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Communications in Financial Markets: A Strategy method Experiment

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ABSTRACT

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Abstract

The main objective of this paper is to analyze the impact of uninformative communications on asset prices. An experimental approach allows us to control for the release of a priori uninformative messages. We introduce the release of messages in standard experimental asset markets with bubbles using a strategy method experiment. We conjecture that messages that are a priori uninformative can significantly

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impact the level of asset prices. Such communications may be used by boundedly rational subjects to compute the fundamental value of the asset. In addition, rational agents may anticipate such an effect and adapt their strategy to the messages received. We asked 182 subjects to construct strategies about their action in a standard experimental asset market environment. Our analysis sheds light on the possibility of manipulation and stabilization of financial markets by influential agents such as financial *gurus* or central bankers.

1 Introduction: 'why words may count?'

> *"... how do we know when irrational exuberance has unduly escalated asset values, which then become subject to unexpected and prolonged contractions as they have in Japan over the past decade?"* (Alan Greenspan, black-tie dinner speech: *The Challenge of Central Banking in a Democratic Society* before the American Enterprise Institute at the Washington Hilton Hotel December 5, 1996)

As pointed out by Sperber (2005), obscurity of expression is considered as a language imperfection, except in the case of *a maître à penser* or *guru*'s speech. Greenspan's seemingly harmless quotation implied a strong reaction in the markets. The Tokyo stock market that opened at the time of his speech, fell sharply, and closed down by 3%. Similarly, stock markets in Frankfurt and London decreased by 4%. The US stock market fell by 2% immediately after its opening (Shiller, 2001). Although the term *irrational exuberance* reached a definition status and is frequently used as a synonym for a heightened state of speculative fervor, it seems disproportionate that markets react all over the world to a question casually thrown out in the middle of a dinner speech (Shiller, 2001). Defenders of full rationality may argue that Greenspan's speech had an informative content since it leads traders to revise upwards the probability of an increase in US interest rates. Experimental markets allow us to disentangle the effects of informative and uninformative messages on asset prices since then we can control for the level of informativeness of messages. Under the full rationality hypothesis, an uninformative communication should not influence asset prices. However, if we consider one of the following situations: *i)* traders are boundedly rational or *ii)* rationality is not common knowledge, uninformative messages are likely to influence prices. First, uninformative communications may be used by boundedly rational subjects to compute the fundamental value of the asset. Second, rational agents that do not believe in others' full rationality may anticipate such an effect and adapt their strategy to the messages received.

As a result, we have to stress that messages that are uninformative under the common knowledge of rationality assumption may appear to be informative if traders are not fully rational.

We therefore address in this paper the question of the sensitiveness of asset market prices to uninformative communications. We build our analysis within an experimental financial market. In particular, we construct a strategy method experiment of the type first described in Selten 1967. Assessing the importance of communications on asset markets prices using real markets data is rendered impossible by the multiplicity and simultaneity of the messages reaching the market. This is why we consider an experimental approach allowing us to control for the release of non-relevant messages. We introduce the possibility of communications in standard experimental asset markets with bubbles described in Smith, Suchanek and Williams (1988). We consider the case in which a message about the price of the experimental asset is sent at the end of a trading period. We decide to use a strategy method experiment in the spirit of Selten, Mitzkewitz and Uhlich (1997) and Sonnemans et al. (2004). In a strategy method experiment, subjects are asked to formulate a complete strategy that corresponds to a description of their decisions in any possible state of the world. Decisions in this type of experiments are not immediate. Subjects have time to elaborate their strategies and to anticipate their implications. In standard experiments, subjects make relatively few decisions in a short period of time. It is then difficult to detect the type of beliefs taken into account by traders when making their decisions.

Our choice has been to test the main hypothesis that uninformative messages impact asset prices in a context that is a priori unfavorable. Indeed, in a strategy method experiment, as subjects have more time to make their decisions, they are less likely to make computational mistakes that are characteristic of boundedly rational traders.[1] As a result, the messages delivered to traders on the market are less likely to modify subjects' beliefs about the fundamental value of the asset. In addition, compared to a standard experiment, traders should anticipate that other participants have more time to make their decisions so that the common knowledge of rationality hypothesis is more likely to hold. In summary, in a strategy method experiment, asset prices should be less sensitive to uninformative messages than in a classical experiment. Therefore, the strategy method experiment can be seen as a stress case for our central hypothesis stated below. If prices are influenced by uninformative messages in that context then there exists a strong support for our research hypothesis. Our research hypothesis is stated below jointly with two complementary hypotheses. Also, choosing a strategy experiment is motivated by our willingness to avoid experimenter effects that may appear due to the position of authority of the experimenter when releasing messages in the market. In a classical experiment, any message may have an effect on subjects' behaviour as long as it

[1] However, traders do not have any opportunities to learn during the experiment as they would do in a classical setting. Subjects may then keep on committing errors along the experiment. This effect goes in the opposite direction as the one stated in the main text.

is delivered by the experimenter.

> **Hypothesis:** *A priori uninformative messages have a significant impact on asset prices.*

Our central hypothesis is motivated by the belief that traders may be boundedly rational or strongly question others full rationality. We argue that uninformative communications may be used by boundedly rational subjects to facilitate the computation of the fundamental value of the asset. This may occur for example if the uninformative message is a repetition of an initially informative message. Repetition can then help traders with cognitive limitations to find out the true value of the asset.

In addition, in the context of experimental markets characterized by bubbles we assert that messages may serve as a focal point for the convergence of beliefs among subjects. If we agree that experimental bubbles occur partly as a result of a divergence in traders' beliefs (as argued for example in Smith et al. 1988), the introduction of messages in the experimental design may significantly reduce bubbles by facilitating the coordination of beliefs. We test our main hypothesis by using the experimental design presented in the next section. Our work can help assess the extent to which asset markets can be manipulated by influential agents such as financial *gurus* or central bankers through the delivery of non-informative messages.

Hypothesis a: *The effect of uninformative messages on asset prices is higher in the case of hard signals than in the case of soft signals (Content dimension).*

A recent strand of literature emphasizes the distinction between hard and soft information (e.g. Petersen, 2004). Hard information is quantitative, verifiable and explicit. Soft information is qualitative, non verifiable and implicit. This type of information is strongly contingent on cognitive factors and subjective judgments. This distinction has been recently used as an alternative explanation of risk decisions of financial intermediaries (Stein, 2002). However, there is hardly any evidence that the type of information impacts financial markets prices.

In this paper we set up an experimental environment in which subjects have full information so that any additional message released to traders is a priori uninformative. As a result, we will refer to hard and soft messages or communications rather than to hard and soft information. The difference between hard and soft messages can be seen as a way to distinguish messages according to their content. We argue in *Hypothesis a* that hard messages, compared to soft messages, are likely to facilitate the coordination of beliefs among traders implying that such communications have a greater influence on asset prices. This should be the case since the interpretation of such messages is more homogenous. Indeed, traders may not agree on a unique interpretation of soft messages. As it is emphasized by Kirschenheiter (2002): "Hard information (...) is when everyone agrees on its meaning. (...) Honest disagreements arise when two people perfectly observe information yet interpret this information differently (i.e. soft information)". In agreement with *Hypothesis a* we should also expect that the variance of asset prices is going to increase more significantly when soft messages are released in the market. It should be the case since then the dispersion in beliefs among traders is going to be higher than in the case of hard communications characterized by a unique interpretation.

> **Hypothesis b**: *The effect of uninformative messages on asset prices is higher the higher is the reliability of the message sender (Source dimension).*

Motives by which one decides to hear and process a message released in the market (the first two steps by which the *power of words* can be characterized) may be internal (related to its content) or external (related to its source) (Sperber, 2005). In this paper we show how uninformative communications are relevant in financial markets in order to achieve coordination and stabilization. The relevance of a message is an indicator of its *power*.[2] The *power* of a message depends on the trade-off between the informational gains associated

[2] The relevance of the message partly depends on the reliability of the sender.

with the reception of the message and the cost involved in processing the message.[3] As a result, deliberately opaque and short formulations that are released by authoritative sources and that replace complicated statements, can have a significant influence on individuals' behavior (Sperber, 2005). Reliability facilitates information processing since then traders do not have to fully examine the steps and reasons underlying the official statement. As the message sender is more reliable, the expected gains of processing a message increase since the informational value of a statement is expected to be higher.

