Tjalling C. Koopmans Research Institute

Discussion Paper Series nr:08-26

Central bank communication and crowding out of private information in an experimental asset market

Menno Middeldorp
Stephanie Rosenkranz

Universiteit Utrecht

Utrecht School of Economics

Tjalling C. Koopmans Research Institute
Utrecht School of Economics
Utrecht University

Janskerkhof 12
3512 BL Utrecht
The Netherlands
telephone +31 30 253 9800
fax +31 30 253 7373
website www.koopmansinstitute.uu.nl

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How to reach the authors

Menno Middelkoop
Stephanie Rosenkranz
Utrecht University
Utrecht School of Economics
Janskerkhof 12
3512 BL Utrecht
The Netherlands.
E-mail: s.rosenkranz@econ.uu.nl

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Menno Middeldorp[1]
Stephanie Rosenkranz

Utrecht School of Economics
Utrecht University

June 2008

Abstract
Theoretical results from previous work, presented in Kool, Middeldorp and Rosenkranz (2007), suggest that central bank communication crowds out private information acquisition and that this effect can lead to a deterioration of the ability of financial markets to predict future policy interest rates. We examine this result in an experimental asset market that closely follows the theoretical model. Crowding out of information acquisition takes place and, where this crowding out is most rapid, there is deterioration of the market's predictive ability. This supports the theoretical result that central bank communication can actually make it more difficult for financial markets to predict future policy rates.

Keywords: Experimental Economics, Private Information Acquisition, Information and Financial Market Efficiency, Central bank transparency and communication

JEL classification: C92, D82, E58, G14

Acknowledgements
The authors would like to thank Vincent Buskens, Thomas Dirkmaat, Franziska Schuetze and Utz Weitzel for valuable input and assistance as well as economists at the Rabobank Economic Research Department who participated in a pilot experiment. The authors would also like to acknowledge financial support from Tjalling C. Koopmans Institute of the Utrecht School of Economics, the use of Rabobank facilities for a pilot experiment and the extensive use of the Experimental Laboratory for Sociology and Economics (ELSE) of the University of Utrecht.

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[1] Part of this research was done while this author was senior economist at the Rabobank Economic Research Department

1 Introduction

This paper examines one potential risk of central bank's revealing more information relevant to the future path of interest rates. Now that central banks have started to give guidance about the future path of policy interest rates or even to provide quantitative forecasts, this question is particularly relevant. Although it is generally accepted that the improved transparency of monetary policy and the associated central bank communication have had their benefits so far, the question remains if central banks should strive to be even more explicit and forward looking in their communication.

There are many aspects of the issue of central bank transparency. This paper relates specifically to the approach taken in Kool, Middeldorp and Rosenkranz (2007). This paper uses a theoretical model to assess the impact of central bank communication on information acquisition in a financial market. It shows that it is theoretically possible for more precise communications from the central bank about the future of policy interest rates to actually impair the ability of a financial market to predict future policy. This is possible because increased precision crowds out private information acquisition. Individual agents decide to listen to the free signal from the central bank rather than invest in costly private information. Although this is rational on an individual basis, aggregated over the market as a whole it can result in a deterioration of the information available and the ability of the market to predict future policy.

Kool, Middeldorp, Rosenkranz (2007) provides an overview of the relevant literature[1] and a detailed examination of the theoretical model. Although a brief overview of our theoretical findings are provided below, this paper focuses on the experimental evidence. Our results are derived from a laboratory asset market that as closely as possible follows the theoretical model. In this market we find evidence that crowding out of information acquisition takes place. Furthermore, we establish that where this crowding out is sharpest that there is a deterioration of the predictive ability of the market.

2 Rational expectations models and crowding out in Kool, Middeldorp and Rosenkranz (2007)

The main finding of Kool, Middeldorp and Rosenkranz (2007) is that it is theoretically possible that the ability of a market to predict monetary policy can actually regress if the central bank communicates. This conclusion is reached by analyzing results from the Diamond (1985) model of a financial market.

[1] Interested readers may also want to consult the literature survey by Blinder, Ehrmann, Fratzscher, de Haan and Jansen (2008) for a general overview.

2.1 Rational expectations models

Diamond (1985) is a variant of the so-called rational expectations asset market model. This type of model explicitly takes into account the role of prices in forming the expectations of traders. Because traders can learn about the private information of other market participants during trading they can revise their expectations anytime they trade. The equilibrium in a rational expectations asset market occurs only when the market clears at a price that does not induce any trader to revise his expectations.

Earlier work by Grossman and Stiglitz (1980), Hellwig (1980) and Verrecchia (1982) already developed the main parts of the model used by Diamond (1985). Grossman and Stiglitz (1980) make a defining and early contribution by exploring the following dilemma. Should markets totally incorporate all information then there is no incentive for traders to invest in private information because it would be completely revealed when trading, leaving them with no advantage for their expenditure. As a result no information would be brought to the market to be revealed. Grossman and Stiglitz (1980) show that there must be some other source of noise which prevents complete revelation if investment in information is to take place. The necessary noise in their model comes from fluctuations in supply. Traders cannot disentangle completely the role of supply from that of information in price movements.

The market in the Grossman and Stiglitz (1980) model is actually a mere transmitter of identical pieces of information. Hellwig (1980) adjusts the model to reflect the idea that markets are also an aggregator of information. Hellwig's traders receive unique noisy signals of the same underlying outcome. Because the noise terms in their signals are independent, aggregating the information from different traders results in improved information.

Verrecchia (1982) adds information acquisition to Hellwig's model. He models the private signal as a separate signal per trader, the precision of which is determined by a cost function. In line with the thinking of Grossman and Stiglitz (1980), this model illustrates that a more informative market allows traders to essentially attain more information for free by observing the market; they are thus less inclined to buy costly private information.

The contribution of Diamond (1985) is to add a public signal to this type of model. This means that the private signal not only competes with the information that can be extracted from the price but also the public information. Apart from this, the main difference with the Verrecchia (1982) model is that the independent private signals have specific precision and fixed cost, which the traders then choose to buy or not.

2.2 Experimental work

The rational expectations models have been tested in numerous stylized experiments. As Plott (2000) discusses, these generally support the theory by showing that simple experimental markets can aggregate information and produce convergent and reasonable prices.

While there is experimental support for the rational expectations models as far as their price predictions are concerned, there is little experimental work regarding information acquisition. Copeland and Friedman (1992) is an exception in this respect. This paper presents evidence from an experiment where information auctions are followed by trading. Trading is conducted in two types of market, a simple market where it is easy for traders to infer private information and a somewhat more complex market where this is more difficult. The latter market results in a positive price for information that corresponds with its value in trading, as predicted by Grossman and Stiglitz (1980). Traders thus make up for their lack of ability to deduce prices in trading by buying information.

Middeldorp and Rosenkranz (2008) use the same data that is discussed in this paper to test predictions about information acquisition from different models in the rational expectations literature. The results indicate that these models overestimate the ability of markets to convey information and traders to extract information from trading. This results in higher private information acquisition in the experimental setting than predicted by the market. This outcome is only indirectly relevant to this paper because our results here are dependent on the rapidity of crowding out of private information rather than the level of information acquisition.

2.3 Basics of the theoretical model

As with all the rational expectations models the asset in Diamond (1985) is liquidated after trading. Traders, however, do not know exactly what the payout will be per asset. The public and private information are noisy (normally distributed) signals about this payout. In equilibrium the price in the market is basically the market's expectation about the payout (plus a discount because the risk averse traders in the model care about supply) given the information provided.

$$(1)\ \tilde{P} = \alpha\left(\frac{h_0}{h_0+\Delta}Y_0 + \frac{\Delta}{h_0+\Delta}(\tilde{u}+\tilde{\zeta})\right) + \beta\tilde{u} - \gamma\tilde{X}$$

where

$$\alpha = \frac{h_0+\Delta}{(h_0+\Delta)+\lambda s+\frac{(r\lambda s)^2}{V}}$$

$$\beta = \frac{\lambda s+\frac{(r\lambda s)^2}{V}}{(h_0+\Delta)+\lambda s+\frac{(r\lambda s)^2}{V}}$$

$$\gamma = \frac{\frac{1}{r}+\frac{r\lambda s}{V}}{(h_0+\Delta)+\lambda s+\frac{(r\lambda s)^2}{V}}$$

$\tilde{}$	random variables
$\widetilde{P}$	equilibrium market price
$\widetilde{u}$	payout
Y_0	mean payout
h_0	precision of payout
$\tilde{\zeta}$	noise public signal
Δ	precision of public signal
s	precision of private signal
$\widetilde{X}$	supply
V	variance of supply
r	risk acceptance

The term behind α is simply the combination of the two sources of public information in the model, i.e. what traders already know about u from its mean and variance (i.e. the inverse of the precision) and the public signal.

