16]</sup>. This meant that only information regarding changes in the dividends on the asset or interest rates should have a direct influence on the price of the asset. The information flow consisted of general news from past real records of Bloomberg news items. News was selected in such a way that the general trend over the 60 consecutive periods was neutral. Then, according to rational expectations, there should be no overall price movement of the asset at the end of the 60 time periods. The price was thus expected to oscillate around the fundamental value throughout the experiment.

Figure 1 to be placed here

**Figure 1 | Outcome of collective decision-making for different groups.** Figure 1a: price behavior (black dots) for a group of male participants. Figure 1b: data of figure 1a together with a price history (white circles) created by collective decision-making in a group of female participants. Figure 1c: as in the first two figures, together with an initial price formation created by another group of female participants (white triangles), resulting in the different (risk-taking) trajectory shown in figure 1d. However, the latter collective risk-taking was completely dwarfed by another group of male participants (black squares), as shown in figure 1e. Figure 1f: price formation in all 10 experiments.

Figure 1a shows the price behavior (black dots) for a group of male participants. The collective decision-making of these participants generated a price history fluctuating around the fundamental value of \$5. Figure 1b also shows the price history (white circles) generated collectively by a group of female participants. The decision-making of the two groups is strikingly similar throughout the two experiments. Figure 1c includes also the price formation created by another group of female participants (white triangles). The outcome of the initial decision-making by this group of women clearly deviates from the behavior reported in figures 1a-b. Indeed, as can be seen in figure 1d, the collective risk-taking generated by this group more than doubled the fundamental value by the end of the experiment. However,

figure 1e shows how this collective risk-taking was completely dwarfed by the price formation generated by another group of male participants (black squares). Figure 1f shows the price formation for all 10 experiments performed at LEEP.

## 2.1 Analysis of the experiments.

Given that the information presented to the participants is the same for all the different groups, *how is it that such different behavior is observed from one group to another?* A first and natural idea would be to try to relate the combination of individual risk-taking tendencies among the participants in a given group to the outcome of collective risk-taking observed in the experiments<sup>[17]</sup>, expecting greater collective risk-taking to be caused by a greater tendency for individual risk-taking among the participants.

In order to test this hypothesis, prior to each experiment, we evaluated the risk profile of each participant using a lottery-choice experiment<sup>[2]</sup> (for more information, see “Methods”). As a measure of individual risk aversion, Table 1 shows the median of the safe choice number generated by the participants in the Holt and Laury lottery-choice experiment<sup>[2]</sup> for a given group (the higher the value of this number, the more risk-averse the choice<sup>[2]</sup>). As expected<sup>[2]</sup>, groups of men were generally less risk-averse than groups of women (the group with least risk aversion was composed of men, whereas the two most risk-averse groups were composed of women), although there were some deviations from this general pattern.

Table 1. Statistics of the 10 experiments.

Serials	Gender	FWHM(t=60)	H&L	$\sigma(t=5)$	P(t=60)
M1	Male	32.92	4.75	0.16	107.41
M2	Male	3.75	6.33	0.08	5.81

M3	Male	3.14	6.00	0.21	7.56
M4	Male	0.94	6.50	0.16	6.97
F5	Female	1.50	7.00	0.10	6.09
F6	Female	1.16	7.00	0.35	14.16
F7	Female	0.45	5.33	0.22	7.38
F8	Female	0.36	6.00	0.15	10.15
H9	Mixed	0.44	6.00	0.18	7.16
L10	Mixed	1.43	8.00	0.15	4.63

**Table 1 | statistics of the 10 experiments.** FWHM( $t=60$ ): full width at half maximum of the loss/gain probability distribution over the duration of the experiments. H&L: median of the safe choice number generated by the participants in the Holt and Laury lottery-choice experiment.  $\sigma(t=5)$ : standard deviation of the loss/gain of the participants after five time steps.  $P(t=60)$ : level of collective risk-taking.