We find support for our main hypothesis stating that uninformative messages on the value of the asset significantly impact the level of asset prices. In particular, in the present environment of experimental markets with bubbles we find that messages limit excessive deviations of asset prices from fundamentals. This stabilization effects of messages is comparable to the role of subjects' experience as it is analyzed Dufwenberg et al. (2005). The introduction of communication is not the first mechanism considered in order to reduce the magnitude of experimental bubbles. Experience of subjects (King et al. 1992, Dufwenberg et al. 2005) and the introduction of future markets (Porter and Smith, 1994) in the experimental design have been found to be particularly effective to limit the occurrence of experimental bubbles. However, the solution proposed here is particularly attractive since much less costly than

[3] The *power* of a message is defined as the magnitude of its effect on asset prices.

the introduction of a new institution like a future market and much faster than training subjects.

We also encounter evidence that volatility in asset prices increases when messages are released. This effect is found to be even more significant for treatments considering imprecise messages. This is the case because soft messages that are characterized by a multiplicity of possible explanation tends to create heterogeneity in beliefs among traders. Stabilization in asset prices is then obtained at the cost of additional trading.

2 Experimental methods: an asset market strategy experiment

2.1 Design of the experiments and treatments

We propose to use the design initially presented by Smith et al. (1988) while considering the parameter values used in Dufwenberg et al. (2005). In these experimental asset markets, a unique asset is traded. The asset releases a dividend at the beginning of each of the 10, 15 or 30 trading periods. The dividend is drawn from a probability distribution known by experimental traders. Subjects are given an endowment in cash and assets at the beginning of the experiment. The market is not reinitialized at the beginning of each period, so that trading periods only differ in the realization of the dividend process. The trading procedure is a computerized double-auction mechanism. Subjects are trading continuously the experimental asset by entering bid and ask prices on a computer screen. A unit of the asset is traded once an ask or a bid price previously entered is accepted by a subject.

The experimental markets are usually characterized by a boom phase (a period where prices are higher than the fundamental value of the asset) followed by a crash period. This is a surprising result, since according to backward induction, risk neutral agents should trade at the fundamental value.

There are two main differences between our approach and the design used by Smith et al. (1988). First, we consider a strategy method experiment, that is an experiment in which participants have to formulate and justify their actions for all the periods and states of the world. Their strategies are then programmed and simulated and they are paid according to the performances generated by their strategy. The second difference is that we allow for the release of messages along the experiment. We characterize messages using three dimensions:

1. *Source* of the message,
2. *Content* of the message,
3. *Frequency* of the message.

We believe that these three dimensions may influence experimental asset prices. Reliability of the person sending the message will influence the degree to which the message is focal to the agent.[4] Reliability is maximal when subjects know that the message is delivered by the experimenter. In Table 1, we propose different alternatives in which the reliability of the sender is likely to be lower, as for example the case of a student sending the message, or as in the case of a random message. We denote Treatment ijk a treatment in which the message has reliability i, content j and frequency k, where i, j and k can be either low (L) or high (H). The content of the message is as well important, a vague statement like *"the average price is too low or too high"* as it is used in Treatments LLH and HLH may have a more reduced impact on subjects' beliefs than a precise statement like *"the average price is x cents of euro too low or x cents of euro too high"* (e.g. in Treatments LHH and HHH). The different dimensions characterizing a message may not be independent. For example, a sender may be perceive as more or less reliable depending on the content of the message he sends.[5] Finally, the frequency of the message is conjectured to be an important variable. We believe that the more frequent is a message, the higher is its impact on traders' beliefs and then on experimental prices. As emphasized by Mullainathan (2002), one can understand individuals' bounded

[4] That is the degree to which the agent is sensitive to the reception of the message.

[5] For example a message sender can gain reliability by providing a very precise message.

Treatment / Description	LLH	LHH	HLH	HHH
Reliability	*Low* An observer	*Low* An observer	*High* Message released by the experimenter	*High* Message released by the experimenter
Content	*Imprecise* Average prices of the last period are too low/high	*Precise* Deviations from fundamental values in c€	*Imprecise* Average prices of the last period are too low/high	*Precise* Deviations from fundamental values in c€
Frequency	*Very frequent* At the end of periods 5 to 9	*Very frequent* At the end of periods 5 to 9	*Very frequent* At the end of periods 5 to 9	*Very frequent* At the end of periods 5 to 9
Number of subjects	39	22	*26*	27

Figure 1: Descriptions of the treatments considered in the paper

rationality by memory limitations. As a result, mechanisms facilitating the work of memory should help boundedly rational traders to compute the fundamental value of the experimental asset. The frequency with which the message is released is then expected to affect the valuation of the asset by non-fully rational traders since memory processes more efficiently pieces of information that are rehearsed.

We considered the 4 treatments specified in Table 1. Evidently, several other configurations $\forall (i,j,k) \in \{L,H\}^3$ can be considered. We can modify the *frequency* of the message and release different types of message such as for example a random statement.

We conjecture that the impact of messages on experimental asset prices will be higher the higher the reliability of the sender, the more precise is the signal and the more frequent are the messages. We consider for the moment only the configuration in which the message is very frequent ($k = H$). We expect to observe some effects of the messages in Treatments LLH, HLH and LHH and more perceptible effects in Treatment HHH. We also consider a benchmark treatment in which no messages are delivered. This treatment corresponds to the case described in Dufwenberg et al. (2005) when traders are inexperienced. The different treatments considered in this paper are summarized in Table 2.

Treatment	Description
Treatment O	No messages are delivered. Design similar to Dufwenberg et al. (2005).
Treatments ijk	Messages are delivered at the end of periods 5 to 9. The content of the message is either precise or vague, The reliability of the sender of the message is either high or low.

Table 2: Summary of the experimental design

Our experimental design allows us to assess how influential agents can impact the level of prices in financial markets.[6] If we find no effects for Treatments ijk presented in Table 1, we can conclude that the impact of such influential agents is limited. To the contrary, if uninformative messages have a significant impact on experimental prices we may conclude that manipulation of prices is possible and relatively easy to achieve. In the context of experimental bubbles considered in this paper, we are prone to analyze stabilization in asset prices obtained through announcements delivered by financial authorities. The issue of destabilization and manipulation of asset prices by financial *gurus* could be studied in a similar setting by considering messages emphasizing that current prices are excessively low.[7]

2.2 Subjects and procedures

This experiment has been conducted in November 2005 at the Burgundy School of Business in Dijon, France. Altogether 182 students were recruited on a voluntary basis in an introduction to Psychology undergraduate course in which there are 272 students aged between 19 and 22. Students in this course usually have an intensive 2 years undergraduate background, and pass an entrance exam to join the school. Subjects received instructions with full information about the market and procedures and had one week to submit their strategies

[6] As influential entities we can think of financial authorities or financial *gurus* that are able to make anouncements in the media.

[7] Such a consideration is the object of a current research.

and comments. Up to 50 subjects participated in each of the five treatments corresponding to Treatments O, HHH, HLH, LHH and LLH. They were asked not to communicate about the experiment during the week and asked to describe their strategies and motivations as accurately as possible.

Subjects were involved in trading an asset with a finite life of ten periods. In each period the asset pay a dividend of 0 or 20 cents, with equal probability. Therefore the expected monetary benefit of holding an asset is 10 cents for each remaining period. They were told that each market will involve 6 traders, who could buy and sell assets. Half of the subjects (3) started with a cash endowment of 200 cents and six assets and the other half (3) with a cash endowment of 600 cents and 2 assets. A trader's cash holding at any point in time differed from his or her cash endowment by accumulated capital gains or losses via market trading, and accumulated dividend earnings via asset units held in inventory at the end of each trading period. All information was common knowledge.

Assuming risk neutrality and no discount factors, the fundamental value of the asset, by backward induction, is equal to $10t$ where t is the number of remaining periods. Subjects had to describe their trading actions and they had to anticipate the market price for the 10 trading periods. Intensive simulations were then performed for each treatment and traders' strategies as we describe in the next section.

Subjects were paid first when they handed in their strategies and were then paid for a second time after simulations of their strategies have been performed. The first payment depended on the effective elaboration of the strategies by the subjects. Subjects that formulated complete plans of actions were paid 15 euros whereas other subjects were rewarded 5 euros. Subjects were then paid an additional amount after simulations have been performed. This additional payment ranging from 0 to 15 euros was computed as a function of subjects' simulated profits. Subjects' profits were determined in agreement with the description of the experimental market in this section.[8] We decided to pay a proportion of the subjects' rewards instantaneously in order to strengthen their incentives to exert effort in the elaboration of their strategies.

