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Abstract

We use experimental evidence from a complex trading environment to evaluate the rational expectations theory of information acquisition in an asset market. Although theoretical predictions correctly identify the main drivers of information acquisition in our experimental data, we observe much higher levels of information acquisition. Our evidence suggests that this comes about because the theory overstates the informativeness of trading and thus predicts that few agents will want to buy information. We use indicators such as trading volume to confirm that information acquisition is sensitive to the informativeness of trading. We also test three other theories presented in recent models in the tradition of the rational expectations approach. We find some confirmation that subjects have a strategic incentive to increase their own acquisition in reaction to the acquisition of others. On the other hand, we find no indications of wealth effects or overconfidence in our experimental setup. Overall our evidence suggests that more realistic assumptions, particularly about the informativeness of trading, are needed to accurately predict the levels of information acquisition.

Keywords: Information and Financial Market Efficiency, Private Information Acquisition, Experimental Economics

JEL classification: G14, D82, C92

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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

The informational efficiency of an asset market is dependent on how much private information traders bring to the market. Thus market efficiency is not only about how well a market integrates this private information but also about how the information gets there in the first place. Agents can be expected to weigh the costs of private information acquisition against its usefulness and against the usefulness of other sources of information. Costly private information must compete not only with costless public information but also with information that can be gathered in the process of trading. Particularly the latter aspect means that information acquisition cannot be treated separately from the functioning of the market. The easier it is for traders to glean information from informed counterparties, the less likely they are to invest in their own information. Furthermore, there are behavioral aspects to be considered. In particular, research suggests that overconfidence in private information might lead to excessive investment in it.

Despite a rich vein of theoretical papers, experimental and empirical work on information acquisition is less common. This paper seeks to fill this gap by analyzing information acquisition in the context of a complex experimental asset market.

We take as our starting point the theory of information acquisition in asset markets developed in the context of so-called rational expectations models of financial markets. Such models explicitly take into account that traders base their expectations in part on prices. They are commonly used in theoretical work. Furthermore, they have been widely tested in experiments that have generally confirmed that prices converge to something close to what these models predict.

We base or model of the asset market on Diamond (1985) and test its predictions on the relationship of information acquisition to public information and the ability of the market to convey information. Although we find that the rational expectations approach describes the basic nature of the relationships well, it fails dramatically to predict the level of information acquisition. Our evidence suggests that the theory grossly overstates the ability of the market to aggregate and convey information. The result is that the theory predicts that agents do not have much of an incentive to buy information. We show that both experimental and real world markets are unlikely to be as informative as the theory assumes for two reasons: first, because there are fewer independent signals available; second, because markets are unlikely to be as efficient in extracting available information. We find evidence for the importance of the latter aspect, in particular by showing that higher trading volume results in lower information acquisition.

We also examine some extensions of the rational expectations model in the literature. Barlevy and Veronesi (2000) change the rigid assumptions of the model and find that, contrary to earlier predictions, the information acquisition by some traders may be an incentive for other traders to buy information. We find some support for this idea, which Barlevy and Veronesi label "strategic complementarity".

Peress (2004) demonstrates theoretically that asset holdings could motivate information acquisition. We find no support for this conclusion, although we suspect the real world value of the holdings introduced are simply too small to be much of a test of this theory.

Overconfidence in private information is a common explanation for investment in information. Because market participants are thought to believe their private information is more accurate than it actually is, they invest more in its acquisition than if they had a realistic view of its accuracy. Ko and Huang (2007) and García, Sangiorgi and Urosevic (2007) are two recent papers that formalize overconfidence in rational expectations type models. They come to different conclusions but do provide some testable implications that allow us to rule out overconfidence in private information as a factor in our data.

Overall our experiment suggests that the basic rational expectations model identifies the correct drivers of information acquisition. Nevertheless, although this type of model produces sensible predictions for the prices of assets in experiments, it fails to do likewise for the level of information acquisition. Models with more realistic assumptions about the amount of information brought to the market and the ability of the market to aggregate this information are needed. Some of the innovations introduced in the recent theoretical work discussed may help to amend such shortcomings, although we can only confirm the usefulness of taking into account "strategic complementarity"

The remainder of this paper has the following structure. First, we review the literature on information acquisition in financial markets and use it to determine testable predictions. Second, we describe the setup of our experiment in relation to the theoretical model we use in this paper. Third, we describe and explain the specific calibration we employ. Fourth, we present our data, contrasting theoretical predictions with our experimental outcomes. Finally, we briefly reflect on the implications of our findings in our conclusion.

2 Literature

Information acquisition has a long history. The main vein of literature, which we cover here, involves theoretical work on so called rational expectations models of asset markets. They explicitly take into account the role of prices in forming the expectations of traders. Without taking this into account it is not possible to describe the trade-off a trader has between investing in private information and learning from the market price.

Grossman and Stiglitz (1980) make a defining and early contribution to the literature on information acquisition in financial markets, where they explore the following dilemma. Should markets totally incorporate all information then there is no incentive for traders to invest in information because it would be completely revealed, 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) shows 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 the model comes from fluctuations in supply. Traders cannot disentangle completely the role of supply from that of information in price movements. The information acquisition in Grossman and Stiglitz (1980) has the feature that all traders receive the same piece of information at a standard cost. An important result is that informed traders realize profits from trading that exactly compensates their information acquisition costs.

Verrecchia (1982) adds information acquisition to a model presented by Hellwig (1980). The important innovation of the latter is that it allows the aggregation of information. While the market in the Grossman and Stiglitz (1980) model is actually a mere transmitter of identical pieces of information, in Hellwig (1980) diverse information is aggregated by the market. This allows Verrecchia (1982) to model information acquisition as a separate signal per trader, the precision of which is determined by a cost function.

Diamond (1985) adds 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. The statistic for the degree of information acquisition is thus the fraction of informed traders rather than the precision of information per trader.