α and β indicate how much the market is influenced by public information and how much it is influenced by private information. Basically α and β are weights that add up to one. The denominator is actually the average amount of information per trader (I):

$$(2)\ I = h_0 + \lambda s + \frac{(r\lambda s)^2}{V}$$

All traders know the public information with the precision of $(h_0 + \Delta)$ and the informed fraction of traders, λ also has a public signal of precision s. The last term is the informativeness of the price. The more supply noise there is, the more difficult it becomes for traders to “read” the market, explaining why V is in the denominator. Regarding the numerator, clearly the more informed traders there are the more private information will be revealed to the market. A similar intuition applies to the precision of the private signal. Finally, the more risk accepting traders are the more aggressively they will trade and the more of their own private information they will reveal.

The better the public information, $(h_0 + \Delta)$, the higher α and the greater the impact of public information on the market price. The more informed traders there are and the better the private signal and the informativeness of the price the more private information influences the market. Note, however, that behind β we see u without a noise term. This is because this represents the combination of all the private signals. Rational expectations models assume an infinite number of traders. This is a common microeconomic assumption that is designed to avoid individual traders having any impact on the market and thus ruling out the possibility of strategic behavior. It also means, however, that the noise terms from the infinite independent signals cancel out to form one perfect indicator of $\tilde{u}$.

The final issue is the acquisition of information. The fraction of informed traders, λ, is endogenously determined and represented by the following equation.

$$(3)\ \lambda = \frac{\sqrt{V}}{rs}\sqrt{\frac{s}{e^{2c/r}-1} - h_0} \in (0,1)$$

The variables are the same as above with the addition of c, which is the cost of the private signal. Intuitively, fewer traders choose to buy private information as other sources of information become more precise. Thus both public information $(h_0 + \Delta)$ and the informativeness of the price, i.e. the term left of the square root sign, have a negative impact on λ. Logically, the cost of information is also negatively related to λ. Risk acceptance and the precision of private information have less clear cut consequences. Clearly the more precise the private signal is the more attractive buying information becomes. However, this precision also "leaks out" via the market, improving the informativeness of the price. The same is true for risk acceptance. Higher risk acceptance reduces the disutility (the cost) of buying information (rational expectations models assume exponential utility). However, it also implies more aggressive trading, thus increasing the informativeness of the price.

2.4 Implications for monetary policy transparency: deterioration of the predictive ability of the market

The payout in the Diamond (1985) model can be interpreted as a central bank policy rate. The market in the model then can be seen as a money market asset or related product, the price of which depends on the outcome of policy rates[2].

[2] The Fed funds future market most closely matches the theoretical setup because the terminal value of the futures is wholly determined by the Fed funds rate.

The question that we are interested in is whether the market's ability to anticipate monetary policy can actually deteriorate the more the central bank communicates. As a prelude to the main evidence, Kool, Middeldorp and Rosenkranz (2008) examine the impact of a more precise public signal on the average amount of information in the market. This is done by taking the derivate of I to Δ from equation 2, where equation 3 is also substituted in for λ.

$$(4)\ \frac{\partial I}{\partial \Delta} = -\frac{\sqrt{V}}{2r\sqrt{\frac{s}{e^{2c/r}-1} - (h_0+\Delta)}}$$

Because of the conditions under which λ is in the range 0 to 1 it can be shown that this derivative is always negative and a real number. As such, it indicates that the average information of traders actually declines as the increase in central bank communication, i.e. rising Δ, crowds out private information.

This does, however, not completely prove that the markets become less able to predict future moves in monetary policy. To examine this issue Kool, Middeldorp and Rosenkranz (2007) define the pricing error as the difference between the market price and the actual payout. In terms of monetary policy, the smaller the gap between the two, the better the market can be seen as predicting actual policy rates.

To examine if the pricing error can ever become wider even as the public signal becomes more precise Kool, Middeldorp and Rosenkranz (2007) examine how the variance of the pricing error, which they label Ω, changes as Δ rises.

$$(5)\ \Omega = VAR(\tilde{P} - \tilde{u}) = E\left[\alpha\left(\frac{h_0}{h_0+\Delta}Y_0 + \frac{\Delta}{h_0+\Delta}(\tilde{u}+\tilde{\zeta})\right) + \beta\tilde{u} - \gamma X - \tilde{u}\right]^2$$

where

$$\alpha = \frac{h_0+\Delta}{(h_0+\Delta)+\lambda s+\frac{(r\lambda s)^2}{V}}$$

$$\beta = \frac{\lambda s+\frac{(r\lambda s)^2}{V}}{(h_0+\Delta)+\lambda s+\frac{(r\lambda s)^2}{V}}$$

$$\gamma = \frac{\frac{1}{r}+\frac{r\lambda s}{V}}{(h_0+\Delta)+\lambda s+\frac{(r\lambda s)^2}{V}}$$

The local and global minima and maxima of this function are identified. The general nature of the function is sketched in figure 1. It shows that over the segment that the number of informed traders declines ($0<\lambda<1$) that the variance of the error increases. That is, the ability of the market to anticipate policy deteriorates. This either happens over this whole segment (from point to

2 point 4 and there is no point 3, Figure 1) or there is a local minimum at point 3 so that the deterioration only takes place between point 3 and 4 (Figure 2). In either case, however, there is an area where more precise communication leads to the crowding out of private information and consequently the deterioration of the ability of the market to predict future policy rates.

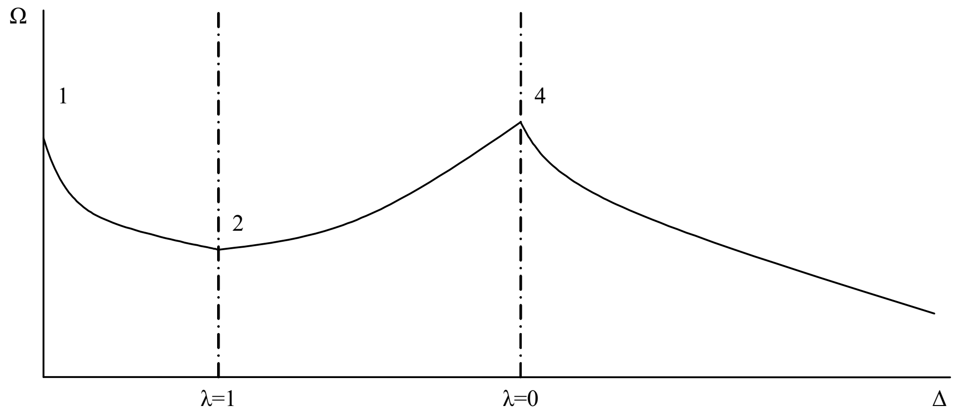


FIGURE 1: NO LOCAL MINIMUM FOR $0<\lambda<1$

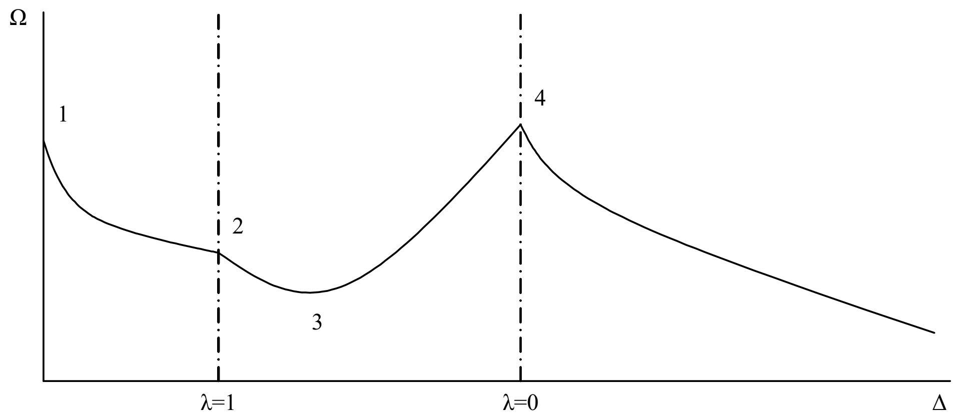


FIGURE 2: LOCAL MINIMUM FOR $0<\lambda<1$

The question before us in this paper is if this pattern can be detected in the experimental asset market described below.