2.3 Simulations

We simulate 5000 ten-period markets composed of 6 traders for each of the treatment that are analyzed in this paper.[9] As it is described in Dufwenberg et al. (2005) we consider two endowment classes. That is, 3 traders are endowed with 6 units of the experimental asset and 200 units of the experimental currency whereas the 3 remaining traders are endowed with 2 units of the asset

[8] That is, traders' profits are computed as in standard experimental asset markets with Bubbles (Smith et al. 1988, Dufwenberg et al. 2006).

[9] The simulations are performed using Matlab 6.5. The program is available upon request from the authors. Details about the convergence of the simulations for 5000 replications are also available.

and 600 units of the experimental currency. The 5000 markets simulated differ in the identity of the subjects that compose the market. Given the strategies formulated by subjects we simulate a market activity by using the following sequence. Each market session starts with a *bid* or an *ask* offer selected randomly from the strategies of the subjects involved in the market. A transaction is then concluded at that price if there exists one of the trader that specifies in his strategy his willingness to buy (sell) the asset at the proposed *ask* (*bid*) price. For a given trading period we repeat N times that procedure by taking a *bid* or an *ask* offer selected randomly from the strategies of the subjects involved in the market. We then replicate 1000 times the sequence of N potential transactions. We ran simulations for $N \in [2, 12]$ and we derive similar conclusions for the different values chosen for N. We present in this paper the results that correspond to the case $N = 4$; that is, at most 4 transactions per period are concluded.

Limitations?

3 Results: 'Do words really matter?'

In this section, we use the data of our strategy experiments in order to test the hypotheses stated in the introduction. We provide statistical tests to assess how uninformative messages affect expected asset prices, bids, asks and simulated

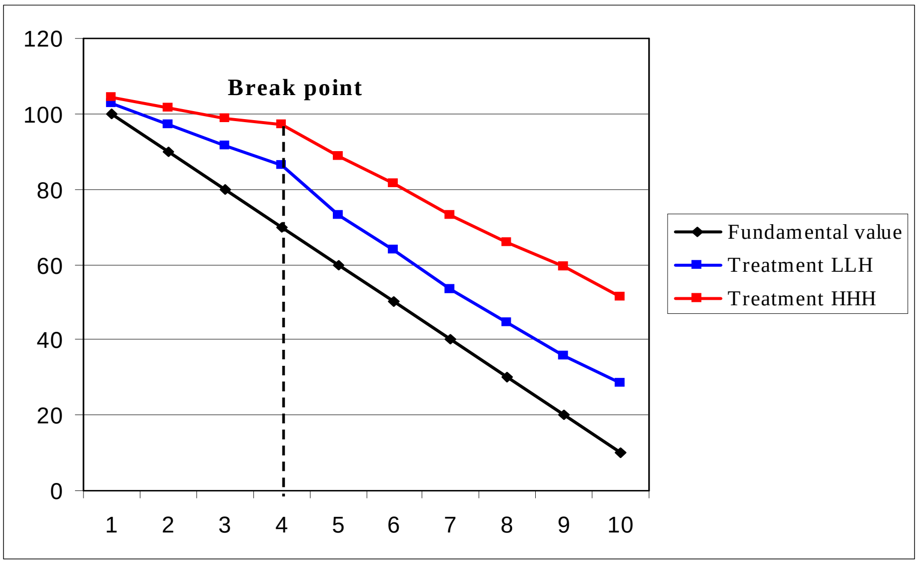

Figure 2: Average expected prices per period for Treatments HHH and LLH asset prices.

3.1 Analysis of expected and simulated asset prices

3.1.1 Stability tests on expected asset prices

We are interested in knowing if there exists a shift in prices expectations in period 5 when messages start to be delivered. In Figure 1, we draw the average expected prices for Treatments O, HHH and LLH. We notice the possible presence of a break point in expected prices between periods 4 and 5.

We test for a shift in expectations using panel data regression methods for Treatments HHH, LHH, LLH and HLH. We run the following trend regression for the various treatments : $f(t) = c(1) + c(2)t + \varepsilon$, where $f(t)$ is the expected price for period t and $c(1)$ and $c(2)$ are the regression coefficients. We first check that, in the full sample, $c(2)$ is highly significant for the different treatments considered. This means that agents are correctly assessing the decreasing pattern of fundamental values. We then compare the estimated trend coefficient $\hat{c}(2)$ for $1 \leq t \leq 4$ and for $5 \leq t \leq 10$. We test for the stability of the trend parameter by running a Wald-test where the null hypothesis is that the coefficient $c(2)$ is the same in the two subsamples (the subsample in which no messages are delivered: $1 \leq t \leq 4$ and the subsample with messages: $5 \leq t \leq 10$). We are unable to reject the stability of the trend coefficient in Treatment O, whereas we strongly reject the stability of the coefficient in Treatment HHH. This effect is observed at a lesser extent for Treatment LLH. Subjects react to messages with anticipation since their prices forecasts start to decline in period 5 whereas the first communication is delivered only at the end of that period. These findings are consistent with our main hypothesis that puts forward the impact of uninformative messages on asset prices. We display in the appendix the outputs for the panel data regressions on the full sample ($1 \leq t \leq 10$) as well as for the stability tests of the trend coefficient $c(2)$.

Result 1.1. *The release of uninformative messages significantly decreases the downard sloping trend in expected asset prices for*

Treatments HHH and LLH.

The break observed in asset prices is stronger for Treatment HHH than for Treatment LLH in agreement with the Hypotheses a and b. As a result, even in a strategy method experiment for which individuals' bounded rationality is limited, uninformative messages may affect expected prices. This occurs even in Treatment LLH, where the sender has low reliability and the uninformative message is imprecise. However, we are unable to find such message effects in Treatments LHH and HLH. Result 1.1 is confirmed if we consider an alternative specification for modelling expected asset prices such as for example $f(t) - f(t-1) = b(1) + b\,(2)\,f(t-1)$.[10]

The impact of uninformative messages on expected asset prices is strongest when the message sender is highly reliable and the message is very precise. According to the stability test detailed in the appendix, the existence of a break is more significant for Treatment HHH than for other treatments since only in that case we can reject the stability of the trend coefficient at a 1% level of significance. The stability of the coefficient $c(2)$ is not rejected at this level of significance in any of the Treatments LLH, LHH and HLH. However, the *Hypothesis* b that puts forward the role of the reliability of the message sender is not supported since a break in expectations is identified for Treatment LLH

[10]This specification is the correct one if $f(t)$ is integrated of order 1.

but not for Treatment HLH. Then, we cannot conclude that the reliability of the message sender is decisive in the present framework. This is not so surprising since we decided to run a strategy experiment in order to limit the experimenter effect. The reliability of the experimenter is then perceived to be comparable to the reliability of an observer.

Concerning the effect of the precision of the message on changes in asset prices (*Hypothesis* a), we have to emphasize that even treatments for which the message delivered to the market is imprecise (Treatment LLH) are characterized by significant effects of uninformative communications on subjects' forecasts. However, as we will analyze in Section 3.3, the precision of the message has a relevant impact on the level of volatility in asset prices.

Our first result emphasizes the effect of messages on subjects' expectations but such conclusions may not directly apply to observed asset prices. We then decide to assess the impact of uninformative communications on the level of asset prices simulated using the algorithm described in Section 2.3.