Diamond (1985) describes the equilibrium fraction of informed traders as an equation that effectively summarizes all the elements of the above literature regarding information acquisition. The following characterizes the equilibrium degree of information acquisition:

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

λ	fraction of informed traders
V	variance of risky asset supply
r	risk acceptance (the inverse of risk aversion)
s	the private signal's precision (the inverse of the square of the standard deviation)
c	cost of the private signal
h_0	the precision of the payout
Δ	the precision of the public signal

There are three information sources in the model. The private signal, the public signal and the informativeness of the price represented by the term in front of the square root. The informativeness of the price is decreasing in the volatility of the asset supply and increasing in risk acceptance and the precision of the private signal. More supply variance obscures the information in the market. However, the higher the precision of the private signal the more information is brought to the market. Furthermore, the more risk accepting traders are the more aggressively they trade on their information and the more private information they reveal. These two factors both increase the informativeness of the price, making it less interesting for traders to invest in information. At the same time, however, the higher risk acceptance and the precision of the private signal, the more inclined the individual trader is to buy them.

The above literature works with quite restrictive assumptions of constant absolute risk aversion (exponential utility) and normal distributions of random variables. This is necessary for tractability. Barlevy and Veronesi (2000), however, manage to solve a model with risk neutral agents and binomial distribution for the payout. Their conclusions contrast with the standard result that an increase in the number of informed agents leads to a more informative market and thus reduces the incentive for further information acquisition. They show that even though an increase in informed traders leads to more extreme prices, under their assumptions, it does not become easier for uninformed traders to identify the underlying information. As a result there is an increased incentive to become informed to better separate identify informational trading by other agents. Barlevy and Veronesi (2000) label this "strategic complementarity" in information acquisition.

Peress (2004) also tackles the assumption of constant absolute risk aversion in order to incorporate wealth effects in a Verrecchia (1982) type model. He shows that investors with more assets will acquire more information. This wealth effect is a result of the total return on information being higher the larger the holding is.

As Thaler (2005) states, there is extensive evidence that people are overconfident in their judgements. As a result there have been attempts to adjust models of the above type to reflect the possibility of overconfidence.

Ko and Huang (2007) develop a rational expectations model similar to that presented by Verrecchia (1982) except that traders are all overconfident. Specifically, this means that for a given expenditure on information they believe they have a more precise private signal than they actually do. Ko and Huang (2007) confirm earlier research that overconfident traders invest more in private information. They also show that in a market with overconfident traders profits are lower than in a market with rational agents because of higher information expenditures. Furthermore, they establish that trading volumes in such a market are also higher.

García et al. (2007) come to a different conclusion regarding the consequences of overconfidence. Their setup is very similar to Diamond (1985) in that it involves a binary choice to buy a private signal of standard precision and fixed cost. Here overconfidence is represented by the perception that the precision is higher than it actually is. Another key assumption is that there are both overconfident and rational traders in the market. They produce the interesting result that informational efficiency and price volatility are not affected by overconfidence of some traders. Rational agents essentially compensate for the effects of their overconfident colleagues. The net effect of the presence of overconfident traders on information acquisition is actually negative. While the overconfident traders buy more information, they also trade more aggressively, thus giving more information away. This means that the remaining rational agents need to buy even less information than they would otherwise. Another consequence of the result that overconfident agents trade more aggressively is that they make higher profits, but not sufficient to compensate the higher risks they take (i.e. their Sharpe ratios are lower). This more aggressive trading also leads to higher volumes in the market overall.

The rational expectations models resulted in a series of experiments designed to test their predictions. As Plott (2000) discusses, these generally support the theory by showing that simple experimental markets can aggregate information and produce 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 the second 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, a result that is relevant to our findings below.

Beyond the laboratory it is difficult to measure information. The variety of information sources is vast. Even when such sources are identified and their cost measured, it is difficult to determine how informative they are. Information conveyed through market prices is also difficult to identify. Clearly, private information by its very nature is often inaccessible. Despite these problems, there are some studies that try to indentify information acquisition in real markets.

Argentesi, Lütkepohl and Motta (2006) use the circulation of the main financial newspaper in Italy to investigate information acquisition. They find no evidence that market volume is related to newspaper sales, as one might expect if trading is the main motivation for such purchases. Market volatility is also not found to lead to higher sales, as financial theory discussed above would indicate. The authors consider cognitive dissonance the motivation behind sales because higher stock prices are associated with higher sales, and vice versa for lower sales. Investors apparently seek confirmation of the wisdom of their equity purchases. The main limit of this work from our perspective is that it is clearly not unique private information that is being purchased but rather access to a semi-public signal. Of the theoretical models discussed above this most closely matches the Grossman and Stiglitz (1980) model.

Guiso and Jappelli (2005) use detailed customer data of a leading Italian bank to examine information acquisition decisions. They show that individual investment in financial information is increasing in risk tolerance and also in wealth, in line with Peress (2004), while it is decreasing in proxies for the cost of information. They also find support for the idea that overconfidence leads to higher investment in information. Those who claim to know stocks well, along with men, and less educated investors, trade more frequently and realize investment returns characterized by lower Sharpe ratios.

Based on the above theoretical literature there are several predictions we can test with our experimental setup.

1) The basic rational expectations asset market model with information acquisition as represented in equation (1) with two general and one quantitative prediction:

a) The fraction of informed traders is decreasing in the precision of the public signal

b) The fraction of informed traders is decreasing in the informativeness of trading

c) The fractional of informed traders as predicted by equation (1) with our experimental calibration as inputs (more on this below).

2) Barlevy and Veronesi (2000) theory of strategic complementarity

a) Higher level of information acquisition than predicted under the standard assumptions of the rational expectations model

b) Information acquisition by other agents increases the incentive to invest in information

3) Peress (2004) theory of a wealth effect in information acquisition: specifically that a higher initial endowment results in higher information acquisition

4) Ko and Huang (2007) model of overconfidence

a) Higher levels of information acquisition than in a model with rational agents

b) The overconfident agents make lower profits than in a model with rational agents

c) A market with overconfident agents has higher trading volumes than in a model with rational agents

5) García et al. (2007) model of overconfidence with heterogeneous agents

a) A market with overconfident and rational agents will have fewer informed traders

b) Informed agents are more likely to be overconfident and to trade more

c) This aggressive trading will result in higher profits but a lower Sharpe ratio

3 The basic experimental setup

This section describes the experimental treatments we use. It places the various aspects of the experiment in the context of the theories outlined above.

The setup of the experiment is based on the Diamond (1985) model described above. This model has all the classic elements of the rational expectations literature including all three potential sources of information: public, private and the market price.