Most importantly, individual risk-taking as measured by the lottery-choice experiments did **not** translate into a greater tendency for collective risk-taking in the market experiments. Out of the 4 experiments with men, only 1 entered a collective speculative state, in which the final price was more than double the fundamental price (last column in table 1), whereas half of the experiments with women entered a collective speculate state. This is all the more remarkable in that the *individual* risk-taking (created collectively) in the experiments, as measured by the full width at half maximum (FWHM) of the loss/gain probability distribution over the duration of the experiments, followed the tendency of the lottery-choice experiments. Indeed, 3 out of the 4 experiments with men had a FWHM at least twice the highest FWHM in the experiments involving women. Furthermore, it should be noted that the excessive price behavior of the group of women in Figure 1d (white triangles) was generated by the group of participants with **least** individual risk-taking (as measured by the FWHM) in the 10 market experiments.

## 2.2 Using agent based modeling to understand the outcome of the experiments.

These facts give a first indication that, on the system level, the pathway to excessive risk-taking cannot be simply deduced by aggregating individual risk profiles. To get a more thorough understanding of the conditions underpinning excessive price behavior, we therefore launched a series of agent-based simulations<sup>[18-21]</sup> (see Fig. 2 for a graphical representation and “Methods” for a precise definition of the model).

Figure 2 to be placed here

**Figure 2 | Agent-based model used to understand the experiments.** I) Agents use the direction of the last  $M$  price moves,  $\vec{h}$ , in their decision-making, adding scores depending on the performance of each of their  $s$  strategies. II) Each agent then uses the *best* strategy and places an order (buy/sell/do nothing). III) All orders from the  $N$  agents are collected to determine a new price movement.

Monte Carlo simulations of the agent-based model allowed us to identify which parameters could have an impact on the creation of excessive risk behavior. Figure 3 plots the probability of generating collective speculative price behavior against a control parameter  $T = \frac{[3^M+1]}{(s+1)N}$ , where  $N$  is the number of agents (i.e., the number of participants in the experiments),  $s$  the number of technical analysis strategies at their disposal, and  $M$  the number of periods the agents use when deciding whether to buy or sell an asset. The first term in the numerator corresponds to the number of independent technical analysis strategies<sup>1</sup> existing over a time period of length  $M$ <sup>[22]</sup>. Adding the strategy which uses the fundamental price analysis, the numerator therefore gives the total number of uncorrelated strategies for a time horizon of  $M$  periods. The denominator gives the number of strategies in the pool of strategies available to the agents. A small value of  $T$  therefore describes a system in which the trading strategies of

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<sup>1</sup> For technical analysis strategies using the direction of price movements.



two agents are likely to overlap, whereas a large value of  $T$  describes the other limit, in which it becomes unlikely to find two agents with any overlap in their trading strategies<sup>[23-24]</sup>.

Figure 3 to be placed here

**Figure 3 | Probability of excessive risk-taking versus  $T$  for groups with different risk profiles.** Collective speculative price behavior, defined as occurring when the final price is more than twice the fundamental price, is plotted against the control parameter  $\frac{[3^M+1]}{(s+1)^N}$ . Inset: simulations of games with different values of  $s$  and  $N$ , but for a fixed value of  $T$  and  $M=2$ . The different symbols correspond to simulations with populations having different risk profiles.

One of our main findings is that given *fixed* values of  $M$  and  $T$  lead to the *same* probability of creating excessive price behavior (see Figure 3 inset, which presents simulations of games with *different* values of  $s$  and  $N$ , but for fixed  $T$  and  $M=2$ ). The simulations were carried out for agents using their total return as payoff function (the  $\$$ -Game<sup>[18]</sup>), but note that different choices of payoff function (see below) gave similar behavior.