3 The experimental setup

3.1 Complex experimental design matching theoretical model

We replicate the model from Diamond (1985) used in Kool, Middeldorp and Rosenkranz (2007) as closely as possible in a laboratory of networked PCs with the commonly used experimental software ZTree 2 (Fischbacher 1990). Matching the model closely results in a rather complicated treatment. This is innovative, in the sense that, as mentioned above, most experiments involve more stylized treatments, which has the advantages of making the experiment easier to mentally process by the subjects while focusing on particular aspects of the theory being tested without producing noise in the data. Our approach also has advantages, however, apart from being merely novel. First, it allows the most complete test of the model possible. Second, the information extraction problem for subjects must not be unrealistically simple as a key difference between the model and real trading is likely to be the degree in which traders can "read" the market.

To alleviate the disadvantages of our setup we do three things:

First, we used more subjects per session than in many earlier laboratory market experiments, between sixteen and twenty, to improve market functioning.

Second, we re-invited those who participated in order to create an experienced group of subjects in the last three sessions. A total of ten sessions were conducted, four pilots and six data sessions. Although, the fundamental setup remained unchanged, it took four pilot sessions to remove technical problems and refine the treatment. Subjects from pilot sessions two to four plus the first three data sessions were re-invited for sessions four through six in order to create the more experienced subject groups. A little under half (47%) of the subjects in the last three data sessions participated in the first three data sessions.

Third, we drop the first five periods of every session from our data in order to give most subjects enough time to learn how the market works. One of the things we asked in our questionnaire is how long it took subjects to understand the market. The median answer is four periods in sessions one through three and one period in sessions four through six where we have more subjects with experience. We exclude five periods, however, because, as we explain below, we cycle through five different precisions of the public signal.

The subjects involved in the experiment were almost all students at the University of Utrecht, from a wide range of faculties. The average age was 22 and between 25% and 50% of the students per session was male. The majority of subjects, ranging from 63% to 85% per session, were Dutch, although 13 other countries were represented.

The following elements in our treatment are copied directly from the Diamond (1985) model. Traders are endowed with a random amount of assets and a fixed amount of money. The former creates the supply noise in the market. Subjects are informed that this is a normally distributed random variable and are given its standard deviation and average. Separately, probability intervals for all the standard deviations displayed in the experiment are provided in the instructions for reference by the subjects (see Appendix A). Assets deliver a random payout, an experimental money amount per asset, at the end of the period, after trading. Some information is provided to the subjects about the nature of the payout. First, they are told that it is a normally distributed random variable and are given its average and standard deviation. Second, a public signal about the payout is released. This is the result of the actual payout plus a normally distributed unbiased noise term. This signal is not presented separately to subjects. Instead they are given the combined information of the moments of the payout and the public signal, called public information. It is made clear that this is a normally distributed noisy signal of the actual payout and that it is the best guess of the payout given public information. The resulting standard deviation is displayed. Finally, subjects are given the option to buy an additional private signal at a given cost. It is a noisy signal of the payout, which is normally distributed and is private in the sense that it is unique per subject. The standard deviation of the combination of the currently available public information plus the as yet unrevealed private signal is given. The subjects thus know the quality of the information they will have after buying the private signal, but not the signal itself. After the private signal purchasing decision has been made trading starts. On their trading screens subjects are told the best guess of the payoff according to both public information and their own information. No subject is notified about the information acquisition of any other.

Information is combined automatically and traders know the quality of all their information. We thus do not test the ability of traders to optimally combine these signals. This leaves only the market as a source of information that requires mental processing.

The rational expectations models make no assumptions about the trading mechanism that is used to reach the equilibrium they describe. The experimental asset market literature generally uses continuous double auctions as the market mechanism. We do the same, allowing traders to post one bid and ask at a time for any quantity that they can afford to buy or have to sell. Allowing subjects to quote in both price and quantity brings the market closer to real world conditions and also allows more information to be transmitted by quotes. Trading lasts for 150 seconds, which is usually enough for price movements to settle.

3.2 Calibration based on empirical measurements

Having explained the basic setup we now indicate which values we actually used for the experiment and how they were determined. We attempt to use a specification that is empirically relevant. We give a description of our approach below followed by a table which provides an overview and the actual specifications.

To calibrate the treatment we base most of our values on the Fed Funds Rate. The standard deviation of the payout is based on the standard deviation of yearly percentage changes in the Fed Funds Rate between 1997 and 2007. The average is set to roughly three standard deviations from zero simply to insure that the risk of hitting zero is low. The standard deviation of the private signal is based on the standard deviation of the error of private sector economists' forecasts of the Fed Funds Target rate a year ahead, also between 1997 and 2007.

The cost of information is clearly difficult to measure. One measure, used by Elton, Gruber, Das and Hlavka (1993), is to interpret mutual fund costs as information expenditure. Actively managed mutual funds are probably the prototype informed investors. However, there are clearly other costs involved. Nevertheless, this could be seen as an upper bound of empirically plausible expenditure costs in financial markets. We use data from the Investment Company Institute, which tracks the investment industry, on the expenses of fixed income funds and determine the percentage costs versus assets. In the model we implement the cost as a fixed percentage over the expected endowment of risky assets.

We use the same source to estimate the total variance of supply from the relative yearly flow in or out of mutual funds. Then, based on a full session of twenty subjects, we calculate the individual supply variance, which is the random variable that is actually programmed. This is simply the total variance multiplied by the number of players. In the actual experiment the total supply changes because we do not have 20 subjects in every session. The average of the supply is, similarly to above, set three standard deviations away so that the chance that any individual has no endowment of risky assets is low.

Endowment money is set so that the probability of traders running out of money is low, but not so high as to dampen the stochastic nature of the endowment too much. In actual trading the subjects have less than 400 units of experimental money at the end of the period 8% of the time. They run out of assets 5% of the time. The exchange rate was chosen so that the average payment was around €10 per hour.

The standard deviation of the public signal changes through the course of the experiment in order to test the theoretical outcome described above. Five standard deviations for the public signals were calibrated in pilot experiments in order to achieve a wide range for the fraction of informed traders. They are cycled through in random order, so that subjects cannot anticipate the level of information in the next period.

The calibration used is summarized in the table presented in the Appendix B.

4 Experimental results, crowding out and rising errors

4.1 Computing errors

The main issue to be determined by our data is to see whether or not there is a deterioration of the ability of the market to predict the payout as the precision of the public signal increases. This requires us first to measure the error between the price and the payout. Then we can examine the development of these errors in relation to the precision of the public signal and test whether there is a significant increase in this error between any two points where the precision of the public signal is increasing.

The issue of measuring the errors is not trivial. Although the value of the payout is clear, it is not obvious what "the" price should be. Every period will see many prices as subjects trade with each other. We take two approaches to determining a price corresponding the to the equilibrium price in the model. First approach is taking the average price per traded asset. The second approach is to calculate the limit towards which the prices appear to be converging.

The average price per asset traded is simply a weighted average, with the individual prices weighted by the number of assets per transaction. The advantage of this approach is that it is straightforward and does not require any additional assumptions. The disadvantage is that it ignores the likely convergence of traded prices as information is impounded into the price as trading progresses. Later prices thus may be better informed and there could be a progression towards a certain price, even if trading ends before the market fully converges.

To measure this type of convergence we estimate the limit of the path of prices for every period. This is done by a utilizing an Ashenfelter-El Gamal (AE) model, following Barner, Feri and Plott (2005)[3]. This means estimating the following equation with moving average terms on the trade prices for each period.

[3]This paper refers to Noussair, Plott and Riezman (1995) who attribute this model to Orley Ashenfelter and Mahmoud El Gamal.