We replicate the model as closely as possible in a laboratory of networked PCs with the commonly used experimental software ZTree 2 (see Fischbacher (1999) for details). Matching the model closely results in rather complicated treatments. This is innovative, in the sense that 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. It is exactly this complexity that allows us to explore how the boundness of rationality of traders possibly influences the predictions of the model.

To alleviate the disadvantages of our setup we use more subjects per session than in many earlier laboratory market experiments, between sixteen and twenty, to improve market functioning. We also 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.

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 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. Assets deliver a random payout, a 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 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, which means that the experiment focuses on the implications of the ability of traders to extract information from trading.

Unlike in Diamond (1985) we have traders with different levels of risk aversion. We measure risk aversion through a test at the beginning of the session in which subjects have to choose between a number of different fixed payments and an all-or-nothing bet. The average of this result is used to calculate the risk aversion used in the aggregate data presented below.

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.

4 Calibration

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 Futures market. There are two reasons for this. First, this experiment was designed in part to test the theoretical paper Kool, Middeldorp and Rosenkranz (2007) which applies the Diamond (1985) model to the issue of central bank communication where the public signal in the model is interpreted as guidance by the central bank on the future of Fed Funds rate. The results of this are discussed in an upcomming working paper. Second, the Fed Funds Futures market is particularly well suited because the elements in our treatment that cannot be observed in other markets can actually be observed in this one. As in the market we create in the lab, in this futures market there is a clear payout when the future expires and the price of the future during trading can be straightforwardly interpreted as the market expectation of this payout.

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 source for this information is the survey of Consensus Economics.

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 (2000,2007), 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 riksy 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 between Experimental Currency Units (ECU) and euros 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. We do this because we use it to test a theory related to central bank communication from Kool et al. (2007). When deciding the question of whether we should manipulate more variables we considered the following. By using several random variables there is already a lot of noise in the experiment, while at the same time we only have six sessions of twenty-five periods, giving no more than 150 datapoints for aggregate period data. We thus have to be economical in the variables we manipulate. Furthermore, the precision of the public signal seems to be best suited for testing information acquisition theory in general because its effects on information acquisition are theoretically clear cut and measurable. In contrast, the private signal's impact is theoretically undetermined and thus any outcome could be defended. Furthermore, we can isolate the impact of the public information, and knowing that the precision of private information remains constant, other informational effects must come from what information the subjects can deduce from the price. 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 calibrations used are summarized and specified in Table 1.

To make predictions based on the theory we also need to measure the risk aversion of the traders. As indicated above, we use a lottery setup. This is similar to the approach used by Heinemann, Nagel and Ockenfels (2004). Subjects are asked to choose between fixed payments and a lottery. The lottery is the same for each choice, namely a 50% chance of nothing vs. a 50% chance of a payment of €140. The fixed payments run from €10 to €130. It is made clear that one of the subjects, chosen at random, will actually have one of their choices executed (typically we made one student very happy per session). Subjects with consistent risk preferences will chose the fixed payment up to a certain amount and then switch to the lottery. The last fixed payment we take as a measure of their risk acceptance. An answer of €70 would be considered risk neutral and there above risk seeking.

Table 1: Variable calibrations

Durations	Information acquisition	15 seconds	
	Trading	150 seconds	
	Profit	10 seconds	
	Total	175 seconds	
Payout	Standard deviation	70 ECU	
	Average	200 ECU	
Private signal	Standard deviation	40 ECU	
	Cost	120 ECU	
Public signal	Standard deviations		
	1 ECU		
	5 ECU		
	10 ECU		
	30 ECU		
	90 ECU		
Supply risky asset	Standard deviation	Individual	20 units
		Whole market with 16 Traders	5 units
		Whole market with 18 Traders	4.7 units
		Whole market with 19 Traders	4.6 units
		Whole market with 20 Traders	4.5 units
Endowment		Average supply	Expected value
	risky asset	60 units	12000 ECU
	money	8000 ECU	8000 ECU
	total		20000 ECU
Exchange rate	ECU per euro	25000	

5 Results

This section describes the results of our analysis. We test the predictions related to information acquisition in financial markets listed at the end of the literature overview. Most of this section relates to tests of the basic rational expectations model.

5.1 Tests of the rational expectations approach (predictions 1a, 1b and 1c)

We have all the variables in equation 1 defined in the experiment or, in the case of risk acceptance, measured. Our raw risk acceptance measure does take some adjusting in this case to make it compatible with this equation. Note that the model assumes homogenous risk attitude so we need one figure per session. We thus take the average of the measurements per session. Then we solve the following equation.

$$(2)\ -e^{-\frac{1}{r}(w+f)} = -\frac{1}{2}e^{-\frac{1}{r}(w)} - \frac{1}{2}e^{-\frac{1}{r}(w+140)}$$

r risk acceptance

f the fixed amount in our risk aversion measure

w the unknown wealth of the average subject

The utility function used in Diamond (1985) and other rational expectations models is $U = -e^{-\frac{1}{r}(w)}$. Here we are thus equating the utility from the fixed amount in our risk measure to the expected utility from the lottery described above. Fortunately, w drops out, so we are left with only one unknown and we can solve for r numerically. The r produced then has to be multiplied by the exchange rate of the experiment to be compatible with the other data. Once this is done we thus have all the values necessary to calculate the theoretical fraction of informed traders.

Chart 1, on page 18, summarizes the results. Each point represents the fraction of informed traders (y axis) per period. The data is ordered according to the five standard deviations of the public signal (x axis). The lines are simple regression lines through the theoretical and experimental data points. Clearly the theoretical level of information acquisition is much lower than what we find in the experiment and the fraction of informed traders is much more responsive to the public signal. While we observe levels of information acquisition between in a wide range between 0.0% and 87.5% the theoretical levels are in a narrow range between 0.5% and 0.7%.

To further examine the drivers of information acquisition we do ordinary linear regressions on both the theoretical and the experimental data. The former is done to create a benchmark of what we would expect to find if we did a linear regression on data that was completely in line with the theory. See Table 2 and Tabl3 on pages 19 and 20 respectively.

Obviously, the linear model does a good job of describing both the theoretical results (R^2 of 95%) and the experimental data (R^2 of 84%). Non-linearities do create some heteroskedasticity in the theoretical data, so we use White standard errors to ensure appropriate inference. The experimental data also has heteroskedasticity and autocorrelation, in part because we cannot use session dummies together with the variance and the risk acceptance because these are the same for each session. To counter this we use Newey-West consistent standard errors.

