Federal Reserve Bank of New York
Staff Reports

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Staff Report no. 487
March 2011

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JEL classification: C92, D82, E58, G14

Abstract

Central banks have become increasingly communicative. An important reason is that democratic societies expect more transparency from public institutions. Central bankers, based on empirical research, also believe that sharing information has economic benefits. Communication is seen as a way to improve the predictability of monetary policy, thereby lowering financial market volatility and contributing to a more stable economy. However, a potential side-effect of providing costless public information is that market participants may be less inclined to invest in private information. Theoretical results suggest that this can hamper the ability of markets to predict future monetary policy. We test this in a laboratory asset market. Crowding out of information acquisition does indeed take place, but only where it is most pronounced does the predictive ability of the market deteriorate. Notable features of the experiment include a complex setup based directly on the theoretical model and the calibration of experimental parameters using empirical measurements.

Key words: experimental economics, private information, financial market efficiency, central bank communication and transparency

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1 Introduction

Central banks have become considerably more communicative and transparent over the last two decades. An important reason is that democratic societies expect more openness from public institutions. Another reason is given by Bernanke (2004) who states that "clear communication helps to increase the near-term predictability of FOMC[1] rate decisions, which reduces risk and volatility in financial markets and allows for smoother adjustment of the economy to rate changes." Empirical research generally suggests that more central bank transparency has indeed improved predictability. However, it is not clear if this means that further increases in transparency will continue to provide improvement. There is theoretical evidence that suggests that there may be adverse effects from too much transparency. Experimental work can shed light on the subject by simulating conditions that may either be difficult to observe or not yet exist in reality to see if subjects respond as predicted by theory.

An example of a theoretical model that predicts adverse effects from rising transparency is presented by Kool, Middeldorp and Rosenkranz (2010). They use the rational expectations asset market model of Diamond (1985), which incorporates costly information acquisition, to demonstrate that central bank communication crowds out private information, resulting in a deterioration of the market's ability to predict monetary policy. Because private information is difficult to measure empirically, an experimental test of the model offers a useful alternative approach. The experiment presented below replicates the model used by Kool et al. (2010) in a laboratory asset market. The parameters used in the experiment are calibrated using empirical observations. Results suggest that predictive ability can decline, but only when crowding out is particularly sharp.

After a short review of the relevant literature we briefly present the theoretical model underlying the experiment. We then describe the laboratory experiment and present our statistical analysis and conclusions.

2 Literature review

The literature on central bank transparency and communication has grown rapidly over the last decade and now consists of hundreds of papers and articles. Different angles have been pursued. Many papers examine the implications of transparency in theoretical (mostly macroeconomic) models. Others examine empirically if transparency has influenced inflation and other macroeconomic variables. The impact of transparency on the financial markets has

[1] The Federal Open Market Committee, the part of the Federal Reserve System which sets US monetary policy. Clearly the reasoning applies to any central bank. Bernanke, who now serves as Chairman, was a Governor at the time of this quote.

also been an important theme in the literature. Especially around the turn of the century, many articles examined if central bank communication had some impact on the financial markets, generally concluding that it does. The question addressed here goes a step further, asking whether transparency improves the predictability of monetary policy in the financial markets. This section reviews the theoretical, experimental and empirical evidence to date regarding the effect of transparency on the predictability of monetary policy in the financial markets[2] and highlights gaps in the literature that are addressed by research below.

2.1 Theory

Intuitively, one would expect better public information to improve market functioning, in the sense that financial markets become better at predicting the outcome of unrealized fundamentals. As demonstrated in the next section, this is true in a basic rational expectations asset market model with exogenous public and private information. Under different assumptions or models, however, better public information can hamper market functioning.

Probably the best known example is the model of Morris and Shin (2002), where the profits of individual agents depend not only on fundamental values but also on the expectations of others (clearly an issue in any market where assets can be sold before the realization of their fundamental value). Under these circumstances a sufficiently clear signal from the central bank can act as a coordinating point that could distract market participants from their private information and possibly away from fundamentals. Svensson (2006) argues that this conclusion is only valid for the unlikely situation where public signals are less precise than private information. However, Demertzis and Hoeberichts (2007) add costly information acquisition to Morris and Shin (2002)'s model and find that it strengthens their result.