In order to take into account populations of agents with different risk and loss aversion, we then modified the payoff function of their strategies according to  $P = \frac{R}{1/2 \sigma_-^\alpha + 1/2 \sigma_+^\beta}$ , where  $R$  is the return on the strategy at the end of the 60 time periods and  $\sigma_\pm$  the standard deviation of the losses (-s), respectively gains (+s). The magnitudes of the exponents  $\alpha$  and  $\beta$  define the risk aversion, while their difference in magnitude defines the loss aversion. For  $\alpha = \beta = 0$  the payoff corresponds to the pure  $\$$ -Game, while for  $\alpha = \beta = 1$  the payoff is similar to the Sharpe ratio. Higher values of  $\alpha$ ,  $\beta$  describe populations with greater risk aversion. The case  $\alpha > \beta$  corresponds to strategies which are loss averse, a well-documented human bias documented in Prospect Theory<sup>[25-27]</sup>. Figure 3 shows simulations using different values of  $\alpha$  and  $\beta$  for  $M=2$  and  $M=4$ . Populations with various degrees of risk aversion ( $\alpha = \beta \neq 0$ ) and various

degrees of loss aversion ( $\alpha > \beta$ ) are compared with a population without risk aversion ( $\alpha = \beta = 0$ , fat solid lines), and it can be seen that the risk profile has a negligible impact on the probability that there will be collective risk-taking. As discussed earlier, this result accords with the observed behavior in the experiments, where the risk composition of the different groups generally seemed to have little impact on the collective formation of risk.

### **3.0 Discussion.**

We will never know in detail the precise reasoning behind the decisions made by each individual in the experiments. However, having interviewed the participants after each experiment, it seems reasonable to assume that each uses a small set of strategies that take into account price changes over the last few time periods. Assuming they use, for example, strategies  $s=3-5$ , the experimentally observed probability of  $3/10$  that they will indulge in excessive risk-taking nicely fits the predictions from game theory for a population using the last  $M=4$  time periods in their decision-making. This can be seen by comparing the populations with different risk profiles obtained in the simulation with the horizontal line indicating the range of  $T$  values that corresponds to experiments where participants use  $M=4$  and  $3 < s < 5$ .

Our experimental findings on the way synchronization can occur in a population have been supported by results from game theory and simulations. Returning to the image of soldiers crossing a bridge in the introduction to our paper, we have seen that it is not how hard each soldier stamps his foot that matters (i.e., the individual risk-taking). Rather, it is the tendency to synchronize that is responsible for generating collective risk-taking. More precisely, the idea of synchronization may well prove relevant in a proper understanding of, for example, the way systemic risk occurs in financial markets. However, the phenomenon of

synchronization could even play a more general role in social interactions and opinion formation; examples include democratic elections<sup>[28,29]</sup>, phone calls<sup>[30]</sup>, email communication<sup>[31]</sup>, and people clapping in phase during rhythmic applause<sup>[32]</sup>.

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## Appendix A: Experimental setup

A series of 10 experiments were performed at the Laboratory of Experimental Economics in Paris (LEEP, <http://leep.univ-paris1.fr/accueil.htm>), using students with at least 4 years of university economics. The experiments were grouped into a series of 8 experiments, each with 10 participants. In 4 of the experiments, all participants were male, and in another 4, all were female. In the remaining 2 experiments, an initial group of 20 participants (female and male) was divided into two groups according to their risk preference. The students received 6 euros just for their presence and were also rewarded by attending a lottery designed to assess the individual risk profiles of the participants<sup>[4]</sup>. The lottery had an average payoff of 10 euros. The final and most important part of the experiment was a financial market experiment (see Figure 4).

Figure 4 to be placed here.

**Figure 4 Setup of the financial market experiment.** Screenshot of the terminal used by participants, showing the shared information, price changes, portfolio value, and buy/sell buttons.