The theory is confirmed from one perspective, namely that all the variables in the experimental data have the signs that we would expect. Specifically we can confirm predictions 1a and 1b. The latter we do on the basis of the fact that the only part of the informativeness of the price in equation (1) that varies in the experiment is V, the variance of supply. Here it has the expected sign.

All the coefficients are, however, much larger than predicted. Specifically information acquisition appears to be 223 times more sensitive to risk acceptance, 388 times more sensitive to the variance of supply and an impressive 3438 times more sensitive to the public signal. We thus reject prediction 1c.

What differences between the theoretical model and our experimental setup could explain this result? First, the utility function could be unrealistic. Second, there are clearly fewer traders than the model assumes. Third, the ability of traders to interpret the price may be lower than assumed by the model.

Regarding the utility function, exponential utility is an assumption primarily made for tractability. Furthermore, there is the possibility that the risk acceptance measure is not appropriate for the values used in our experiment. To evaluate the consequences of these problems we examine how sensitive the results are to changes in risk acceptance. This directly tests the possibility of incorrect measurement. It also indirectly tests the utility function used. Even if exponential utility and the associated constant absolute risk aversion are not generally correct, they will produce workable results locally if the correct level of risk aversion is specified. So, if there is no level of risk aversion that produces the high level of information acquisition we observe, then it is not likely that another utility function will do this.

We indeed find that even though the fraction of informed traders is sensitive to the level of risk aversion, another level would not be sufficient to fill the gap between the theoretically predicted and the empirically observed fractions. Chart 2, on page 21, illustrates this sensitivity by showing how information acquisition changes with the level of risk acceptance for each of the levels of public information used. The following elements are represented. The curved unbroken lines are the theoretical predictions for the fraction of informed traders at each level of the public signal. The straight dashed lines are the average levels of information acquisition in our experiment. The colors correspond to the theoretical levels. The blue shaded area represents the range of risk acceptances measured in the experiment and measured in experimental currency.

It is clear that the theoretical results are sensitive to risk attitude. We measure a high level of risk acceptance in relation to the other variables, between 2.6 and 5.7 million (blue shaded area). This is an important driver of the theoretical result. This certainly does not mean that the utility function does not operate properly with these high levels of risk acceptance or that it is a strange result. The high risk acceptance is measured in experimental currency and its high value relative to the other values in the experiment simply reflects the fact that the real-life values of the amounts traded are small. The result is that the market we simulate approaches risk neutrality, i.e. infinite risk acceptance.

Note, however, that even if we assume very different levels of risk acceptance we still cannot match the theoretical results with the experimental results. The highest possible level of information acquisition with our calibration is 42% at a public signal with a standard deviation of 90. This is a little over half of what we actually observe.

Chart 3 (page 22) illustrates the gap that remains. This represents the highest fraction of informed traders per standard deviation of the public signal for any level of risk aversion. These correspond to the peaks of the curved lines in Chart 2. This stretches the model beyond its limits (at least with constant absolute risk aversion) in the sense that these points are at highly different levels of risk acceptance ranging between 460 and 768000. To explain our data another utility function would have to unite these very different levels of risk acceptance, and even then it would not match the high levels of information acquisition we observe.

The higher the risk acceptance, the more informative the theoretical market becomes because traders are not afraid to trade aggressively. The more informative market then reduces the need for traders to invest in their own information.

Under the assumptions in the model with our calibration the market becomes extremely informative. The average information available per trader (I) can be defined as the following.

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

This is the sum of the precisions of the public information $(h_0 + \Delta)$, private information, λs, and the information that can be extracted from the price, $\frac{(r\lambda s)^2}{V}$. The precisions that we get from the theoretical calculation, with our "high" risk acceptances, range from 6.7 to 14.8. The associated standard deviations are only 0.26 and 0.39. Remember, our empirically calibrated private information has a standard deviation of 40 and the public signal ranges from 1 to 90. The high levels of information are almost entirely due to the infomativeness of the price, as can be seen from Chart 4 on page 23).

Chart 1: Theoretical versus experimental information acquisition

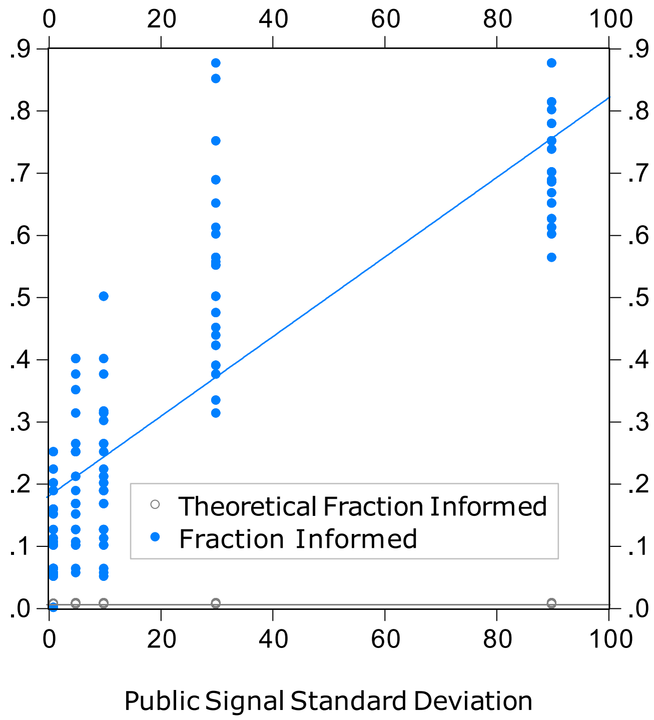


Table 2: Results of benchmark regression on theoretical data

Dependent Variable: Theoretical fraction informed
Method: Least Squares

Sample: 1 150

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
risk acceptance	-1.11E-09	6.00E-11	-18.49524	0.0000
public info std	3.22E-06	5.42E-07	5.939502	0.0000
supply variance	0.000335	3.03E-05	11.02735	0.0000
Constant	0.003136	0.000431	7.276470	0.0000