(6) $P_t = b\frac{1}{t} + l\frac{(t-1)}{t} + u_t$

$u_t = mu_t - 1 + \varepsilon_t$:

Where

P_t	price per trade
t	trade index
b	estimated start price
l	estimated limit of series
u_t	moving average term
m	moving average parameter
ε_t	error term

The estimated parameter l is what we are after. This represents the limit of the series of trade prices which is interpreted as the convergence or equilibrium price of the market. The convergence is quite tight, with all the estimates for l significant with a median T-stat of 90.

Errors are computed using data from both methods by simply subtracting the payout from the average price and the limit price respectively. Because we are interested in the size of the errors and not their sign we take absolute values. We do this, instead of taking squares, to keep the errors on the same scale as the standard deviations that we used in the experiment.

4.2 Graphic evidence of rising errors in aggregate and session data

To examine the evidence of crowding out and the market's predictive ability, we start with a simple graph of the errors versus the standard deviation. Chart 1 is analogous with the theoretical sketch in Figure 1 except that we use absolute value of the errors instead of their variance and standard deviations of the public signal instead of its precision (note that this implies a horizontal flip of the chart). We also provide the percentage of informed subjects. The individual points are measurements from each period. The lines represent a neighborhood fitted linear regression which fits the closest fifth of the sample.

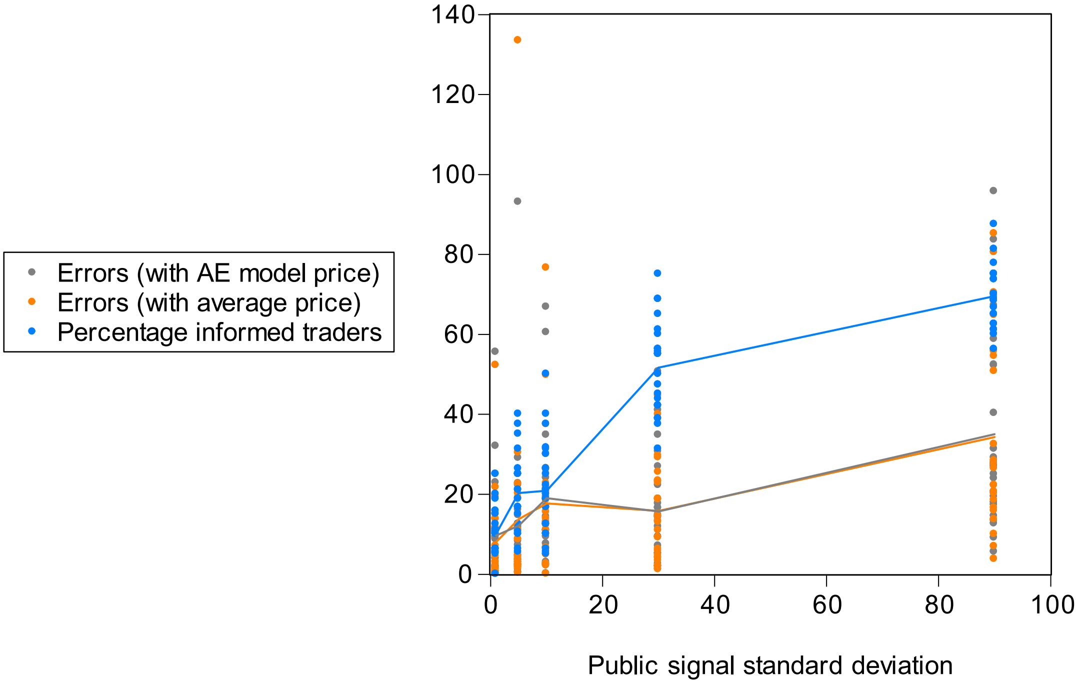


Chart 1: Crowding out of information acquisition and the markets predictive ability

The overall trend is that the number of informed traders declines but that this does not lead to an increase in the error. There is an exception, however, between the standard deviations of 30 and 10 the rapid decline of the fraction of informed traders is reflected in an increase in the errors. The effect is slightly more pronounced in the AE model measure of the errors. This would suggest that it is indeed the case that crowding out of private information acquisition can lead to a deterioration of the predictive ability of a market.

A look at the data per session gives a clearer picture. The chart below is similar to the one above except that now we show the relationship per session. The errors are based on the equilibrium prices according to the AE model. Four out of five sessions show the predicted deterioration of the market's predictive ability. These relationships are lost by averaging the results over the sessions in the aggregate data.

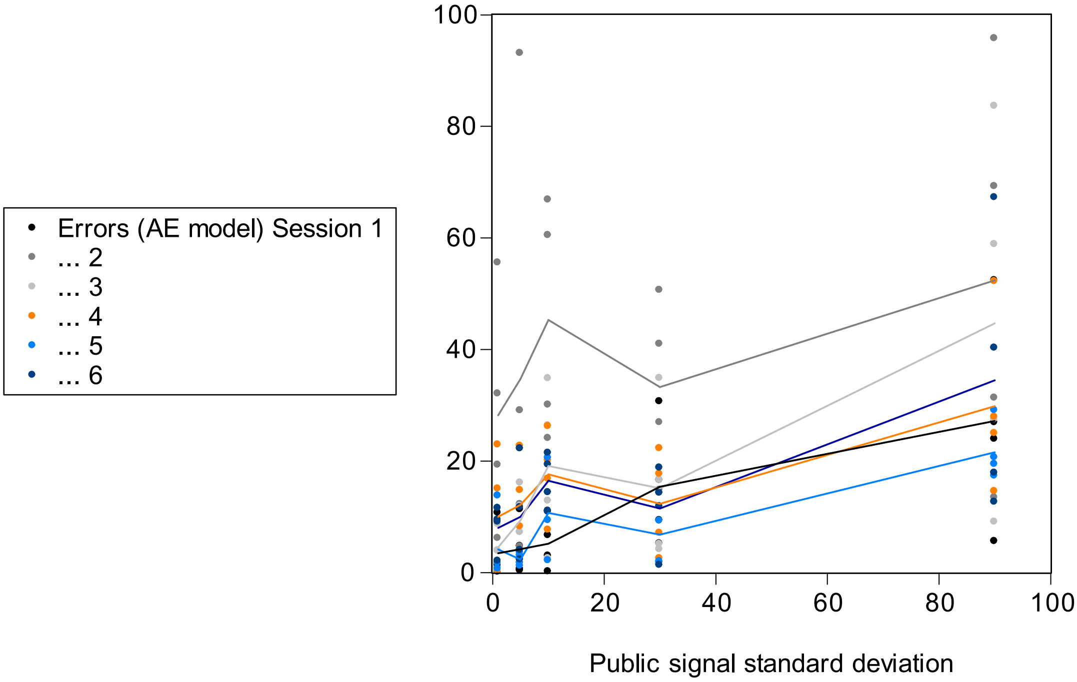


Chart 2: Markets predictive ability per session

All but one of the sessions show an increase in errors as the standard deviation of the public signals declines from 30 to 10. The form of the pattern changes somewhat over the sessions. However, the last three sessions, with the most experienced traders, seem to have a fairly stable pattern, not only around the segment of rising errors but over the line as a whole. The consistency of the effect across session reduces the risk that this phenomenon is spurious.

4.3 Regressions on period data confirm evidence of rising errors

Although the graphs reveal a clear pattern they cannot be used to test for significance, which is clearly an issue considering the substantial variance in the data. To do such testing, we run two regressions between the public signal standard deviation per session and our two errors from the two different price measures. We use session dummies to identify some of the variance. We also add the absolute value of the deviation of per capita supply because it is independent of the information provided and should influence the error according to equation 5. We use dummies for the levels of precision of the public signal so as to identify the average impact per communication level. Because the graphic results suggest a more consistent pattern for the experienced sessions we use separate dummies for the first three and the last three sessions[4]. Wald tests can then be used to determine if there is indeed a significant difference between the error level for standard deviations 10 and 30 in either the experienced or inexperienced sessions.