Each experiment ran for 60 time periods lasting 15 seconds each. In each time period a participant could choose either to do nothing or to buy or sell one share of an asset. The initial price of the asset was fixed at \$5, with an expected 10 cent dividend at the end of the 60 time periods. The participants were told that the asset was correctly priced according to rational expectations<sup>[16]</sup>, that is, the price of the asset was assumed to reflect all future discounted cash flow accrued to the asset. In each time period, the students were provided with a couple of lines of real financial news items of a general nature, supplied by Bloomberg over a two week period. The students were told that the asset represented a portfolio of assets like an ETF or an index. All were simultaneously presented with the same information, which was

intended to reflect general financial news such as good or bad U.S. employment figures, price changes of commodities, trends in exchange rates, etc. The news items were the same in all 10 experiments and were chosen without any overall positive or negative bias. At the end of each time period, participants' orders were gathered and a new price was calculated on the basis of the order imbalance (with the sign and magnitude determining the direction and size of the price movement, respectively). The new price was then shown to the participants graphically on their computer screen. Throughout the experiment, participants had a continuous update of their shareholding and their gains/losses. They were allowed to borrow money to buy shares at an interest rate of zero and short-selling was also allowed. At the end of each of the 10 experiments, a pool of 200 euros was distributed pro rata among those participants who had a positive gain.

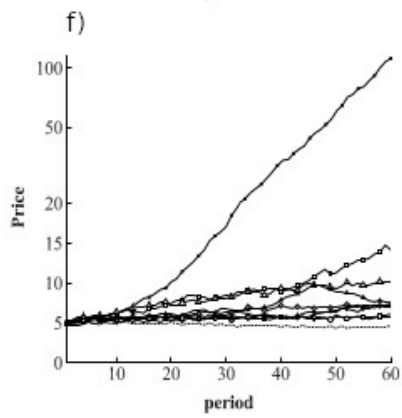
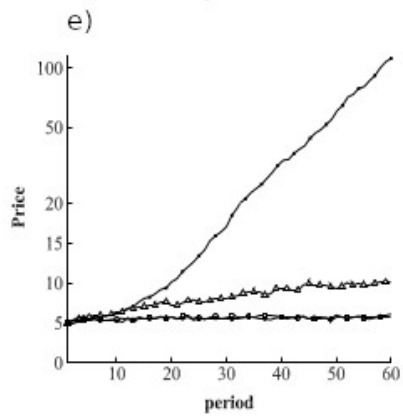
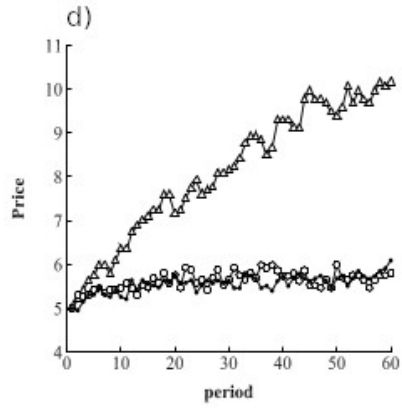
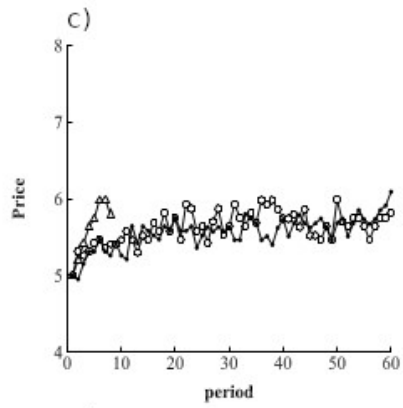
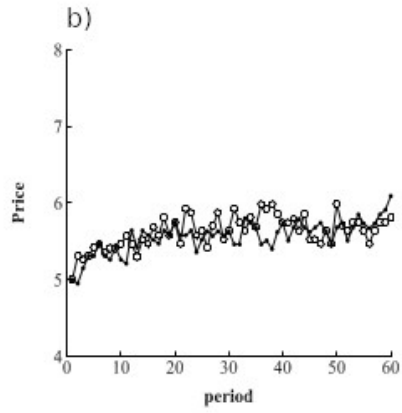
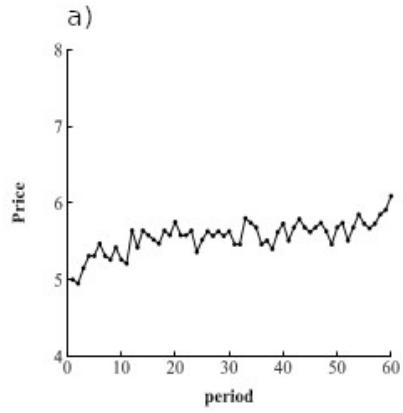
## **Appendix B: Multi-agent based modeling.**