Another theoretical model by Dale, Orphanides and Osterholm (2008) demonstrates that if the private sector is not able to learn the precision of the central bank's information, it may overreact to central bank communication.

Although Demertzis and Hoeberichts (2007) examine information acquisition, they do so in the context of the Morris and Shin (2002) model with higher order expectations. The contribution of the theoretical work presented in the next section is that it isolates the effect of information acquisition on predictability in an otherwise standard rational expectations asset market model.

[2] Blinder, Ehrmann, Fratzscher, de Haan and Jansen (2008) and van der Cruijsen and Eijffinger (2007) offer broader overviews also covering effects of transparency outside of financial markets.

2.2 Empirical studies

Many empirical research papers have tried to assess if transparency improves the predictability of monetary policy in the financial markets.[3] The general approach is to select a watershed communication reform and test the difference between predictability before and afterwards. US studies typically use the first announcement of the Federal Open Market Committee's (FOMC) rate decisions in February 1994, while for other countries the introduction of an inflation target, with its accompanying communication tools, is used. One can measure predictability in at least three ways. The first is to measure interest rate movements around policy decisions. The second extracts expectations from the yield curve or futures to see how accurate they are. The third uses professional forecasts of interest rates. Taken together the evidence to date suggests that transparency improves predictability.

The first approach to assessing the predictability of monetary policy is to examine market movements close to policy decisions. Little reaction in money market rates following a policy rate change may suggest that it has been priced in and that policy is predictable. Money market movements prior to the decision in the same direction as the rate change can be interpreted as anticipating the move. Swanson (2006) finds that US interest rates show less reaction to Fed decisions over the period where the Fed reformed its communication policy. Holmsen, Qvigstad, Øistein Røisland and Solberg-Johansen (2008) find lower volatility on the days the Norges Bank announced its decisions after it started to release forecasts of its own interest rates. Murdzhev and Tomljanovich (2006) and Coppel and Connolly (2003) show that policy changes have become better anticipated in, respectively, six and eight advanced economies. Although such an approach is fairly intuitive and clear cut, its disadvantage is that it only provides a measure of market expectations between meetings and at the time of rate announcements. Communication reforms that allow market interest rates to anticipate monetary policy earlier than one meeting ahead can't be identified.

A second method is to measure market expectations of monetary policy and examine how accurate these are. Typically expectations are either extracted from the yield curve or futures data. Here too, findings suggest that transparency improves predictability. Rafferty and Tomljanovich (2002) and Lange, Sack and Whitesell (2003) find better accuracy for the US Treasury yield curve. Lildholdt and Wetherilt (2004) use a term structure model to show an improvement in the predictability of UK monetary policy. Similarly, Tomljanovich (2004) extracts expectations from bond yield curves and finds that

[3] A related strand of the literature does not address predictability in the financial markets but examines the usefulness of central bank communication in contructing forecasts of monetary policy. Some studies have simply asked if communications contain predictive power in itself; examples include Mizen (2009) and Jansen and de Haan (2009). Other studies examine if communication is useful in improving models that forecast monetary policy, such as the Taylor rule; recent examples are Sturm and de Haan (2009) for the ECB and Hayo and Neuenkirch (2009) for the FOMC.

forecast errors decline in seven advanced economies after transparency reforms.

Regarding futures rates, Swanson (2006) and Carlson, Craig, Higgins and Melick (2006) find that the fed funds futures are better able to predict US monetary policy after communication reforms. Kwan (2007) concludes that forward looking language or guidance, introduced in 2003, has helped to lower the average error between the fed funds futures and the actual outcome of the fed funds rate.