Dependent Variable: Errors (with average price)
Method: Least Squares

Sample: 6 25 31 50 56 75 81 100 106 125 131 150
Included observations: 120
Newey-West HAC Standard Errors & Covariance (lag truncation=4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Session 1- 3, Public signal standard deviation = 5	10.37486	11.47268	0.904310	0.3679
Session 1- 3, Public signal standard deviation = 10	**10.75550**	**5.467566**	1.967145	0.0518
Session 1- 3, Public signal standard deviation = 30	**8.817325**	**6.306315**	1.398174	0.1650
Session 1- 3, Public signal standard deviation = 90	30.67653	8.592406	3.570190	0.0005
Session 4 - 6, Public signal standard deviation = 5	1.799984	3.236766	0.556106	0.5793
Session 4 - 6, Public signal standard deviation = 10	**9.004063**	**2.764254**	3.257322	0.0015
Session 4 - 6, Public signal standard deviation = 30	**6.351285**	**2.649492**	2.397171	0.0183
Session 4 - 6, Public signal standard deviation = 90	22.95723	6.187982	3.709971	0.0003
Session = 1	-8.368259	5.214366	-1.604847	0.1115
Session = 2	15.54297	6.055892	2.566586	0.0117
Session = 3	-0.739662	5.074929	-0.145748	0.8844
Session = 4	-2.272417	3.542450	-0.641482	0.5226
Session = 5	-6.133212	3.062430	-2.002727	0.0478
abs(Per capita supply – 60)	0.609786	0.508813	1.198449	0.2334
C	5.655226	3.870337	1.461172	0.1470

R-squared	0.373155	Mean dependent var	17.93742
Adjusted R-squared	0.289575	S.D. dependent var	20.83781
S.E. of regression	17.56351	Akaike info criterion	8.685992
Sum squared resid	32390.06	Schwarz criterion	9.034429
Log likelihood	-506.1595	Hannan-Quinn criter.	8.827494
F-statistic	4.464672	Durbin-Watson stat	2.099273
Prob(F-statistic)	0.000003		

Table 1: Errors of average price regression

[4] Regressions using dummies for all sessions together are presented in Appendix C together with the associated Wald tests.

Dependent Variable: Errors (with AE model price)
Method: Least Squares

Sample: 6 25 31 50 56 75 81 100 106 125 131 150
Included observations: 120
Newey-West HAC Standard Errors & Covariance (lag truncation=4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Session 1- 3, Public signal standard deviation = 5	4.711754	7.726920	0.609784	0.5433
Session 1- 3, Public signal standard deviation = 10	**11.15931**	**4.126413**	2.704361	0.0080
Session 1- 3, Public signal standard deviation = 30	**9.067333**	**5.038693**	1.799541	0.0748
Session 1- 3, Public signal standard deviation = 90	30.18535	8.958024	3.369644	0.0011
Session 4 - 6, Public signal standard deviation = 5	0.834398	3.168433	0.263347	0.7928
Session 4 - 6, Public signal standard deviation = 10	**7.912147**	**2.844581**	2.781481	0.0064
Session 4 - 6, Public signal standard deviation = 30	**2.729485**	**2.564575**	1.064303	0.2896
Session 4 - 6, Public signal standard deviation = 90	21.47542	5.305283	4.047931	0.0001
Session = 1	-9.853658	4.595794	-2.144060	0.0343
Session = 2	18.14627	5.914237	3.068235	0.0027
Session = 3	-1.354835	4.598305	-0.294638	0.7689
Session = 4	1.074696	3.345889	0.321199	0.7487
Session = 5	-5.989342	3.238299	-1.849533	0.0672
abs(Per capita supply – 60)	0.517819	0.451061	1.148000	0.2536
C	7.030731	3.807462	1.846566	0.0676

R-squared	0.469151	Mean dependent var	18.32976
Adjusted R-squared	0.398372	S.D. dependent var	19.58290
S.E. of regression	15.18942	Akaike info criterion	8.395543
Sum squared resid	24225.43	Schwarz criterion	8.743980
Log likelihood	-488.7326	Hannan-Quinn criter.	8.537045
F-statistic	6.628325	Durbin-Watson stat	2.006603
Prob(F-statistic)	0.000000		

Table 2: Errors of AE model price regression

The regressions suggest that for both groupings of sessions there is an identifiable increase in errors as the standard deviation of the public signal declines from 30 to 10. This effect is somewhat stronger for the experienced sessions. The question is, however, are these differences significant? To check this we do Wald tests between the coefficients for public signal standard deviation 30 and 10. We find that only the errors calculated using the AE model show an increase that is significant, although at only a 10% probability level.

Wald Test:
Equation: Errors (with AE model price)

Test Statistic	Value	df	Probability
F-statistic	2.920997	(1, 105)	0.0904
Chi-square	2.920997	1	0.0874

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(6) - C(7)	5.182662	3.032406

Restrictions are linear in coefficients.

Table 3: Test of significance of increase in errors

4.4 Panel data results show clear evidence of rising errors

To reduce the noise in our data we use our panel data. This allows us to make full use of the dataset we have and remove individual and period fixed effects from the residuals. In making use of our panel data we define an individual error. This is the absolute difference of the average trading price per unit of the transactions of a particular subject with the final payout per unit. This is the dependent variable in our panel regression and a lag of this variable of one period is also used in order to combat autocorrelation in the data. Again, we split the communication level dummies into two sets according to experience[5].

[5] The aggregate regression can be found in Appendix D.

Dependent Variable: Individual error
Method: Panel Least Squares

Sample: 6 25
Periods included: 20
Cross-sections included: 94
Total panel (unbalanced) observations: 901
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Individual error (-1)	-0.004042	0.044282	-0.091275	0.9273
Session 1- 3, Public signal standard deviation = 5	11.07275	3.710804	2.983921	0.0029
Session 1- 3, Public signal standard deviation = 10	**11.49887**	**2.648956**	4.340908	0.0000
Session 1- 3, Public signal standard deviation = 30	**5.613704**	**3.247695**	1.728520	0.0843
Session 1- 3, Public signal standard deviation = 90	28.92987	3.057917	9.460647	0.0000
Session 4 - 6, Public signal standard deviation = 5	3.519118	2.032373	1.731532	0.0838
Session 4 - 6, Public signal standard deviation = 10	**8.882465**	**1.774486**	5.005655	0.0000
Session 4 - 6, Public signal standard deviation = 30	**4.103488**	**1.885095**	2.176806	0.0298
Session 4 - 6, Public signal standard deviation = 90	21.24430	2.497149	8.507422	0.0000
abs(Per capita supply – 60)	0.023273	0.031594	0.736617	0.4616
C	9.321835	1.334314	6.986238	0.0000

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.481340	Mean dependent var	18.92524
Adjusted R-squared	0.400008	S.D. dependent var	24.04923
S.E. of regression	18.62833	Akaike info criterion	8.813495
Sum squared resid	269977.4	Schwarz criterion	9.469246
Log likelihood	-3847.480	Hannan-Quinn criter.	9.063983
F-statistic	5.918198	Durbin-Watson stat	2.085784
Prob(F-statistic)	0.000000		

Table 4: Panel data regression

Wald Test:
Equation: Individual error

Test Statistic	Value	df	Probability
F-statistic	2.978808	(1, 778)	0.0848
Chi-square	2.978808	1	0.0844

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(3) - C(4)	5.885169	3.409869

Restrictions are linear in coefficients.

Table 5: Test of significance in inexperienced sessions

Wald Test:
Equation: Individual error

Test Statistic	Value	df	Probability
F-statistic	6.744969	(1, 778)	0.0096
Chi-square	6.744969	1	0.0094

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(7) - C(8)	4.778977	1.840115

Restrictions are linear in coefficients.

Table 6: Test of significance in experienced sessions

The panel data results are broadly similar to the results from the period data. There is an increase of the errors in the same region. Conflicting with our earlier results, however, the size of the increase in the errors is larger for the inexperienced sessions. It remains the case, however, that the results for the experienced sessions are more reliable. The Wald test rejects the null-hypothesis of equal coefficients at a only a 10% probability level for the inexperienced sessions while it rejects this at a 1% probability level for the experienced sessions. There is thus clear evidence of an increase in errors in the area where there is a rapid crowding out of private information acquisition associated with the decline in the standard deviation of the public signal from 30 to 10.

4.5 Relevance of our evidence

Clearly our experimental asset market is much smaller than a real world asset market and the traders are relatively unsophisticated. This means that external validity is not ensured and thus there is an open question whether results are directly applicable to real world markets.