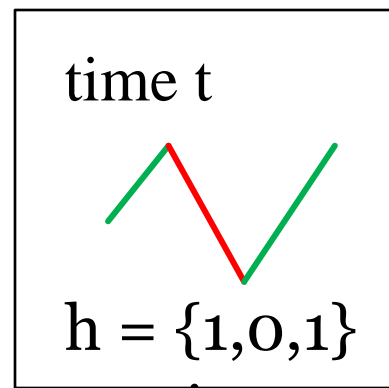
The \$-Game was used as theoretical framework to understand the outcome of the experiments<sup>[18]</sup>. This is a multi-agent based model that corresponds closely to the setup of the experiments. The game consists of  $N$  agents which, in each time period, can buy or sell a share or simply do nothing, like the participants in the experiments. In order to make decisions, the agents have at their disposal  $s$  technical analysis strategies (assigned randomly at the beginning of the game), whose aim is to profit from the directions of the  $m$  past price changes, together with a fundamental analysis strategy, based on the expectation of future dividends, buying when the present price is considered undervalued and selling when it is overvalued. Figure 2 illustrates the dynamics of the model, with prices increasing whenever there are more buyers than sellers according to



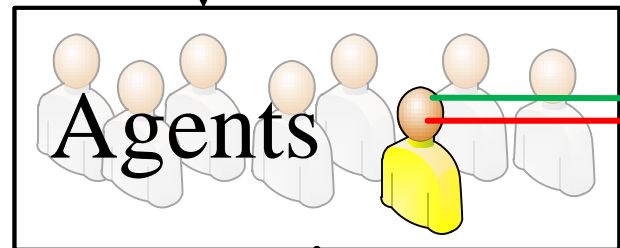
$$P(t + 1) = P(t)e^{\frac{\text{excess demand}(t)}{\text{liquidity}}} \quad (1)$$

This is similar to the price update used for the experiments (in particular, the liquidity was chosen as in the experiments). Figure 2 also illustrates the importance of feedback loops seen in both the experiments and the agent-based simulations: as the market changes, the strategies of the participants change, and this in turn changes the market. In the \$-Game, the payoff function of the strategy is the return implied by a given decision of the strategy.



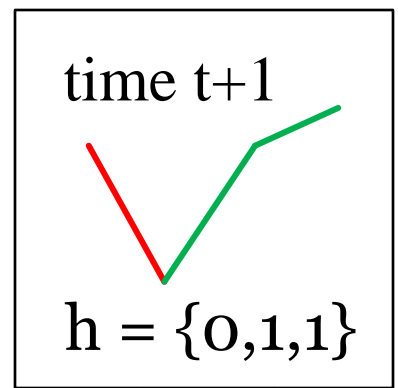


Observe market movement

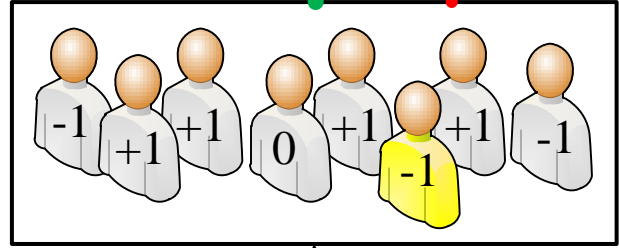


Update score of strategies depending on the history performance

...	010	011	100	101	110	...
...	-1	0	+1	-1	-1	...
...	...	...	...	...	...	...
...	+1	-1	0	+1	+1	...
...	...	...	...	...	...	...