R-squared	0.945125	Mean dependent var	0.006074
Adjusted R-squared	0.943997	S.D. dependent var	0.000606
S.E. of regression	0.000143	Akaike info criterion	-14.83709
Sum squared resid	3.00E-06	Schwarz criterion	-14.75680
Log likelihood	1116.781	Hannan-Quinn criter.	-14.80447
F-statistic	838.1962	Durbin-Watson stat	1.971202
Prob(F-statistic)	0.000000		

Table 3: Results of regression on experimental data

Dependent Variable: Fraction informed
Method: Least Squares

Sample: 1 150

Newey-West HAC Standard Errors & Covariance (lag truncation=4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
risk acceptance	-2.48E-07	5.55E-08	-4.467475	0.0000
public info std	0.011069	0.000351	31.51481	0.0000
supply variance	0.130107	0.029297	4.440896	0.0000
Constant	-1.734833	0.426442	-4.068161	0.0001

R-squared	0.839088	Mean dependent var	0.355267
Adjusted R-squared	0.835781	S.D. dependent var	0.248730
S.E. of regression	0.100795	Akaike info criterion	-1.725151
Sum squared resid	1.483307	Schwarz criterion	-1.644867
Log likelihood	133.3863	Hannan-Quinn criter.	-1.692534
F-statistic	253.7757	Durbin-Watson stat	1.696236
Prob(F-statistic)	0.000000		

Chart 2: Sensitivity of theoretical information acquisition to risk acceptance

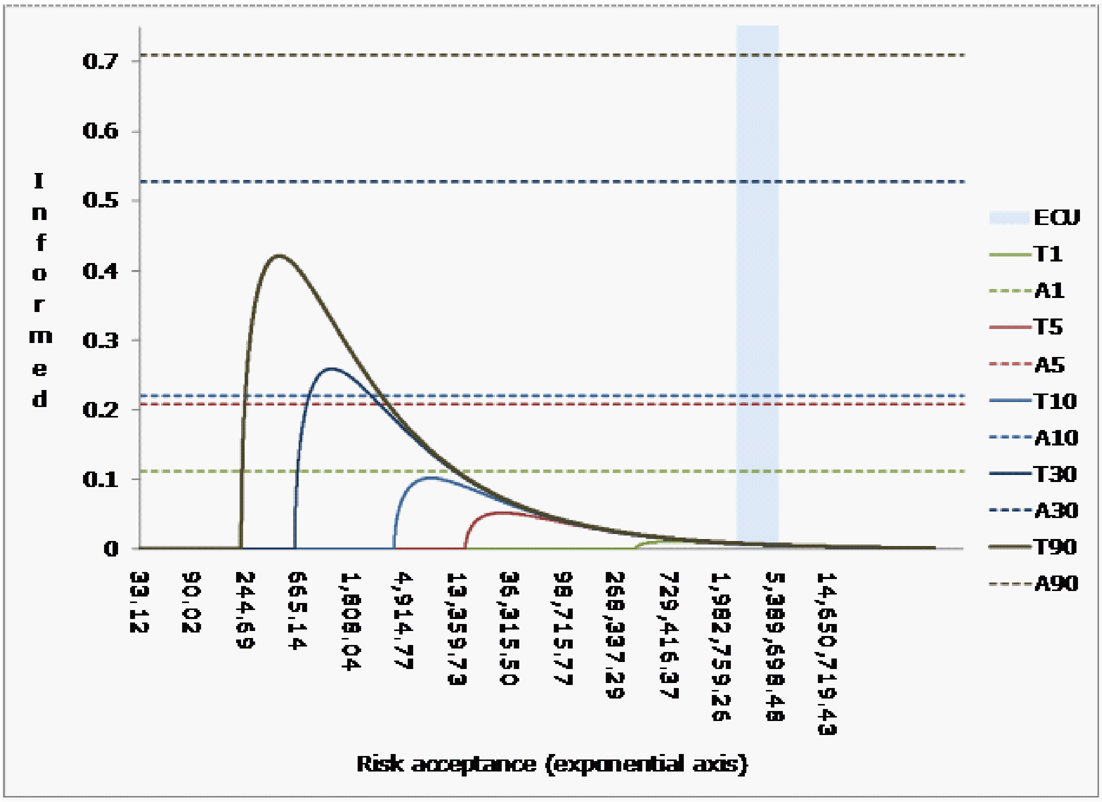


Chart 3: Gap between model and experimental findings

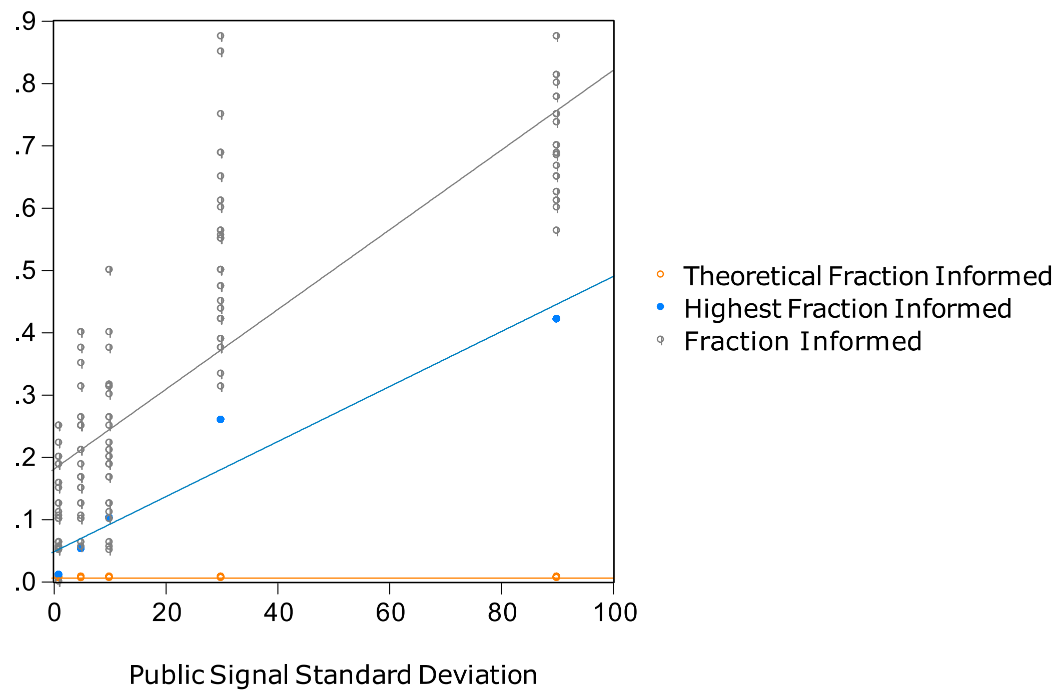
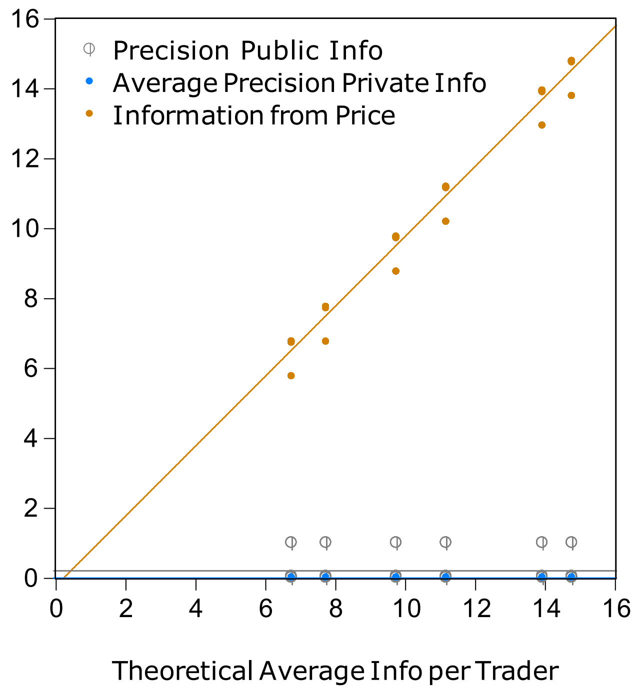