Nevertheless, our results do allow us to say something about these issues because we have different numbers of subjects (between 16 and 20) and different levels of experience (first three vs. last three sessions). Overall the only session in which there is not at least some evidence of rising errors during the area of sharpest crowding out is session 1. This is one of two sessions with only 16 subjects and a session with inexperienced traders. It also the session in which, according to the answers to our questionnaire, it took the longest for the subjects to understand the market (median of 5.5 periods versus 3.0 and 3.5 in the two other inexperienced sessions).

Having more traders in the market and more experienced traders does not seem to remove the effect, if anything the evidence is stronger. This is not necessarily because the effect is stronger, it may just be because there is less noise allowing it to be easier to establish. Nevertheless, over the modest fluctuation in scale and experience that we have, there is little evidence that the deterioration of the predictability of prices is alleviated.

Another important point is that our results are based on empirically calibrated variables. The precision of the central bank signal versus private information is of particular interest. It is plausible that a central bank is better at predicting its own monetary policy than any individual market participant (Note that this is not the same as saying they should be better than the market as a whole which can aggregate information form a diverse set of participants). Indeed even regarding general macro-economic variables there is evidence, presented by Romer and Romer (2000), that the US Federal Reserve is better at forecasting inflation than private sector economists. This means that the range in which we see crowding out, below a standard deviation of the private signal of 40, is plausible and relevant.

Overall, given that extra subjects and more experienced subjects do not change the basic results, and given that we use an empirically derived calibration, there is reason to believe that our evidence has real-world applicability.

5 Conclusion

Central banks have become more and more explicit and forward looking in communicating about future monetary policy. Although past experience in increased monetary policy transparency has been good, it is not clear how much further central banks should go. Our research presents a note of caution. Theoretical evidence from our earlier paper, Kool, Middeldorp Rosenkranz (2007) suggests that it is possible that a more precise public signal from a central bank can crowd out private information acquisition. This reduces the amount of private information for the market to aggregate and thus leads to a deterioration of the ability of the market to predict future monetary policy.

This theoretical evidence has been given experimental support in this paper. In an experimental asset market very similar to the theoretical model we show that crowding out of private information takes place and that this can lead to a deterioration of the ability of the market to predict. The error between the market price and the payout of the market's asset increases where crowding out is fastest.

Although an experimental asset market is inherently limited due to the use of a small number of unsophisticated traders, our evidence does appear to be applicable to real world market. Markets with more numerous and experienced subjects actually produced stronger evidence of the effect. Furthermore, we calibrate our experiment with empirical measurements to improve its applicability.

Our experimental results thus support our theoretical findings that increasingly explicit central bank communication does have a potential risk for the informational efficiency of financial markets and their ability to predict future monetary policy.

6 Appendix A: Instructions

[Note, this is not the original layout]

Welcome to this experiment, we appreciate your participation.

Please do not talk or otherwise communicate with other participants.

Try to understand as much of these instructions as you can. To help Dutch readers, translations of some terms are provided in Dutch between brackets [haakjes]. The exact workings of the experiment will become clear during the practice round. At that time you will have the opportunity to ask questions.

This experiment consists of an introductory and a main experiment.

The first is a brief exercise in which you will have to choose between a certain payment and a lottery.

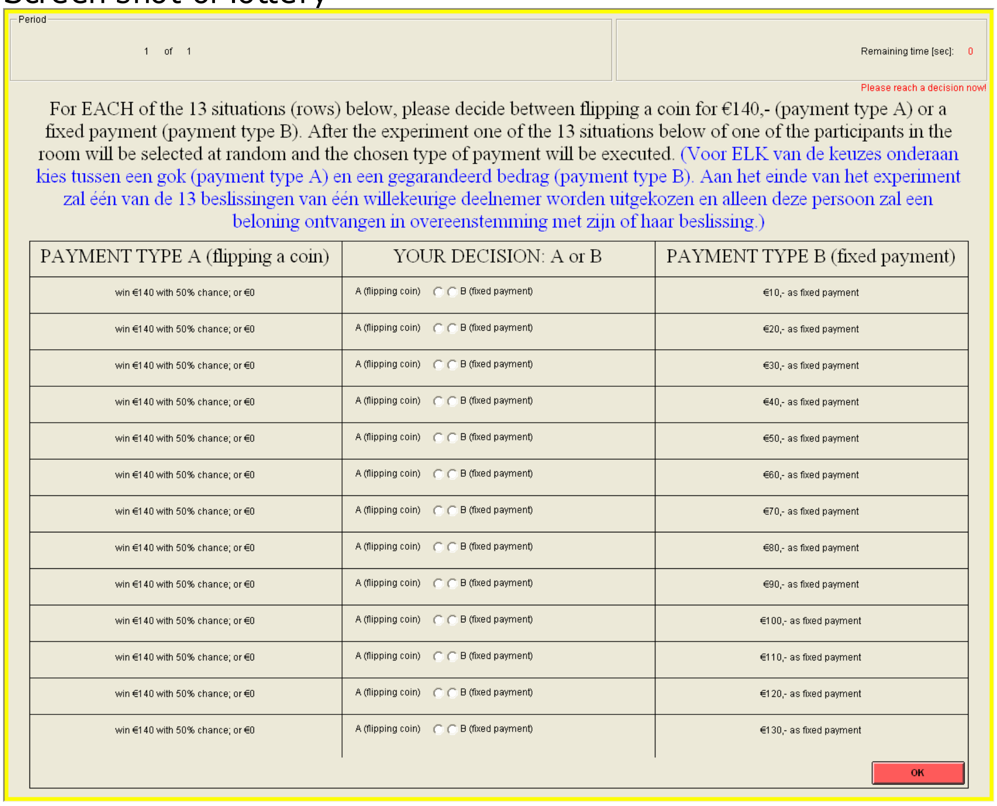
During the main experiment, you will be trading in a simulated financial market. You will be able to buy and sell securities [effecten] from and to other participants. Security is the general term for a financial market product like a stock [aandeel] or bond [obligatie].

6.1 Introductory experiment

You will be given a list of 13 choices. For each of these you must select which of the two options you prefer (see screen shot below). The left options will consist of a certain payment. The right options will be an uncertain payment, in the form of a simple lottery.

At the end of the session, one of the participants will be chosen at random [willekeurig] and for that person one of the 13 choices will be randomly picked. Should this choice be for a certain payment (left), this amount will be added to the cash earnings of the participant. Should this choice be for a lottery (right), this lottery will be conducted and the indicated amount (if any) will be awarded.

Screen shot of lottery



Period

1 of 1

Remaining time [sec]: 0

Please reach a decision now!

For EACH of the 13 situations (rows) below, please decide between flipping a coin for €140,- (payment type A) or a fixed payment (payment type B). After the experiment one of the 13 situations below of one of the participants in the room will be selected at random and the chosen type of payment will be executed. (Voor ELK van de keuzes onderaan kies tussen een gok (payment type A) en een gegarandeerd bedrag (payment type B). Aan het einde van het experiment zal één van de 13 beslissingen van één willekeurige deelnemer worden uitgekozen en alleen deze persoon zal een beloning ontvangen in overeenstemming met zijn of haar beslissing.)

PAYMENT TYPE A (flipping a coin)	YOUR DECISION: A or B	PAYMENT TYPE B (fixed payment)
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€10,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€20,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€30,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€40,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€50,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€60,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€70,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€80,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€90,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€100,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€110,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€120,- as fixed payment
win €140 with 50% chance; or €0	A (flipping coin) ◯ ◯ B (fixed payment)	€130,- as fixed payment

OK

6.2 Main experiment

The main part of this experiment consists of 25 periods plus one practice periods. At the beginning of each period you will be given a certain amount of experimental cash and a number of securities. You can buy these securities from and sell them to other participants. At the end of each period the securities in your possession will be converted into cash. The payout per security is determined randomly. However, you will be given some information regarding the potential payout and have the opportunity to buy more information. The cash earnings in one period will not be available for trading in later periods. However, the total cash earnings of all periods will be converted into euros (at an exchange rate [wisselkoers] indicated below) to take with you at the end.