3.1.2 Stability tests on simulated asset prices

We test for a shift in expectations using panel data regression methods for Treatments HHH, LHH, LLH and HLH. We model simulated asset prices represented in Figure 2 for the different treatments as an $AR(1)$ process around a trend. That is, $P(t) = b(1) + b(2)t + b(3)P(t-1) + \nu$, where $P(t)$ is the

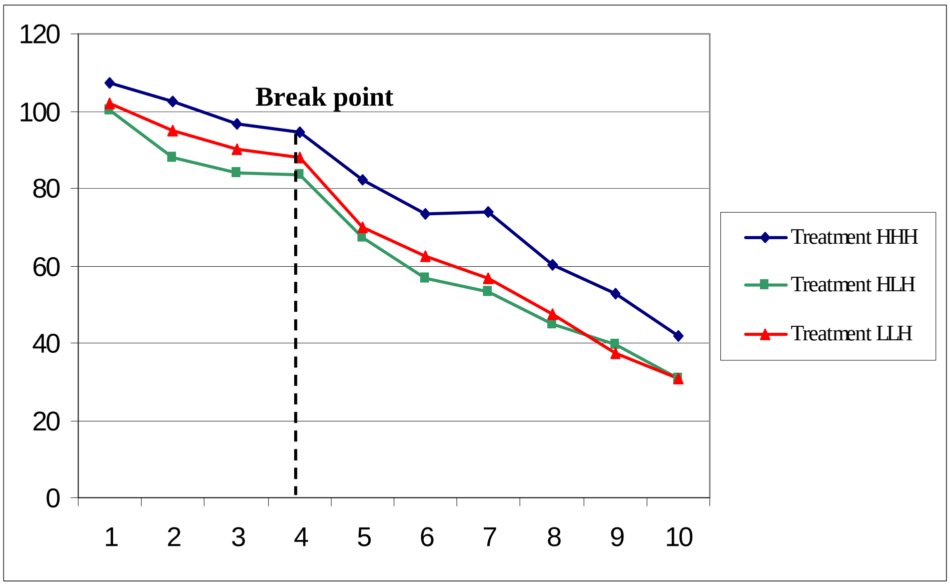

Figure 3: Average simulated prices per period in Treatments HHH, HLH and LLH

average simulated price for period t and $b(1)$, $b(2)$ and $b(3)$ are the regression coefficients. This specification is used since it allows for the best fit of simulated asset prices.

We test the stability of the model specification by comparing the estimated coefficients $\hat{b}(2)$ and $\hat{b}(3)$ for the samples $1 \leq t \leq 4$ and $5 \leq t \leq 10$. We first consider a panel data regression for each treatment. The results of the estimations and the stability tests are summarized in Tables 2 and 3.

Treatments	HHH	LLH	HLH	LHH
$b(2)$ $for\ t \in [1,4]$	2.51	2.47	2.10	-2.67
$b(2)$ $for\ t \in [5,10]$	-0.75	-0.39	-0.53	-2.80

Table 2: $b(2)$ and $b(3)$ values for $t \in [1,4]$ and $t \in [5,10]$

Treatments	HHH, LLH, HLH	LHH
Test for $b(2)$ p-value	0.000***	0.752
Test for $b(3)$ p-value	0.000***	0.028**

Table 3: Stability tests (Wald-tests) for coefficients $b(2)$ and $b(3)$

We find that trend coefficients are not stable for Treatments HHH, LLH and HLH. In particular the estimated trend coefficient is negative for $1 \leq t \leq 4$ and becomes positive for the second part of the sample, that is for $1 \leq t \leq 4$. In that sense the break in simulated asset prices appear to be even more pronounced than the shift identified for expected prices

Result 1.2. *The rising trend in simulated asset prices is reversed by the release of uninformative messages from period* 5 onwards *for Treatments* HHH, LLH and HLH.

We obtain a similar result by pooling prices simulations for the different treatments. We reject the stability of the trend coefficient as it is displayed in the appendix. Also, by running regressions of simulated prices on fundamentals we find that the goodness of fit for associated to messages treatments is 0.93 whereas it is 0.05 for the benchmark Treatment O.[11] As a consequence, uninformative communications appear to impact significantly the level of expected and simulated asset prices. In the next section we consider the role of messages on asset mispricing.

3.2 Mispricing, bubbles and stabilization

We analyze in this section the impact of messages on the patterns of mispricing in the simulated asset markets. We consider the price amplitude of a bubble, the normalized average price deviation, the goodness of fit and the break period as measures of mispricing (Table 4). The price amplitude is defined as the difference between the maximum and the minimum deviation of asset prices with respect to fundamentals. The price amplitude for Treatment k is $PA_k \equiv Max\left\{\frac{|P_t-F_t|}{F_t}\right\} - Min\left\{\frac{|P_t-F_t|}{F_t}\right\}$, where P_t is the average simulated price of the asset in period t and F_t is the value of fundamentals for that period.

[11]The main difference is that we consider in that case that the result of S simulations as a single observation. Statistical tests that are performed under that hypothesis are then much more conservatives. However, we are able even in that case to reject the stability of trend coefficients.

The normalized average price deviation is computed as $NAPD_t \equiv \sum_{t=1}^{10} \frac{|P_t - F_t|}{F_t}$. We assess the goodness of fit by the R^2 associated to the regression of asset prices on the fundamentals. We finally determine the *Break* period as the first period in which the price deviation ($i.e.\, |P_t - F_t|$) decreases. We provide in the next table a summary of the different measures of mispricing for the treatments considered in the paper as well as for Treatment $D0$ ($D2$) that involves inexperienced (twice-experienced) traders in Dufwenberg et al. (2005).

Treatment	HHH	LLH	HLH	LHH	O	$D0$	$D2$
Price Amplitude	3.17	1.95	2.13	1.68	8.98	7.24	5.4
Normalized Average Price deviation	0.84	0.46	0.45	0.42	1.98	1	0.64
Goodness of fit	0.70	0.80	0.75	0.95	0.05	-	-[12]
Break period	5	5	5	5	8	None	8

Table 4: Summary statistics for mispricing

Table 4 as well as Figure 3 suggest that the level of mispricing for messages treatments (i.e. Treatments HHH, LLH, HLH and LHH) is significantly reduced compare to the Benchmark Treatment O.

[12] Goodness of fit measures are not comparable with the ones obtained from simulated prices. We prefer then to omit their values here. From Dufwenberg at al. (2006), the goodness of fit (Haessel-R^2) is 0.37 for Treatment $D0$ and 0.64 for Treatment $D2$.

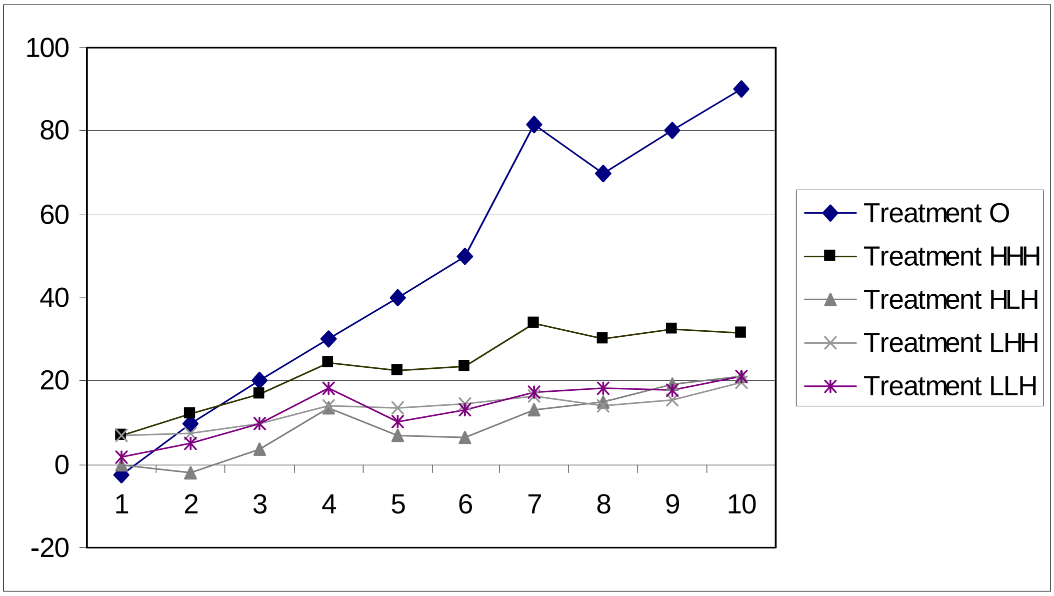

Figure 4: Deviations of average simulated prices with respect to fundamentals for each treatment.

We test the conjecture that messages treatments are characterized by reduced mispricing with respect to Treatment O by running regressions for prices deviations ($B_t \equiv P_t - F_t$) for the different treatments. In Table 5.1 we display the models that best fit prices deviations for messages treatments and for the benchmark Treatment O. We find that in the case of messages treatments there exists a trend in B_t in the first part of the sample, that is for $t \in [1, 4]$. However, this linear trend disappears in the second part of the sample when messages start to be delivered. For Treatment O, the linear trend is present in the two subsamples. We can then conclude that the release of messages tend to cancel the linear trend present in the bubble component B_t.