The disadvantage of using bond market expectations, is that such estimates are likely to be biased. The failure of the expectations hypothesis for the Treasury yield curve is a well-documented empirical result (e.g. Cochrane and Piazzesi (2005), Campbell and Shiller (1991), Stambaugh (1988), Fama and Bliss (1987)). Risk premiums on interest rates are positive on average and time-varying. Sack (2004) and Piazzesi and Swanson (2008) show that fed funds futures rates also include risk premiums, particularly at longer maturities. Piazzesi and Swanson (2008) demonstrate an approach to adjusting fed funds futures rates for time-varying risk premiums using business cycle data. Middeldorp (2010) contributes to the literature on transparency by applying their correction to the question of the accuracy of the fed funds futures and showing that both the early FOMC communication reforms of the mid 1990's and the explicit policy guidance starting in 2003 improved the accuracy of future rates.

A third approach is to use predictions by professional forecasters to assess predictability. These are a direct measure of expectations and also allow one to observe individual forecasts. There are several studies that look at US interest rates. Swanson (2006) finds an improvement in the accuracy of private sector interest rate forecasts. Berger, Ehrmann and Fratzscher (2006) find that communication reduces the disparity of fed funds target rate predictions produced by forecasters from different locations. Hayford and Malliaris (2007) and Bauer, Eisenbeis, Waggoner and Zha (2006) find declining dispersion in US T-bill forecasts. Regarding other central banks, Mariscal and Howells (2006b) find a growing dispersion of private sector forecasts of Bundesbank and ECB monetary policy up to 2005, a result which runs counter to that for most others studies, including that of their own (2006a) research for the Bank of England. Ehrmann, Eijffinger and Fratzscher (2010) use various measures of central bank transparency to show a convergence of professional forecasts of both economic variables and interest rates in twelve advanced economies. Middeldorp (2011) finds that greater transparency lowers forecast errors and interest rate volatility in a panel of 24 countries.

A disadvantage of professional forecasts versus the expectations embedded in interest rates, is that it is not obvious that they are relevant to the transmission of monetary policy. It is, nevertheless, likely that they both reflect and influence monetary policy expectations. Large financial institutions are the most common employers of professional forecasters and their views are actively dispersed to market participants and widely reported on in the press.

2.3 Experimental evidence

The empirical studies discussed above are inherently backward looking. Therefore, as central banks becoming more and more communicative it can not be ruled out that greater transparency may still have some adverse effects as some of the theories discussed above predict. A major advantage of an experimental approach is that it can test a theoretical model even when variable values may not (yet) exist in nature. This should be of particular interest to policy makers, because it allows policies to be tested in the laboratory before policy makers "experiment" on the economy.

Another related benefit of laboratory research is that it is possible to define the value of variables that may not be easy to observe in nature. Private information is by its very nature difficult to measure, so that empirical research to determine if it is being crowded out by greater central bank transparency is inherently difficult. Experimental research offers an alternative route.

Nevertheless, experimental work in the area of monetary policy transparency is very limited. Ackert, Church and Gillette (2004) is, as far as we are aware, the only previous experimental contribution to the transparency literature. They present evidence from a laboratory asset market in which traders receive public signals of different quality. Their results suggest that traders over-react to public information with low reliability and under-react to highly reliable public information. Their experimental setup does not include private information.

3 Theoretical background

This section briefly describes the background and nature of the basic rational expectations asset market model and related experimental work. It then proceeds to describe the setup and results which form the basis for the experiment reported below.

3.1 Rational expectations asset market models

Rational expectations asset market models are widely used in the finance literature because they provide a very general and widely applicable model of a financial market. A core feature is that they take into account that market participants learn about the private information of other traders from prices.

Grossman and Stiglitz (1980) realized, if prices are perfectly informative then there is no point in trading on private information, removing the incentive to bring information to the market in the first place. They resolve the paradox by introducing an additional source of uncertainty to the market, which is modeled as a random supply of assets, which obfuscates private information. Hellwig (1980) takes the Grossman and Stiglitz (1980) model and adds diversely informed traders to illustrate how the market acts as an aggregator of diffuse private information. Verrecchia (1982) solves a model where traders can invest in costly information. Diamond (1985) then adds public information to a similar model, showing how it can crowd out private information. Kool et al. (2010) use this model to study the effects of crowding out on the ability of the market to predict monetary policy.