The endowment: starting cash and securities

At the beginning of each period you will receive your endowment of starting cash and securities. You will receive the same amount of cash as every other participant, namely ECU 8000, where ECU stands for Experimental Currency Unit. The number of securities, on the other hand, will be allocated randomly per participant. As a result the number of securities you have will be your secret [geheim] and you will not know how many the other participants have.

What you do know is that the number of securities per participant per period will fluctuate randomly according to a normal probability distribution [normale kansverdeling] with an average [gemiddelde] of 60 and a standard deviation [standaarddeviatie] of 20. What this means is that over many periods the allocation will average around 60. The standard deviation indicates how much the number of securities will fluctuate per period. Most of the time the allocation will be no more than one standard deviation away from the average and only very rarely more than two standard deviations away. To be specific, a little more than two-thirds of the time the number of securities will be between 40 and 80 and 95% of the time the number of securities will be between 20 and 100.

Distribution of supply		
Average	60	
Standard deviation	20	
68% range	40	80
95% range	20	100

6.2.1 The payout and information

At the end of the period, after trading (more about this later), for every security you own you will receive a certain amount of experimental money called the payout [uitbetaling]. You will not know what it is at the beginning of the period. It will be announced only at the end. You do know, however, that the average payout is 200 per security.

6.2.2 Public information

The payout will be the same for all participants and will be determined randomly. You and all other participants will be given some information about what the possible payout will be. This information we call the "public information" [openbare informatie] because all participants receive identical information.

This information will be imperfect, however. It is essentially an estimate [schatting] about what the payout will be. Sometimes it will be close to the actual payout and other times it will be further away.

The quality of the guess is governed by a normal distribution. This means that the standard deviation is sufficient information to judge the quality of the estimate. The lower the standard deviation the better the estimate is. Per period the public information will have one of five randomly selected standard deviations (see table). The lower the standard deviation the surer you can be that the actual payout is close to this estimate. About 68% of the time the actual payout will be within one standard deviation of the public information you receive. This means that the range within which the actual payout can be found about two-thirds of the time is twice the standard deviation. Likewise, the range within which the payout can be found 95% of the time is four times the standard deviation. The following table shows how each standard deviation relates to the certainty ranges.

Reliability of public information		
Standard deviation	**Width 68% range**	**Width 95% range**
1.0	2.0	4.0
5.0	10.0	19.9
9.9	19.8	39.6
27.6	55.1	110.3
55.3	110.5	221.0

6.2.3 Private information

After you and all the participants have been given the public information you will be given the option of improving your information at the cost of ECU 120. This means that the estimate of where the actual payout is will get better, in other words, it will have a lower standard deviation. In contrast to the other information provided above, this will be your secret information. Other participants may also buy improved information, but theirs will be determined separately per participant and might only be equal to yours by coincidence [toeval]. You will not know the private information of others, nor they yours; nor will you know who has bought improved information and who hasn't.

What you and all the other participants do know, however, is the quality of the private information. The following standard deviations and associated certainty ranges show how precise the improved information is. This precision depends on the how good the public information is because it supplements [vult aan] the public information with additional private data to produce the private information. The private information is thus always better than the public information because it includes all information in the public information. The question is whether the additional precision is worth ECU 120. The following table shows the quality of the private information associated with every level of public information.

Reliability of private information			
Public information Standard deviation	**Private information Standard deviation**	**Width 68% range**	**Width 95% rang**
1.0	1.0	2.0	4.0
5.0	4.9	9.9	19.8
9.9	9.6	19.2	38.4
27.6	22.7	45.4	90.8
55.3	32.4	64.8	129.6

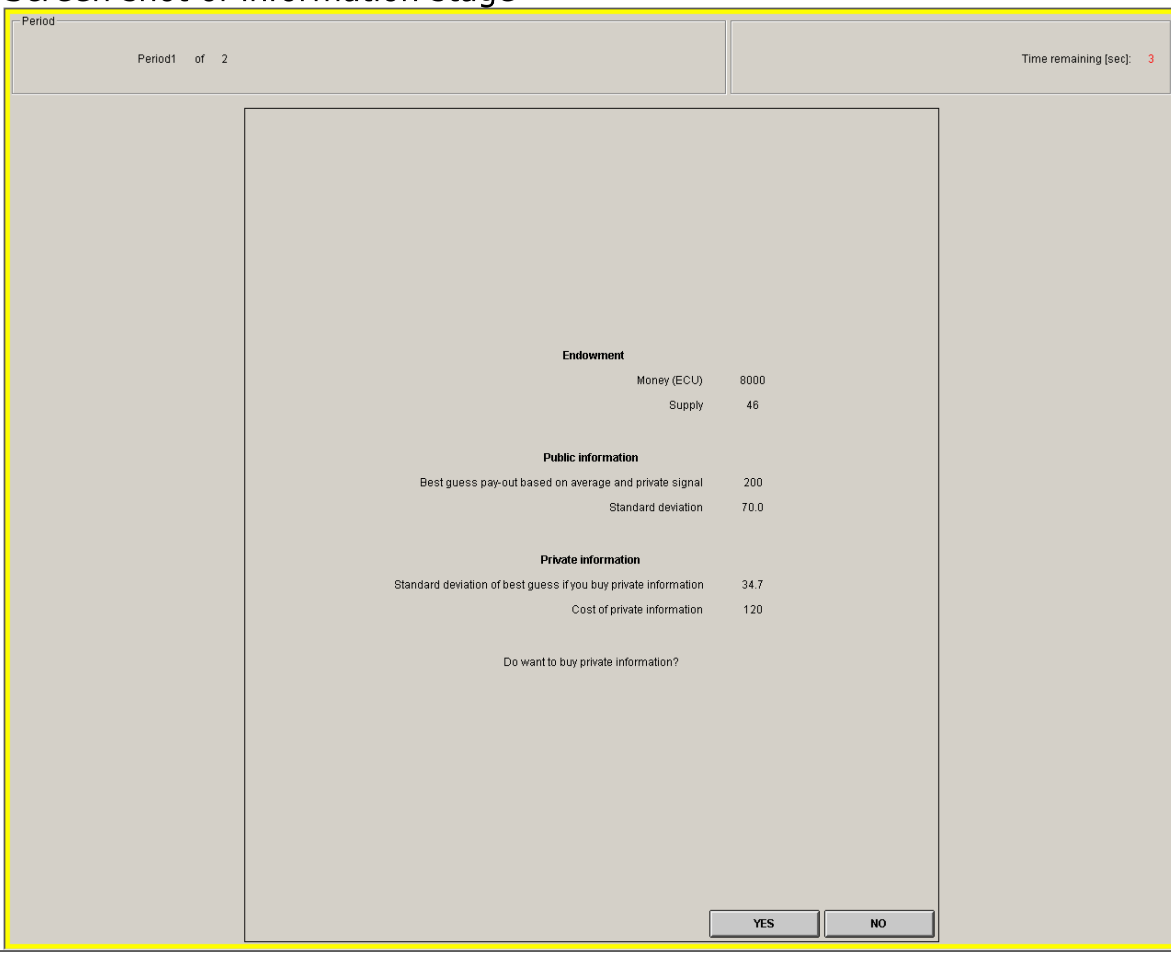
What you and all the other participants do know, however, is the quality of the private information. The following standard deviations and associated certainty ranges show how precise the improved information is. This precision depends on the how good the public information is because it supplements [vult aan] the public information with additional private data to produce the private information. The private information is thus always better than the public information because it includes all information in the public information. The question is whether the additional precision is worth ECU 120. The following

table shows the quality of the private information associated with every level of public information.

Reliability of private information			
Public information Standard deviation	**Private information Standard deviation**	**Width 68% range**	**Width 95% range**
1.0	1.0	2.0	4.0
5.0	4.9	9.9	19.8
9.9	9.6	19.2	38.4
27.6	22.7	45.4	90.8
55.3	32.4	64.8	129.6

You will have ten seconds to make your decision on private information acquisition [aanschaf]. You will be given the public information and its standard deviation plus the standard deviation of the private information. These will be the same as the table above. Please make your decision within the time limit so the experiment can proceed. This may be a challenge at first, but you will learn how to make the requirement judgments rapidly as the experiment progresses. You can also familiarise yourself with the table above now. The following screen shot shows you how this information is presented in a typical case.