Treatment	Messages treatments Pooled data	Treatments O
Model specification for $t \in [1,4]$	AR(1) and linear trend $\hat{B}_t = -0.12 + 2.33t + 0.98\hat{B}_{t-1}$ $R^2 = 0.894$	Linear trend $\hat{B}_t = -1.55 + 10.66t$ $R^2 = 0.997$
Model specification for $t \in [5,10]$	AR(1) $\hat{B}_t = 2.61 + 0.90\hat{B}_{t-1}$ $R^2 = 0.736$	Linear trend $\hat{B}_t = 7.54 + 9.39t$ $R^2 = 0.804$

Table 5.1: Models specifications for simulated prices in messages treatments and in Treatment O

As a result, uninformative messages delivered in the market appear to have a stabilizing effect on asset prices. Asset bubbles trending patterns are significantly reduced by the release of messages.

Result 2.1. *The increasing trend in the bubble component disappears in the treatments with messages.*

The observation of Table 4 and Figure 4 below suggests that patterns of mispricing for the messages treatments considered in this paper are similar to the ones obtained in the case of twice-experienced traders in Dufwenberg et al. (2005).

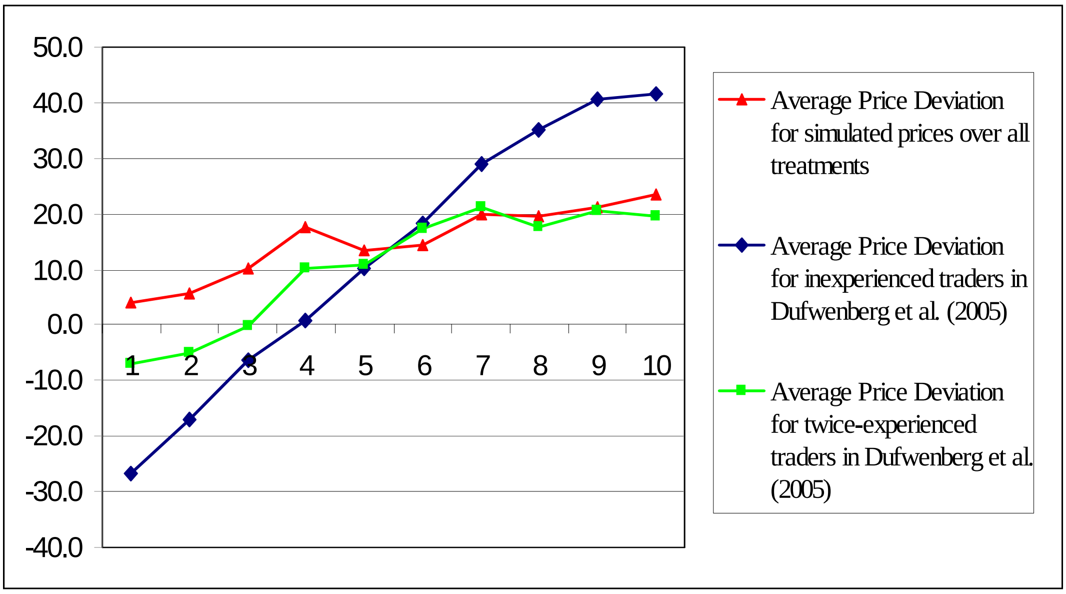

Figure 5: Average asset prices deviations for messages treatments and Treatments $D0$ and $D2$ in Dufwenberg at al. (2005).

We test this conjecture in Table 5.2 by comparing by providing a regression analysis for asset prices in Treatment $D2$ (twice-experienced traders) undertaken in Dufwenberg et al. (2005).

Treatment	Treatment $D2$
Model specification for $t \in [1, 4]$	AR(1) and linear trend $\hat{B}_t = -3.92 + 4.56t + 0.88\hat{B}_{t-1}$ R^2= 0.843
Model specification for $t \in [5, 10]$	AR(1) $\hat{B}_t$= $5.88 + 0.78\hat{B}_{t-1}$ R^2= 0.696

Table 5.2: Models specifications for simulated prices in Treatment $D2$

We notice that the regression model that best fit asset prices in the case of Treatment $D2$ is similar to the model selected for the simulated prices in our messages treatments. That is, we find that asset prices in Treatment $D2$ are characterized by the presence of a trend in B_t in the first part of the sample but this linear trend disappears in the second part of the sample when messages start to be delivered. It seems then that messages play a role similar to traders' experience given that patterns of mispricing in messages treatments are comparable with the case of treatments involving twice-experienced traders in Dufwenberg et al. (2005). The conjecture derived from Figure 4 is then confirmed by our regression analysis. In short, releasing a priori uninformative messages is found to reduce asset bubbles in the same magnitude as training subjects twice. This conclusion is captured in the following result.

> **Result 2.2.** *The patterns of bubbles for treatments with messages are comparable with Treatment $D2$ that involves twice-experienced traders in Dufwenberg et al. (2005).*

As it is stated in Results 2.1 and 2.2, asset prices do react to uninformative communications in a direction that tend to reduce asset market bubbles. We then provide experimental foundations for the design by financial authorities of communications strategies that attempt to regulate the market.

We also test our auxiliary Hypotheses a and b by assessing the impact of the type of messages on mispricing. However, we are unable to reject that the level of mispricing in treatments that involve imprecise and precise messages are the same. This conclusion is similar when testing if normalized average price deviation differ between treatments with highly reliable and poorly reliable message senders. As we encountered in Section 3.1 for the case of expected and simulated prices, the reliability of the message sender and the precision of the message are not conclusive in the present framework.[13]

3.3 Patterns of volatility in expected and simulated prices

In this paper we are not only concerned with the impact of communications on the level of asset prices but we are also concerned with the influence of messages on asset prices volatility. In Figure 5, we draw the volatility of simulated asset prices for the ten periods of the market in the different messages treatments.[14] We define volatility (V_t) as the standard deviation of simulated asset prices per period divided by the average price in that period.

The patterns of volatilities appear to be modified with the release of messages from period 5 onwards. The level of volatilities increase steadily after period 5. We test this hypothesis by comparing the mean volatility in the

[13] Details of the tests are available upon request.
[14] Volatility values are normalized to one.

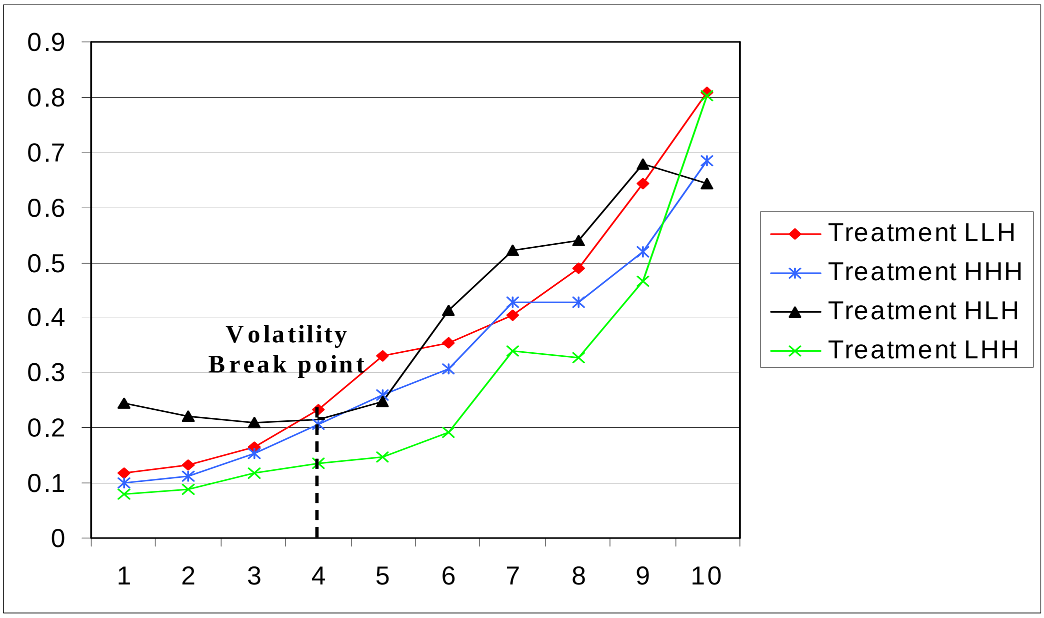

Figure 6: Patterns of volatility for simulated prices

two subsamples. We find that the mean volatility is significantly higher for $t \in [5, 10]$ than for $t \in [1, 4]$. Similar results are obtained for the case of volatility in expected asset prices. To the contrary, volatility in asset prices in the case of markets involving inexperienced traders in Dufwenberg et al. (2005) does not rise after period 5. The details of the tests are available in the appendix. The findings about the patterns of volatility are summarized in the following result.