Chart 4: Components of theoretical average information of traders



The rational expectations theory assumes an infinite number of traders. This is a common assumption that is necessary in order to rule out individual traders having an influence on the price. It does have significant consequences, however, for the informativeness of the price. It means that the infinite number of independent signals of the traders could be combined to perfectly predict the payout. The only thing that prevents the payout from becoming the price (i.e. fully revealing prices) is the noise in the market which blunts the informativeness so that it is individually rational for traders to factor in public information. In our experiment, however, it is clearly not possible that there is so much information. Even if all twenty subjects were informed, their optimally combined independent signals would only have a precision of 0.0125.

To match the lower bound of precision of 6.7 to become available at all, with the highest level of public information we test (never mind be reflected in the price), would require over 9 thousand informed traders with independent signals. Over all levels of risk aversion and over the wide range for the public signal that we test, the model only theoretically predicts this for a fraction of informed traders under 0.01, so there would have to be more than 900 thousand traders in the market total. This shows that it is best not to take the rational expectations approach to information acquisition too literally.

The final difference between the Diamond (1985) model and the experiment is that we cannot expect the subjects to be able to optimally infer information from the price. This bounded rationality has the same effect as the lower amount of information available to the market, it reduces the informativeness of the price, thus increasing agents' incentives to invest in their own information.

Returning to the information acquisition equation, we see that the term outside of the square root relates to the informativeness of the price. Less information for the market due to fewer traders and a limited ability by subjects to infer information from the market could be thought of as a separate variable that impacts the informativeness of the price in a similar way V does. This additional variable would impact all the others in the equation because it multiplies through to all of them. The result in a linear regression of such an unspecified variable would be to increases all the coefficients. This, of course, is what we find in the data. It is an indication, at least, that a lower informativeness of the price is an important cause of the discrepancy between the theoretical and actual level of information acquisition.

It would be possible to better examine this relationship if there was another indicator of the informativeness of the price. There is one such device that we can use, namely the volume of trades conducted per period. Theoretically an increase in volume should mean that more information is conveyed by the market. Higher volume markets should thus have less private information acquisition because more information can be extracted through the market.

We examine this in the regression presentd in Table 4. We use the volume over the previous five periods as an indicator of how informative the market is. Past sessions are used because the information decision is made before trading and expectations of market volumes can only be based on past market conditions. We use a moving average of the last five sessions to smooth over possible effects of the five different levels of public information (taking just one period and controlling for the public signal also works, but less well). In the resulting regression, shown below, volume is highly significant and improves the R^2.

Another sign that the informativeness of the price is an important indicator in explaining the high level of information acquisition can be found in the subject level panel data. After the sessions we asked subjects how many periods out of 25 they used particular strategies. One question, labeled observe, asked whether they looked at market activity to make a guess about the actual payoff. This is represented in Table 5 as "observe", which is the precentage of periods that the subject used this tactic.

Unfortunately, due to such subject specific data, such as risk acceptance and the questions we are interesting in, we cannot use subject fixed effects. We do employ session dummies and a lag of the dependent variable. The latter appears to pick up part of the subject fixed effect and corrects autocorrelation. Due to some risk seeking subjects, we use the raw risk atttitude measure in the panel data regressions. Because the dependent variable is binary, we use white standard errors to correct for the resulting heteroskedasticity.

Table 4: Volume as indicator of informativeness of the price

Dependent Variable: Fraction Informed
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.
risk acceptance	-1.26E-07	5.89E-08	-2.138689	0.0346
public info std	0.010927	0.000359	30.44685	0.0000
supply variance	0.068612	0.029144	2.354277	0.0203
volume 5ma (-1)	-0.000407	8.63E-05	-4.723097	0.0000
Constant	-0.655182	0.420985	-1.556306	0.1224

R-squared	0.876838	Mean dependent var	0.345099
Adjusted R-squared	0.872554	S.D. dependent var	0.243467
S.E. of regression	0.086917	Akaike info criterion	-2.006956
Sum squared resid	0.868772	Schwarz criterion	-1.890810
Log likelihood	125.4173	Hannan-Quinn criter.	-1.959788
F-statistic	204.6817	Durbin-Watson stat	1.709216
Prob(F-statistic)	0.000000		