Screen shot of information stage



6.2.4 Trading

Once you and the other participants have decided whether or not to buy private information trading starts. Trading lasts two and a half minutes (150 seconds). The information you have, public and private is shown on the screen.

This experiment uses a so-called continuous double auction system [voortdurende dubbele veiling]. At any time during the course of trading you have four options.

1 You can offer securities for sale [effecten aanbieden] at a price and quantity that you wish (bottom right in screen shot below). By doing so no transaction takes place until another participant elects to trade with you at the indicated amount and price.
2 You can post a bid [bod doen] for a certain number of securities (bottom left). Again, you must wait until another participant accepts your offer before a trade is conducted.
3 You can sell securities directly at an offer that another participant has made.
4 You can buy securities immediately at a bid that another participant has made.

Screen shot of double auction market

Bids and offers can be made in the lower left and right corners. Just fill in the price and quantity that would like to trade. The respective amounts are then shown in the columns just to the left and right of the centre of the screen. These bids and offers are public and seen by all participants. No trade takes place until another participant chooses to trade with you at the price and quantity that you have indicated.

The bids and offers of other participants are also shown in the two columns just mentioned. To trade at the indicated prices and quantities all you have to do is click on the appropriate bid or offer and press the sell or buy buttons respectively.

Once a trade has been executed the associated price and amount will be shown in the middle column, this is also public. However, if you are involved in a trade a private record of the price and quantity at which you traded is given in the columns on the far left and right. This way you know what you've bought and sold and at which prices.

As you trade the amount of money and securities you have will change accordingly. These are indicated in the top left. The value of your securities and total holdings [totaal bezit] are also shown. The securities are valued at the most recent price that has been traded ("valued at last price"). To calculate the value of the total holdings the cash is added on ("all holdings"). Note that these values may be different from those determined by the final payout at the end of the period. Every security you hold will be valued at the end of the game according to the final payout not the last price of the trading period.

In the upper right you see the public information about the payout and your private information. If you have not bought private information then both will be the same.

6.2.5 Earnings

The final part of the period is the earnings [inkomen] stage. Here you will be told what the payout is. Your securities will be converted into cash at this payout. The total amount of cash you have at the end of the period will be totalled up with the earnings from the previous period. Earnings from past periods are not available for trading in later periods. However, at the end of the experiment the total earnings of the entire experiment will be added up and converted from ECU to euros at an exchange rate of ECU 25000 per euro. After you have completed the questionnaire, this money will be given to you.

7 Appendix B: Variable Calibration

Durations (in seconds)		
Information acquisition	15	
Trading	150	
Profit	10	
Total	175	
Payout		
Standard deviation	70	
Average	200	
Private signal		
Standard deviation	40	
Cost	120	
Public signal		
	Standard deviation	
StD 1	1	
StD 2	5	
StD 3	10	
StD 4	30	
StD 5	90	
Supply risky asset		
	Standard deviation	
Individual	20	
Per number of traders		
16	5.0	
18	4.7	
19	4.6	
20	4.5	
Endowment	*Average supply*	*Expected value*
risky asset	60	12000
Money	8000	8000
Total		20000
Exchange rate per euro	25000	

8 Appendix C: Results of aggregate regression on period data

Dependent Variable: Errors (with average price)
Method: Least Squares

Sample: 6 25 31 50 56 75 81 100 106 125 131 150
Included observations: 120
Newey-West HAC Standard Errors & Covariance (lag truncation=4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Public signal standard deviation = 5	6.047693	5.976349	1.011938	0.3138
Public signal standard deviation = 10	**9.858201**	**3.101920**	3.178096	0.0019
Public signal standard deviation = 30	**7.597265**	**3.343985**	2.271920	0.0251
Public signal standard deviation = 90	26.75969	5.251058	5.096057	0.0000
Session = 1	-4.221479	3.793712	-1.112757	0.2683
Session = 2	19.65770	6.074663	3.236014	0.0016
Session = 3	3.296322	4.033588	0.817218	0.4156
Session = 4	-2.356344	3.547974	-0.664138	0.5080
Session = 5	-6.240854	2.984436	-2.091133	0.0388
abs(Per capita supply – 60)	0.553430	0.486726	1.137045	0.2580
C	3.893144	4.720567	0.824720	0.4113

R-squared	0.366479	Mean dependent var	17.93742
Adjusted R-squared	0.308358	S.D. dependent var	20.83781
S.E. of regression	17.32977	Akaike info criterion	8.629918
Sum squared resid	32734.98	Schwarz criterion	8.885438
Log likelihood	-506.7951	Hannan-Quinn criter.	8.733686
F-statistic	6.305437	Durbin-Watson stat	2.097203
Prob(F-statistic)	0.000000		

Wald Test:
Equation: Errors (with average price)

Test Statistic	Value	df	Probability
F-statistic	0.231691	(1, 109)	0.6312
Chi-square	0.231691	1	0.6303

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(2) - C(3)	2.260936	4.697141

Restrictions are linear in coefficients.

Dependent Variable: Errors (with AE model price)
Method: Least Squares

Sample: 6 25 31 50 56 75 81 100 106 125 131 150
Included observations: 120
Newey-West HAC Standard Errors & Covariance (lag truncation=4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Public signal standard deviation = 5	2.755291	4.157018	0.662805	0.5089
Public signal standard deviation = 10	9.526068	2.556358	3.726421	0.0003
Public signal standard deviation = 30	5.904211	2.858730	2.065326	0.0413
Public signal standard deviation = 90	25.80479	5.165631	4.995476	0.0000
Session = 1	-5.399297	3.539196	-1.525572	0.1300
Session = 2	22.58628	4.958392	4.555163	0.0000
Session = 3	3.049924	4.262134	0.715586	0.4758
Session = 4	1.037123	3.287420	0.315482	0.7530
Session = 5	-6.037531	3.109078	-1.941904	0.0547
abs(Per capita supply – 60)	0.492589	0.428634	1.149206	0.2530
C	4.942918	4.316470	1.145130	0.2547

R-squared	0.463477	Mean dependent var	18.32976
Adjusted R-squared	0.414255	S.D. dependent var	19.58290
S.E. of regression	14.98758	Akaike info criterion	8.339510
Sum squared resid	24484.39	Schwarz criterion	8.595030
Log likelihood	-489.3706	Hannan-Quinn criter.	8.443278
F-statistic	9.415994	Durbin-Watson stat	1.997729
Prob(F-statistic)	0.000000		

Wald Test:
Equation: Errors (with AE model price)

Test Statistic	Value	df	Probability
F-statistic	0.907876	(1, 109)	0.3428
Chi-square	0.907876	1	0.3407

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(2) - C(3)	3.621857	3.801178

Restrictions are linear in coefficients.

9 Appendix D: Results of aggregate regression on panel data

Dependent Variable: Individual error
Method: Panel Least Squares

Sample: 6 25
Periods included: 20
Cross-sections included: 94
Total panel (unbalanced) observations: 901
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Individual error (-1)	-0.003689	0.042105	-0.087608	0.9302
Public signal standard deviation = 5	7.465237	2.044855	3.650741	0.0003
Public signal standard deviation = 10	**10.31781**	**1.680221**	6.140747	0.0000
Public signal standard deviation = 30	**4.949502**	**1.980274**	2.499402	0.0126
Public signal standard deviation = 90	25.38081	2.040488	12.43860	0.0000
abs(Individual supply – 60)	0.020798	0.031768	0.654671	0.5129
C	9.267862	1.317363	7.035161	0.0000

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.477835	Mean dependent var	18.92524
Adjusted R-squared	0.399043	S.D. dependent var	24.04923
S.E. of regression	18.64330	Akaike info criterion	8.811351
Sum squared resid	271801.8	Schwarz criterion	9.445776
Log likelihood	-3850.514	Hannan-Quinn criter.	9.053693
F-statistic	6.064509	Durbin-Watson stat	2.085348
Prob(F-statistic)	0.000000		

Wald Test:
Equation: Individual error

Test Statistic	Value	df	Probability
F-statistic	7.722025	(1, 782)	0.0056
Chi-square	7.722025	1	0.0055

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(3) - C(4)	5.368313	1.931845

Restrictions are linear in coefficients.

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