Result 3.1. *Volatility in asset prices increases significantly when messages start to be delivered (i.e. from period 5 onwards).*

It appears that the release of messages tends to reduce mispricing at the cost of an increased volatility in asset markets. Messages even though they are uninformative significantly modify subjects' beliefs. In addition, experimental traders seem to interpret communications differently. As a results, messages tend to increases the dispersion in beliefs among subjects and then asset prices volatility. This argument is confirmed in Result 3.2 when comparing asset prices volatility in treatments involving precise and imprecise messages. In agreement with our interpretation of Result 3.1, the level of volatility in simulated asset prices appear to be significantly higher for imprecise messages treatments. Indeed, imprecise messages (*Average asset prices in the last period are too high*) lead to multiple interpretations about mispricing of the experiment asset whereas a precise statement (*Average asset prices in the last period are 5% too high*) tends to lead to a unique interpretation.

> **Result 3.2.** *From period 5 onwards, volatility in asset prices is significantly higher for treatments with imprecise messages (HLH, LLH) compared to precise messages treatments (HHH, LHH).*

Result 3.2 suggests that financial authorities willing to stabilize asset market prices by communicating to the market have to take into account the possible negative effects of their announcements on asset prices volatility. The release of messages creates an additional uncertainty in the market that is especially pronounced when statements are imprecise. The content of the message is a crucial element in the design of optimal communications strategies by financial authorities.[15] The communications strategy should consider communications costs related to increased uncertainty and excessive trading (Section 4).

3.4 Trading volume in simulated markets

As it is argued in the previous section, the optimal communications policy depends on the impact of messages on the trading volume. In Figure 6, we draw the average trading volumes in the case of messages treatments and in the case of the treatment involving inexperienced traders in Dufwenberg et al.(2005).[16]

We observe that trading volumes tend to decrease in the benchmark treatment considered by Dufwenberg et al. (2005) whereas they tend to rise in the case of messages treatments. This observation is confirmed by comparing the mean trading volume for $t \in [1, 4]$ and for $t \in [5, 10]$ in the different treatments. We find as it is summarized in the appendix that trading is more intense in the first part of the sample for messages treatments whereas it is less intense for the benchmark treatment considered by Dufwenberg et al.(2005).

Result 4.1. *There exits an increasing patterns of trade in the*

[15] We analyze optimal communications strategies in another work in which we do not consider strategy method experiments but standard experimental asset markets.

[16] Trading volumes are normalized to one.

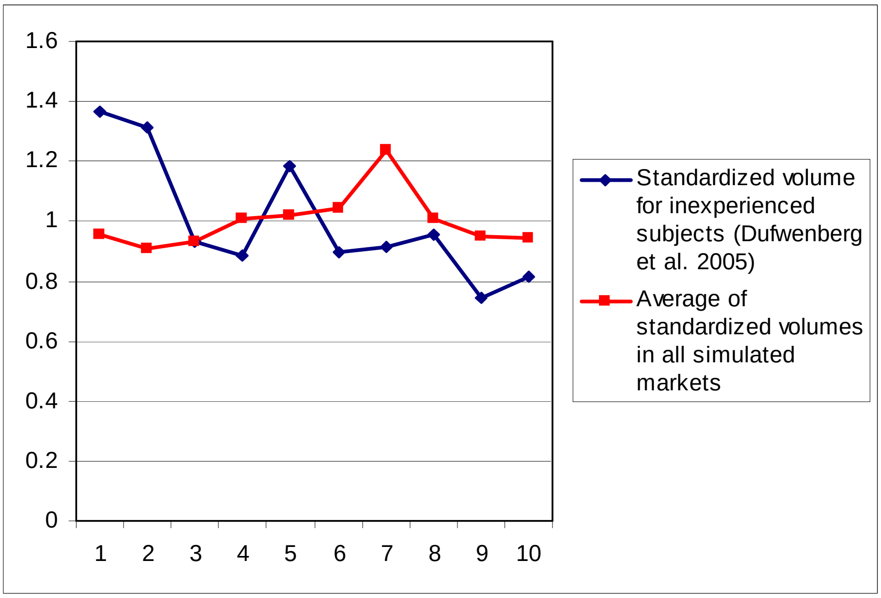

Figure 7: Trading volumes for messages treatments and for the benchmark treatment in Dufwenberg et al. (2005).

messages treatments in opposition to the benchmark treatment considered in Dufwenberg et al. (2005).

Result 4.1 is in agreement with the finding of the last section stressing that messages tended to increase the dispersion in beliefs among subjects. Then, as a result of this increased divergence in beliefs, individuals tend to engage in more intensive trading. In real markets trading is costly so that messages policies are likely to be associated with efficiency costs. This cost is higher when the messages released are imprecise since then trading volumes are even more sensitive to communications. This finding is stated below as Result 4.2.

Result 4.2. *Trading volumes for treatments involving imprecise* *messages (HLH, LLH) are significantly higher for* $t \in [5, 10]$ than for $t \in [1, 4]$.

However, trading volumes for treatments involving precise messages (HHH, LHH) are not significantly different for $t \in [5, 10]$ and for $t \in [1, 4]$.

Result 4.2 is consistent with the finding that asset prices in imprecise messages treatments are characterized by a particularly high volatility (Result 3.2) The high trading volume observed under such treatments is a direct consequence of an extensive dispersion in beliefs among subjects provoked by the release of imprecise messages.

4 Concluding remarks

This paper analyzed the issue of communication in asset markets. In particular, we focused on the case in which uninformative messages delivered in the market may stabilize asset prices. Our main hypothesis being that uninformative messages significantly impact the level of asset prices. We proposed an experimental approach of the question in order to be able to control for the level of informativeness of messages reaching the market. More specifically, we used a strategy approach so as to limit the impact of experimenter demand effects. Such effects may lead subjects to overreact to any announcement made by the experimenter along the market experiment.

We found that experimental asset prices simulated using pre-established subjects' strategies strongly react to uninformative communications. More precisely, we put forward that messages limit excessive deviations of asset prices from fundamentals. This stabilization effects of messages was found to be comparable to the role of subjects' experience as it is analyzed in Dufwenberg et al. (2005).

Despite the fact that the precision of the message or the reliability of the sender were not determinant in assessing the magnitude of the effects of communications, they were decisive in accounting for the volatility in asset prices and the volume of trade. Indeed, we found that volatility in asset prices and trading volumes increased significantly when messages were released and this effect was even stronger for treatments considering imprecise messages.

We can then argue that stabilizing asset prices by the release of messages may generate costs associated to additional uncertainty and excessive trading in the markets. Financial authorities should take into account their potential destabilizing power when considering their communication policy. Financial authorities, when designing an optimal communications strategy, should envision the negative effects of imprecise statements.

5 Appendix

5.1 Instructions

We consider the instructions for the case of Treatment HHH (English translation).

This is an experiment in the economics of market decision-making. The instructions are simple and if you follow them carefully and make good decisions, you might earn a considerable amount of money. The experiment will consist of a sequence of trading periods in which you will have the opportunity to buy or sell in a market. All trading will be in terms of points.

Please do not communicate with any other participants before you hand in your strategies. You should be able to elaborate a complete strategy of this game in two hours.

Please read the following instructions carefully in order to be able to construct your strategy.

In this game, you have to formulate a strategy. A strategy is a complete plan of actions. If you give your strategy to another person, she should be able to behave exactly as you would have behaved in this experiment. A strategy has to be i) complete (that is an action has to be recommended in any possible situation of the game), ii) unambiguous (that is only one action can be chosen for a given situation of the game) and iii) correct from an informational point of view (you have to use the data presented in the current instructions).

Examples of incomplete strategies

a) In the first period my forecast for the price of the asset is 40. In the following periods my forecast is 70 if the price is higher than 50 and 40 if the price is smaller that 50.

This strategy is incomplete since it does not predict anything if the price of the experimental asset is exactly 50.

b) In the first period my forecast for the price of the asset is 45. In the following periods my forecast will depend on the actual price in Period 5. If in Period 5 the actual price is smaller (higher) than 50, I will (decrease) increase my forecast by 5. This strategy is incomplete since there is no rule to construct forecasts from periods 2 to 5.