Table 5: Determinants of individual information acquisition

Dependent Variable: Bought private signal
Method: Panel Least Squares

Sample (adjusted): 6 25
Periods included: 20
Cross-sections included: 109
Total panel (balanced) observations: 2180
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
bought private signal (-1)	0.267891	0.018513	14.47029	0.0000
public signal std	0.006828	0.000271	25.17389	0.0000
observe	-0.096018	0.028780	-3.336327	0.0009
risk acceptance	0.001177	0.000368	3.197581	0.0014
volume 5ma (-1)	-0.000413	0.000178	-2.324452	0.0202
Session dummy 1	-0.006559	0.041865	-0.156673	0.8755
Session dummy 2	0.014536	0.038977	0.372939	0.7092
Session dummy 3	-0.022499	0.029127	-0.772434	0.4399
Session dummy 4	-0.015721	0.028319	-0.555143	0.5789
Session dummy 5	0.026670	0.032613	0.817778	0.4136
Constant	0.264732	0.106263	2.491288	0.0128

Effects Specification

Period fixed (dummy variables)

R-squared	0.300863	Mean dependent var	0.345413
Adjusted R-squared	0.291432	S.D. dependent var	0.475612
S.E. of regression	0.400353	Akaike info criterion	1.020727
Sum squared resid	344.6077	Schwarz criterion	1.098989
Log likelihood	-1082.592	Hannan-Quinn criter.	1.049338
F-statistic	31.90408	Durbin-Watson stat	2.040851
Prob(F-statistic)	0.000000		

The results support the importance of the informativeness of the price in explaining information acquisition. The observe variable is negative and significant, indicating that the more periods a subject infers data from the market the less likely they are to buy information. Volume remains significant in the individual equation.

Also interesting is that the risk acceptance variable has switched signs. This is completely logical on the individual level. Note that risk acceptance occurs twice in the information acquisition equation (1): once at the left where it is part of the impact of the informativeness of the price and once on the right, where it is related to the cost of the private signal. On the individual level these two become separate entities. On the left we have average risk aversion of the market which impacts how much information is released through the aggressiveness of trading. In the regression this is picked up by the volume. On the right we have the disutility cost of the private signal, which is individual in nature. In the aggregate data the former effect dominates. Note that this evidence supports the empirical findings of Guiso and Jappelli (2005) who also find that higher risk acceptance leads to higher information acquisition on an individual level.

The volume and questionnaire data further support prediction 1b, that a more informative market leads to less information acquisition. It is important to note, however, that we refer here to a broader concept of informativeness that is not only dependent on risk acceptance, private information and the variance of supply but one that also reflects the limited number of traders and the limited ability of real people to infer information from the price.

In this subsection we have had an extensive look at the predictions of the rational expectations model of information acquisition in an asset market as represented by Diamond (1985). The overall conclusions of the model hold in the sense that the basic mechanisms predicted are at work. Prediction 1a and 1b are confirmed. The level of information acquisition is, however, much higher in our experiment than the model predicts, rejecting prediction 1c. The evidence points to the conclusion that the rational expectations model dramatically overestimates the informativeness of the price resulting in the theoretical agents having much less need for private information than what we find in our experiment. The source of this is likely to be both in the high demands the model places on the ability of the traders to infer prices as well as the assumption of an infinite number of traders. Although the latter issue is probably less severe in larger markets, the simple calculations shown demonstrate that even then the informativeness of the price assumed by the rational expectations approach is excessive.

5.2 Strategic complementarity (prediction 2a and 2b)

The conclusion of Barlevy and Veronesi (2000) is that traders will have more incentive to buy information than the rational expectations model assumes (prediction 1b) resulting in higher levels of information acquisition (prediction 1a). Their model employs a payout with a binomial distribution, so our experiment, with all normal random variables should not strictly fall under their predictions. Nevertheless, they also assume risk neutral traders, which our experiment arguable approaches. Furthermore, their intuition might be applicable if for some other reason traders cannot identify the consequences of a higher fraction of informed traders as informationally driven, perhaps due to bounded rationality. If this is the case it would be intimately related to the effect we discussed above. Indeed, if there is “strategic complementarity” it supports the idea that bounded rationality plays a role in the higher level of information acquisition rather than just the number of traders.

Clearly from the above information, we can confirm prediction 2a, as we observe a higher level of information acquisition than predicted by the traditional rational expectations assumptions.

The real question is, however, if this is due to “strategic complementarity”. One post-session question does help us to identify such an effect. We asked how often subjects took into account the fact that others also bought a private signal. When the answer to this question as % of 25 periods, "info others", is added to the panel data regression results presented earlier, we find that it is significant and positive. This does lend some support to the idea that traders are responding to the level of information acquisition by others and supports prediction 2b.

Table 6: Test of "strategic complementarity"

Dependent Variable: Bought private signal
Method: Panel Least Squares

Sample (adjusted): 6 25
Periods included: 20
Cross-sections included: 109
Total panel (balanced) observations: 2180
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
bought private signal (-1)	0.249332	0.018515	13.46655	0.0000
public signal std	0.006791	0.000269	25.28551	0.0000
volume 5ma (-1)	-0.000416	0.000176	-2.362390	0.0182
info others	0.249433	0.042074	5.928461	0.0000
observe	-0.149720	0.028947	-5.172150	0.0000
risk acceptance	0.000949	0.000371	2.556038	0.0107
Session dummy 1	-0.033260	0.041760	-0.796470	0.4258
Session dummy 2	-0.015187	0.038411	-0.395380	0.6926
Session dummy 3	-0.050358	0.029298	-1.718837	0.0858
Session dummy 4	-0.014610	0.028204	-0.518009	0.6045
Session dummy 5	-0.024088	0.033556	-0.717842	0.4729
Constant	0.287984	0.105412	2.731981	0.0063

Effects Specification

Period fixed (dummy variables)

R-squared	0.312960	Mean dependent var	0.345413
Adjusted R-squared	0.303369	S.D. dependent var	0.475612
S.E. of regression	0.396967	Akaike info criterion	1.004190
Sum squared resid	338.6450	Schwarz criterion	1.085061
Log likelihood	-1063.567	Hannan-Quinn criter.	1.033755
F-statistic	32.63032	Durbin-Watson stat	2.027906
Prob(F-statistic)	0.000000		

5.3 Wealth effect (prediction 3)

Peress (2004) identifies a wealth motivation for information acquisition (prediction 3). To try and identify this we use our panel data. We simplify the above regressions by setting subject fixed effects, which effectively captures all individual elements, including risk acceptance, and all session effects. We find no evidence that the endowment influences the decision to buy a private signal. This cannot be seen as a strong rejection of prediction 3, however, considering that in actual money the endowment is very limited.