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. However, there is little experimental work regarding information acquisition in rational expectations models. 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 markets, 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 (2011) 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, which results in higher private information acquisition in the experimental setting than predicted by the theoretical asset market model. This outcome is only partially relevant to our results below because we are more interested in whether crowding out of private information takes place and particularly if it hampers predictability.

3.2 Setup of Diamond (1985)

The experimental market used in this model is based closely on Diamond (1985). As with all the rational expectations models the asset in this model is liquidated after trading. Traders, however, do not know exactly what the payout per asset will be. 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 given the information available plus a discount because the risk averse traders in the model care about supply.

$$(1)\ \tilde{P} = \left(\tfrac{h}{I}\right) Y + \left(\tfrac{\Delta}{I}\right) \left(\widetilde{u} + \tilde{\zeta}\right) + \left(\frac{\lambda s + \frac{(r\lambda s)^2}{V}}{I}\right) \widetilde{u} - \left(\frac{\frac{1}{r} + \frac{r\lambda s}{V}}{I}\right) \widetilde{X}$$

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

$\tilde{}$	random variables
$\widetilde{P}$	equilibrium market price
$\widetilde{u}$	payout
Y	mean payout
h	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

I represents the average precision of information per trader. All traders know the public information with the precision of $(h + \Delta)$ and a fraction of traders, λ are informed by a private signal of precision s. The last term is the informativeness of the price. Clearly the greater the fraction of informed traders, λ, and the more precise their private signal, s, the more private information leaks into prices. This information is obscured by the unrelated noise from the random supply of the risky asset. The higher the supply variance, V, the more difficult it becomes for traders to "read" the market. Similarly, the less risk tolerant, r, traders are, the more prices respond to changes in supply.

The first three terms in (1) are the best estimate of the payout, $\tilde{u}$, given the available information. Each source of information is weighed by their relative precision, i.e. the coefficients sum to unity. The first two terms indicate how public information (any information which all traders know) influences the price while the third term shows how private information affects the price. Note that private information influences the price directly through the fraction of informed traders and indirectly through the informativeness of the price. The final term represents both a risk premium due to the fact that traders are not completely risk tolerant, which means they care about how many risky assets they hold, $\frac{1}{r}$, and the effect of traders mistaking supply shocks for information, $\frac{r\lambda s}{V}$.

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

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

Intuitively, the fraction of informed traders is positively related to the precision of the private information, s, and negatively related to the disutility of its cost, c (rational expectations models assume exponential utility). Furthermore, fewer traders choose to buy private information as other sources of information become more precise. Thus both public information $(h + \Delta)$ and the informativeness of the price have a negative impact on λ.

3.3 Implications for monetary policy transparency

The payout in the Diamond (1985) model can be interpreted as a central bank policy rate. The market in the model accordingly represents any market which closely depends on the outcome of policy rates[4]. Kool et al. (2010) define an appropriate measure of the accuracy of market prices as the variance of the error of the price versus the policy rate.

$$(4) Var(\tilde{P} - \tilde{u}) = \frac{1}{(h+\Delta) + \lambda s + \frac{(r\lambda s)^2}{V}} + \frac{\lambda s + \frac{V}{r^2}}{\left((h+\Delta) + \lambda s + \frac{(r\lambda s)^2}{V}\right)^2}$$

Note that this measure not only represents the accuracy of prices but also characterizes the volatility of the market beyond that caused by movement in $\tilde{u}$. Any impact central bank communication has on the accuracy of prices thus also directly affects volatility.