Example of an ambiguous strategy: in the first period my forecast for the price of the asset is 70. In the following periods I will increase my forecast by 10 if my previous prediction was smaller than the actual price, I will decrease it by 10 if my previous prediction was higher than the actual price and I will maintain my forecast if my forecasting error in the previous period is smaller than 5.

This strategy is ambiguous since we do not know what would be your forecast if the previous prediction was for example 3 points below the actual price. Should we maintain the forecast or should we decrease it by 10? What is the dominant rule?

Market description:

Each market is composed of 6 participants. At the beginning of the market half of you will have an endowment of 6 goods (called X) and 200 points and the other half will be endowed with 2 goods (called X) and 600 points.

You have an endowment of 2 goods X and 600 points.

The market has 10 periods.

In each period, you may buy or sell units of a good called X. X can be considered an asset with a life of 10 periods, and your inventory of X carries over from one trading period to the next. Each period lasts for 2 minutes. At the end of each trading period, each unit of X pays a dividend. The dividend will be either 0 or 20 cents, which is randomly decided by the computer with a 50 % chance of each dividend. Thus, the average dividend per period is 10 cents. Your profits in the market will be equal to the total of the dividends that you receive on units of X in your inventory at the end of each of the market periods plus the cash you have at the end of the market.

The way to calculate your earnings is described in Table 1.

You can use Table 1 to help you make decisions. There are 5 columns in the table. The first column, labeled Ending Period, indicates the last trading period of the market. The second column, labeled Current Period, indicates the period during which the average holding value is being calculated. The third column gives the number of holding periods from the period in the second column until the end of the market. The fourth column, labeled Average Dividend Value Per Period, gives the average amount that the dividend will be in each period for each unit held in your inventory. The fifth column, labeled Average Holding Value Per Unit of Inventory, gives the expected total dividend for the remainder of the experiment for each unit held in your inventory for the rest of the market. That is, for each unit you hold in your inventory for the remainder of the market, you receive in expectation the amount listed in column 5. The number in column 5 is calculated by multiplying the numbers in columns 3 and 4.

Suppose for example that there are 4 periods remaining. Since the dividend paid on a unit of X has a 50% chance of being 0 and a 50% chance of being 20, the dividend is in expectation 10 per period for each unit of X. If you hold a unit of X for 4 periods, the total dividend paid on the unit over the 4 periods is in expectation $4 \times 10 = 40$.

Your earnings in each period equal the value of the dividends you receive at the end of the period for the units of X in your inventory at the end of the period. That is, YOUR EARNINGS FOR A PERIOD = DIVIDEND PER UNIT $\times$ NUMBER OF UNITS IN INVENTORY AT THE END OF PERIOD.

Your total earnings for one market are the total of your earnings for periods

Ending Period	Current Period	Number of holding Periods ×	Average Dividend = Value Per Period	Average Holding Value Per Unit of Inventory
10	1	10	10	100
10	2	9	10	90
10	3	8	10	80
10	4	7	10	70
10	5	6	10	60
10	6	5	10	50
10	7	4	10	40
10	8	3	10	30
10	9	2	10	20
10	10	1	10	10

Figure 8:

1-10 plus the amount of cash that you have at the end of period 10.

That is YOUR TOTAL EARNINGS IN THE MARKET =

EARNINGS FOR PERIOD 1 + EARNINGS FOR PERIOD 2 + EARNINGS FOR PERIOD 3 +

EARNINGS FOR PERIOD 4 + EARNINGS FOR PERIOD 5 + EARNINGS FOR PERIOD 6 +

EARNINGS FOR PERIOD 7 + EARNINGS FOR PERIOD 8 + EARNINGS FOR PERIOD 9 +

EARNINGS FOR PERIOD 10 + CASH ON HAND AT THE END OF PERIOD 10.

Your activity on the market consists in selling and buying units of X. For

Period	Ask	Bid	Price forecast	I sell (yes /no)	I buy (yes /no)	Number of units of X at the beginning of the period and associated expected dividend	Number of units of X at the end of the period and associated expected dividend	Cash at the beginning of the period	Cash at the end of the period
1									
2									
3									
4									
5									
6									
7									
8									
9									
10									

Figure 9: Market activity table

each period, you have to make the following decisions.

- Establish a price for which you are willing to sell a unit of X.

- Establish a price for which you are willing to buy a unit of X.

- Decide whether to sell a unit of X given the actual market price (yes or no).

- Decide whether to buy a unit of X given the actual market price (yes or no).

The actual market price of transactions will depend on all the bids and asks of traders in your market as well as your decisions to buy and sell the asset.

Example: Treatment HHH

During the first 4 periods, market activities will take place as specified above. From Period 5 onwards, at the end of each period, the experimenter will announce publicly that the actual market price for one unit of X in this period is 5% too high given the fundamentals of the Economy.

Thanks to complete Table 1 and provide explanations for your choices.

5.2 Results on stability tests

Panel regressions for expected asset prices

Treatments	HHH	LLH	HLH	LHH
$c(2)$ $for\ t \in [1, 4]$	-2.38	-6.41	-6.55	-7.08
$c(2)$ $for\ t \in [5, 10]$	-7.38	-8.73	-8.18	-7.95

Table: Trend coefficient values $c(2)$ for $t \in [1, 4]$ and $t \in [5, 10]$

Coefficients stability tests for expected asset prices

Treatments	HHH	LLH	LHH	HLH
Test for $c(2)$ p-value	0.004***	0.051*	0.596	0.461

Table: Stability tests for the trend coefficient $c(2)$

Dependent Variable: Expected Asset Prices				
Method: Pooled Least Squares				
Sample: 1 10				
Included observations: 10				
Number of cross-sections used: 19				
Total panel (balanced) observations: 190				
Cross sections without valid observations dropped				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(0)	108.3633	3.597931	30.11821	0.0000
C(1) (TREND COEFFICIENT)	-6.047624	0.673954	-8.973344	0.0000
R-squared	0.299868	Mean dependent var		81.14895
Adjusted R-squared	0.296144	S.D. dependent var		31.80478
S.E. of regression	26.68297	Sum squared resid		133852.4
F-statistic	80.52091	Durbin-Watson stat		0.077123
Prob(F-statistic)	0.000000			

Figure 10: Panel data regression for Treatment HHH

Dependent Variable: Expected Asset Prices				
Method: Pooled Least Squares				
Sample: 1 10				
Included observations: 10				
Number of cross-sections used: 30				
Total panel (balanced) observations: 300				
Cross sections without valid observations dropped				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	104.5351	2.579182	40.53035	0.0000
C(2)	-8.601166	0.483125	-17.80319	0.0000
R-squared	0.515411	Mean dependent var		65.82990
Adjusted R-squared	0.513784	S.D. dependent var		34.46932
S.E. of regression	24.03517	Sum squared resid		172151.4
F-statistic	316.9535	Durbin-Watson stat		0.099089
Prob(F-statistic)	0.000000			

Figure 11: Panel data regression for Treatment LLH

Dependent Variable: Expected Asset Prices				
Method: Pooled Least Squares				
Sample: 1 10				
Included observations: 10				
Number of cross-sections used: 19				
Total panel (balanced) observations: 190				
Cross sections without valid observations dropped				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	103.6677	3.447895	30.06695	0.0000
C(2)	-7.727911	0.645850	-11.96549	0.0000
R-squared	0.432321	Mean dependent var		68.89211
Adjusted R-squared	0.429301	S.D. dependent var		33.84792
S.E. of regression	25.57028	Sum squared resid		122921.7
F-statistic	143.1729	Durbin-Watson stat		0.045805
Prob(F-statistic)	0.000000			

Figure 12: Panel data regression for Treatment LHH

Dependent Variable: Expected Asset prices				
Method: Pooled Least Squares				
Sample: 1 10				
Included observations: 10				
Number of cross-sections used: 22				
Total panel (balanced) observations: 220				
Cross sections without valid observations dropped				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	107.7893	5.180095	20.80835	0.0000
C(2)	-7.634986	0.970321	-7.868518	0.0000
R-squared	0.221188	Mean dependent var		73.43182
Adjusted R-squared	0.217616	S.D. dependent var		46.73514
S.E. of regression	41.33840	Sum squared resid		372532.2
F-statistic	61.91357	Durbin-Watson stat		0.125888
Prob(F-statistic)	0.000000			

Figure 13: Panel data regression for Treatment HLH

Wald Test:			
Equation: POOLALL			
Null Hypothesis:	C(2)=-2.38		
F-statistic	8.842090	Probability	0.003605
Chi-square	8.842090	Probability	0.002944

Figure 14: Stability test for expected prices and Treatment HHH

Wald Test:				
Equation: POOALL				
Null Hypothesis:	C(2)=-6.41			
F-statistic	3.860354		Probability	0.050996
Chi-square	3.860354		Probability	0.049440

Figure 15: Stability test for expected prices and Treatment LLH

We test (Wald coefficient test) if C(2) - the coefficient of the trend is stable- To do so we test if the trend coefficient in the regression for periods 5 to 10 is equal to -2.38. We have to REJECT the absence of breaks. This implies that estimated prices are not stable. There is a break in period 5 (we would obtain similar result for a break in period 6).