Table 7: Testing for wealth effect in data

Dependent Variable: Bought private signal
Method: Panel Least Squares

Sample (adjusted): 6 25
Periods included: 20
Cross-sections included: 109
Total panel (balanced) observations: 2180
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
public signal std	0.010888	0.000391	27.82925	0.0000
supply	0.000133	0.000381	0.348837	0.7272
volume 5ma (-1)	-0.000408	0.000148	-2.766159	0.0057
Constant	0.344736	0.085748	4.020327	0.0001

Effects Specification

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

R-squared	0.519240	Mean dependent var	0.345413
Adjusted R-squared	0.488737	S.D. dependent var	0.475612
S.E. of regression	0.340075	Akaike info criterion	0.738909
Sum squared resid	236.9688	Schwarz criterion	1.080656
Log likelihood	-674.4108	Hannan-Quinn criter.	0.863845
F-statistic	17.02306	Durbin-Watson stat	2.087847
Prob(F-statistic)	0.000000		

5.4 Overconfidence (predictions 4a, 4b, 4c, 5a, 5b, and 5c

Finally we deal with overconfidence as a potential explanation of information acquisition. García et al. (2007) and Ko and Huang (2007) formalize this in asset market framework in the tradition of the rational expectations approach. These papers have opposite predictions regarding the level of information acquisition. The setup of heterogeneous rational and overconfident traders in García et al. (2007) actually results in a lower level of information acquisition (prediction 5a) versus a purely rational model. This clearly is not compatible with our findings and we reject this prediction.

García et al. (2007) show that informed traders are more likely to be overconfident and thus likely trade more aggressively (prediction 5b). We find the opposite effect, our subjects are actually slightly less likely to trade if they are informed.

García et al. (2007) also predict that informed traders are more likely to be overconfident and that they should earn higher profits, but have a lower risk reward ratio (prediction 5b). As they indicate, this is a result that is confirmed by earlier research on overconfidence. We find that informed traders do indeed earn higher profits, even correcting for their higher information costs. However, their reward-risk ratio, measured by Sharpe ratios, is also higher. This also suggests that our subjects do not suffer from overconfidence, which rejects prediction 5b.

Ko and Huang (2007) predict higher information acquisition with overconfidence, which is the result one would expect considering traders are overconfident about the private information and confirms earlier research which they cite. Clearly our research supports this conclusion, confirming prediction 4a. However, the question is if this is the result of overconfidence. Strictly speaking we cannot test this under the assumption of Ko and Huang (2007) that all traders are homogenously overconfident. Nevertheless, if there is overconfidence in our data, some of our traders are likely to be more confident than others, so it is reasonable to assume that predictions 4b and 4c can be tested on the subset of traders that would be overconfident, namely those that buy information. Under this assumption the tests used for García et al. (2007) become directly applicable. Our informed traders do not make lower profits (they actually make higher profits) and they do not trade more (they actually trade less). We thus reject predictions 4b and 4c.

We find little evidence of overconfidence in our data, at least not in the sense that traders believe their private signal to be superior. This should perhaps be no surprise, because in our treatment the level of private information was unambiguously communicated and it was made clear that all subjects had a signal of the same precision. As we noted above, overconfidence is considered one of the most robust findings in psychology and an important result in behavioral finance. Perhaps the fact that we were able to eliminate overconfidence by being explicit about the nature of the private signal is an indication that overconfidence about the precision of the private signal is actually the correct way to think about this concept.

Table 8: Test of overconfidence in experimental data

Dependent Variable: Trades as % of total volume
Method: Panel Least Squares

Sample: 1 25
Periods included: 25
Cross-sections included: 109
Total panel (balanced) observations: 2725
White diagonal standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
risk acceptance	0.000415	9.28E-05	4.468505	0.0000
bought private signal	-0.011308	0.004605	-2.455577	0.0141
Session dummy 1	0.022917	0.006226	3.680964	0.0002
Session dummy 2	0.020628	0.006177	3.339500	0.0009
Session dummy 3	0.008361	0.005612	1.489933	0.1364
Session dummy 4	0.004255	0.006887	0.617815	0.5367
Session dummy 5	0.002597	0.006642	0.391024	0.6958
supply	0.000176	9.73E-05	1.811164	0.0702
public signal std	0.000118	0.000111	1.064002	0.2874
Constant	0.069724	0.008164	8.540019	0.0000

R-squared	0.022761	Mean dependent var	0.110092
Adjusted R-squared	0.019521	S.D. dependent var	0.100979
S.E. of regression	0.099988	Akaike info criterion	-1.763863
Sum squared resid	27.14367	Schwarz criterion	-1.742174
Log likelihood	2413.264	Hannan-Quinn criter.	-1.756024
F-statistic	7.026007	Durbin-Watson stat	0.735599
Prob(F-statistic)	0.000000		

5.5 Conclusion

Our experimental asset market has allowed us to examine several theories of information acquisition. The rational expectations approach seems to offer a good starting point, in that it identifies variables that in our experiment are related to information acquisition in roughly the way that the theory predicts. The level of information acquisition is much higher, however. The limited number of traders and the bounded rationality of agents in the face of a relatively complex market experiment appear to limit the informativeness of the price. Contrasting theory with our experimental setup suggests that this is the main reason for the high level of information acquisition. Traders in our experiment need to buy more information because they cannot extract as much from the price as their model counterparts. This is supported by evidence that indicators of informativeness, such as volume, illustrate the importance of market informativeness for information acquisition. Furthermore, some simple calculations imply that even in real world markets the informativeness of the price assumed in the rational expectations models is too high and the corresponding level of information acquisition too low. We also find evidence that agents respond strategically to the higher information acquisition by other agents. Wealth effects or overconfidence do not seem to be a factor in our data, although these cannot be ruled out in other settings.

Our experiment indicates that while rational expecations models produce meaningful predictions of prices, unrealistic assumptions lead to unrealistically informative markets and correspondingly implausibly low levels of information acquisition. Although, some of the adjusted models we test take steps that might address this problem, our finding suggest that more realistic assumptions the informativeness of the price are also needed to produce more plausible results and further the understanding of market efficiency.

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