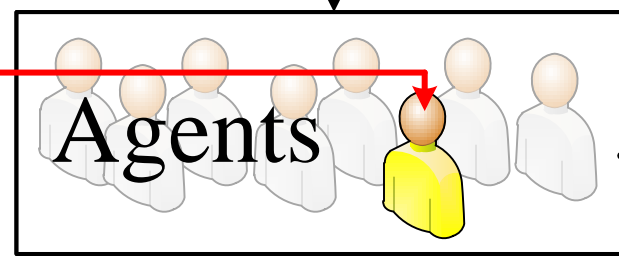


Price move depending on order imbalance



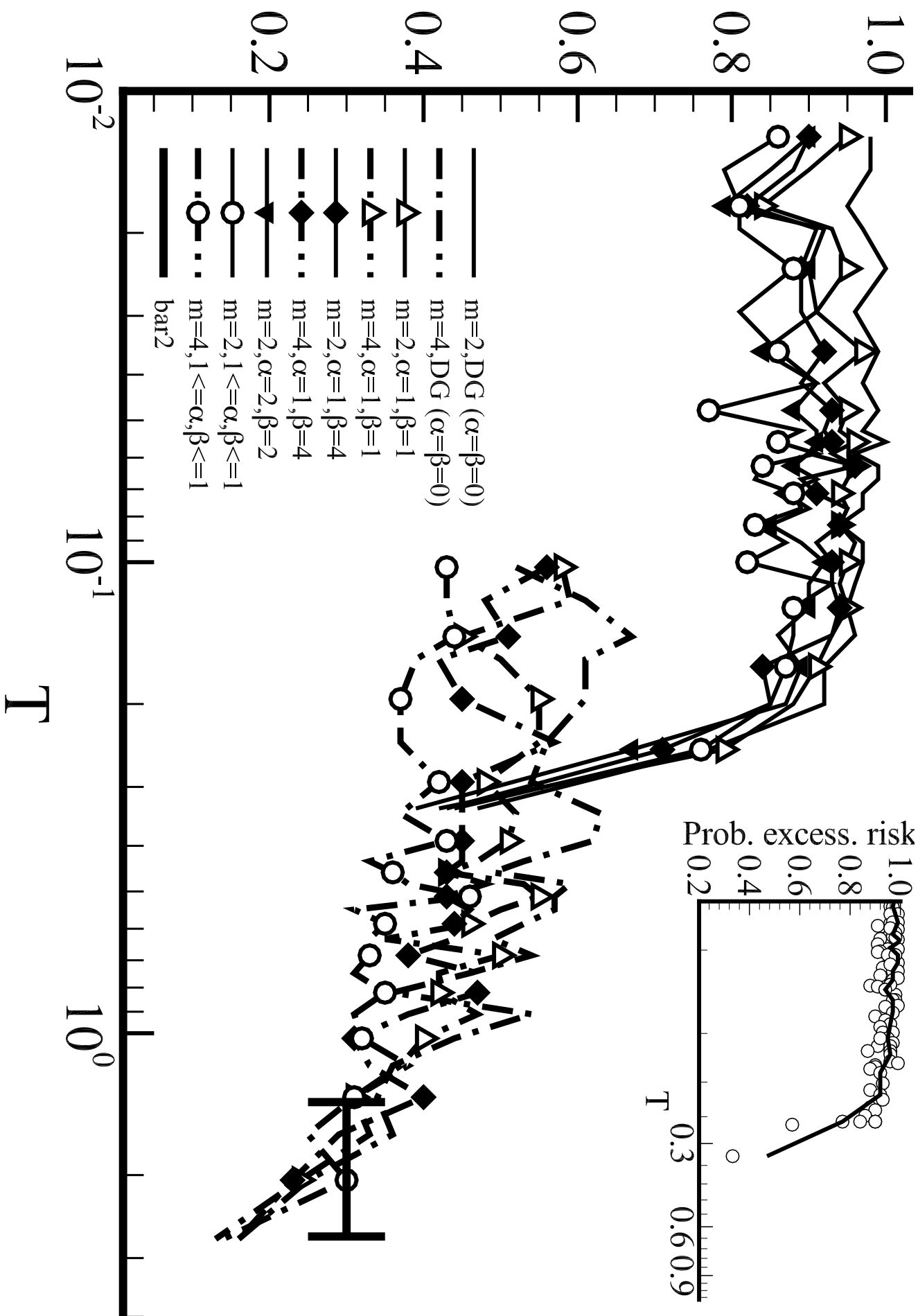
Place order

...	010	011	100	101	110	...
...	-1	0	+1	-1	-1	...
...	...	...	...	...	...	...
...	+1	-1	0	+1	+1	...
...	...	...	...	...	...	...



Use best strategy to make investment decision

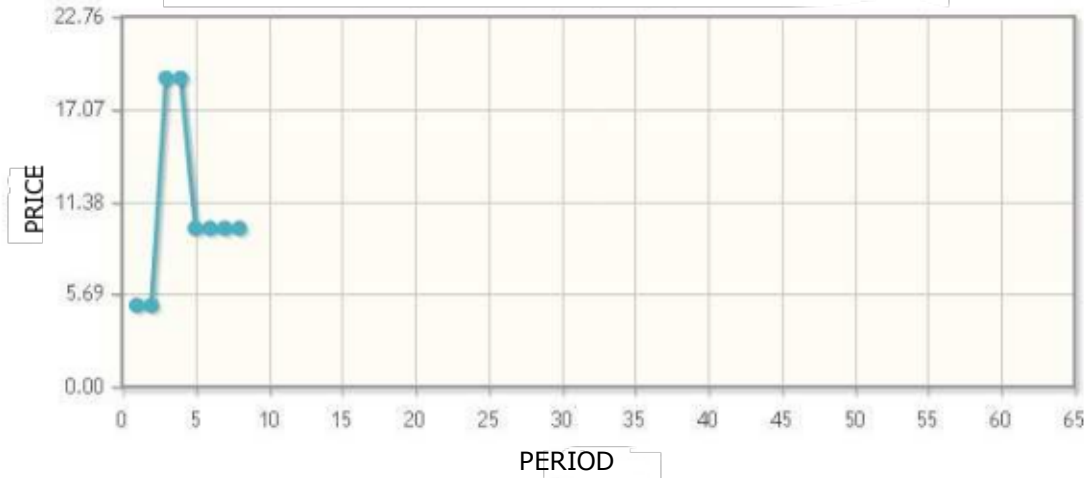
# Prob. excess. risk



History of each period

Per. No	PRICE	Number of \$	Number of assets	Value of portfolio
8	9.74	-5	1	4.74
7	9.74	-5	1	4.74
6	9.74	-5	1	4.74
5	9.74	-5	1	4.74
4	18.97	-23.97	2	13.97
3	18.97	-5	1	13.97
2	5	0	0	0
1	5	0	0	0

Price per period



Financial information

**Value of portfolio :** 4.74 \$  
Gain/loss since last period : 0 \$

Information Bloomberg :

European Stocks Rise Amid M&A Deals; Orkla, Douglas Gain  
Saudi Shares Drop Most in 4 Months as Banks Miss Profit Estimate  
German Stocks Gain as U.S. Sales Rise Beat Forecasts

Number of dollars in assets  
(value negative for borrowed money) :

-5\$

BUY

SELL

Number of stocks (negative for borrowed assets): 1

Remaining time : 12 second(s)