Here is the result:

We CANNOT REJECT the absence of breaks at a 5% level of significance. However at a 10% level we REJECT the absence of a break at t=5. This implies that estimated prices are more stable than under Treatment HHH (what we

Wald Test:				
Equation: POOLALL				
Null Hypothesis:	C(2)=-7.07			
F-statistic	0.282135		Probability	0.596357
Chi-square	0.282135		Probability	0.595305

Figure 16: Stability test for expected prices and Treatment LHH

Wald Test:				
Equation: POOLALL				
Null Hypothesis:	C(2)=-6.54			
F-statistic	0.547079		Probability	0.460847
Chi-square	0.547079		Probability	0.459514

Figure 17: Stability test for expected prices and Treatment HLH

should expect). However, there is evidence of a break in period 5 (we would obtain similar result for a break in period 6).

Stability tests for the trend coefficient in pooled simulated asset prices

5.3 Volatility analysis

5.3.1 Sample of average simulated prices (Result 3.1)

Standard Two-Sample t-Test

Wald Test			
Pool: POOLED DATA			
Test Statistic	Value	df	Probability
F-statistic	8.432260	(1, 21)	0.0085
Chi-square	8.432260	1	0.0037
Null Hypothesis Summary:			
Normalized Restriction (= 0)		Value	Std. Err.
-2.47 + b(2)		-3.155715	1.086740

Figure 18:

Variable x is the dataset of average simulated prices volatilities over all treatments for $t \in [1, 4]$

And y is the dataset of average simulated prices volatilities over all treatments for $t \in [5, 10]$

$t = -6.3425, df = 38, p - value = 0$

Alternative hypothesis: true difference in means is less than 0

Sample estimates:

Mean of x and mean of y are respectively:

0.1584317 and 0.457264

Exact Wilcoxon rank-sum test

Rank-sum statistic: $W = 150, n = 16, m = 24, p - value = 0$

Alternative hypothesis: true difference in means is less than 0

5.3.2 Sample of average prices per period for inexperienced subjects in Dufwenberg et al. (2006) (Result 3.1)

Standard Two-Sample t-Test

Variable x is the dataset of average prices volatilities for $t \in [1, 4]$

And y is the dataset of average prices volatilities for $t \in [5, 8]$

$t = -0.3792, df = 78, p - value = 0.3528$

Alternative hypothesis: true difference in means is less than 0

Sample estimates:

Mean of x and mean of y are respectively:

0.5595014 and 0.5775037

Exact Wilcoxon rank-sum test

Rank-sum statistic: $W = -0.866, p - value = 0.1932$

Alternative hypothesis: true difference in means is less than 0

Standard Two-Sample t-Test

Variable x is the dataset of average prices volatilities for $t \in [9, 10]$

And y is the dataset of average prices for $t \in [1, 8]$

$t = 3.1588, df = 98, p - value = 0.0011$

Alternative hypothesis: true difference in means is greater than 0

Sample estimates:

Mean of x and mean of y are respectively:

0.8218102 and 0.568875

Exact Wilcoxon rank-sum test

Rank-sum statistic: $W = 2.0645, p - value = 0.0195$

Alternative hypothesis: true difference in means is greater than 0

5.3.3 Result 3.2. Asset prices volatility, Imprecise and precise messages treatments

Exact Wilcoxon rank-sum test

Null hypothesis: Average asset prices volatility is the same in precise messages and imprecise messages treatments.

Alternative hypothesis: Average asset prices volatility is greater for precise messages than for imprecise messages treatments.

Rank-sum statistic: $W = 174, n = 12, m = 12, p - value = 0.0891$

5.4 Results on trading volumes

5.4.1 Sample of average simulated prices (Result 4.1)

Standard Two-Sample t-Test

Variable x is the dataset of average standardized volumes of trade for $t \in [1, 4]$

And y is the dataset of average prices for $t \in [5, 10]$

$t = -1.5007, df = 38, p - value = 0.0708$

Alternative hypothesis: true difference in means is less than 0

Sample estimates:

Mean of x and mean of y are respectively:

0.9508498 and 1.032767

Exact Wilcoxon rank-sum test

Rank-sum statistic: $W = 286, n = 16, m = 24, p - value = 0.1276$

Alternative hypothesis: true difference in means is less than 0

5.4.2 Sample of average prices per period for inexperienced subjects in Dufwenberg et al. (2006) (Result 4.1)

Standard Two-Sample t-Test

Variable x is the dataset of average volumes of trade for $t \in [1, 4]$

And y is the dataset of average prices for $t \in [5, 10]$

$t = 2.0545, df = 98, p - value = 0.0213$

Alternative hypothesis: true difference in means is greater than 0

Sample estimates:

Mean of x and mean of y are respectively:

1.122093 and 0.9186047

Exact Wilcoxon rank-sum test

Rank-sum statistic: $W = 2.0473, p - value = 0.0203$

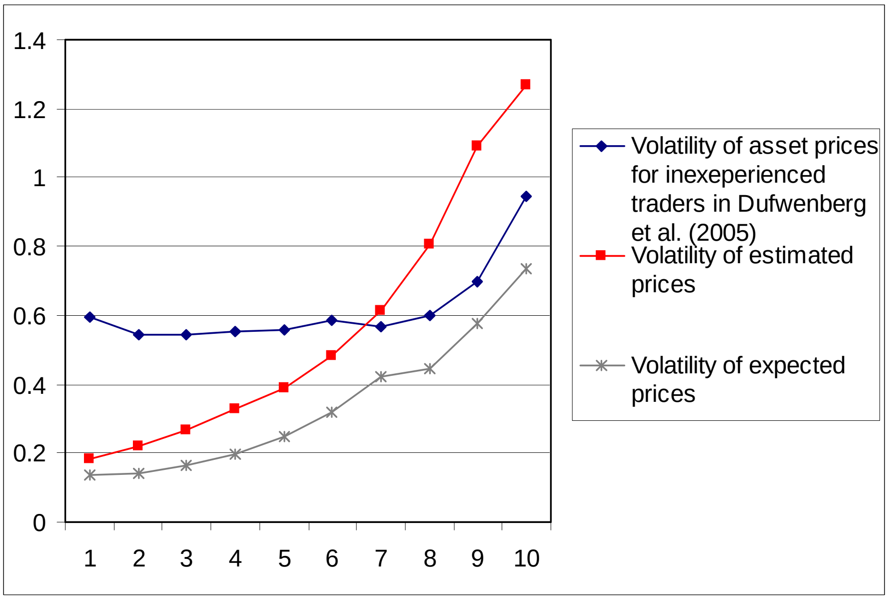

Figure 19: Average volatility of asset prices in messages treatment and in the benchmark treatment in Dufwenberg et al. (2005).

Alternative hypothesis: true difference in means is greater than 0

5.4.3 **Result** 4.2. **Trading volume, Imprecise and precise messages treatments**

Precise messages treatments

Exact Wilcoxon rank-sum test

Rank-sum statistic $W = 132$, $n = 12$, $m = 8$, $p - value = 0.3392$.

We cannot reject that the trading volume is the same for $t \in [1, 4]$ and for $t \in [5, 10]$.

Alternative hypothesis: the mean trading volume is higher for $t \in [5, 10]$.

Imprecise messages treatments

Exact Wilcoxon rank-sum test

Rank-sum statistic $W = 151$, $n = 12$, $m = 8$, $p - value = 0.0287$.

We reject at a 5% level that the trading volume is the same for $t \in [1, 4]$ and for $t \in [5, 10]$.

Alternative hypothesis: the mean trading volume is higher for $t \in [5, 10]$.

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