After substituting Equation (3) for λ it can be shown that $Var(\tilde{P} - \tilde{u})$ is strictly increasing in Δ for $0 < \lambda < 1$ and strictly decreasing otherwise. In

[4] 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.

other words, central bank communication hurts the accuracy of the market and increases volatility when it causes the crowding out of private information. To illustrate the implications for central bank transparency in Figure 1 we plot $\frac{1}{Var(\tilde{P}-\tilde{u})}$, i.e. the precision of the price error (upper panel), and the fraction of informed traders (lower panel) against the precision of public information, $h+\Delta$.[5]

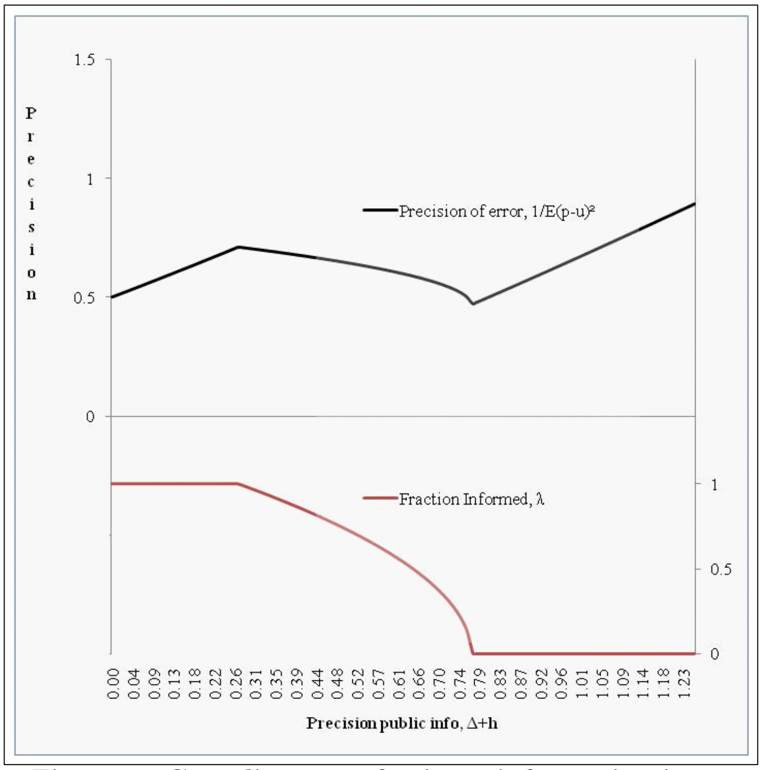

Figure 1: Crowding out of private information in a theoretical asset market

The remainder of this paper tests whether an experimental asset market that closely resembles the theoretical model also exhibits the crowding out of private information and rising errors as the precision of the public signal increases.

[5] Parameters for Figure 1 are set at r=2, s=0.5, c=0.5 and v=2.

4 The experimental setup

This section describes the treatments we used. The setup of the experiment was based on the Diamond (1985) model described above. We replicated the model as closely as possible in a laboratory of networked PCs with the commonly used experimental software ZTree 2 (see Fischbacher (2007) for details).

At the start of the session between 16 to 20 subjects were seated at partitioned computers and asked to read the instructions for the experiment and not to talk with other participants until after the completion of the experiment. The experimenter then gave an oral description of the instructions and subjects had the opportunity to ask questions. The oral and written instructions were kept constant over all sessions.

All subjects participated in two treatments. The first treatment served to measure the subjects' risk attitudes, the second was the actual market experiment with two decision stages, an information stage, and a trading stage.

For the first treatment we chose an approach similar to that used by Heinemann, Nagel and Ockenfels (2008). Subjects were asked to make a sequence of binary choices between a fixed payment and a lottery. The lottery was the same for each choice, namely a 50% chance of winning nothing versus a 50% chance of a payment of €140. The fixed payments ran from receiving €10 to €130. It was made clear that one of the subjects, chosen at random, would actually have one of their choices executed and paid at the end of the experiment. The outcome of all random variables in the experiment were determined automatically by the experimental program. Subjects with consistent risk preferences would be expected to choose the lottery up to a certain amount and then switch to the fixed payment. The lowest fixed payment we take as a measure of their risk tolerance. Choosing the lottery at €70 would be considered risk neutral and above that risk seeking.

After the first preliminary risk-aversion treatment, subjects were guided through a trial of the second treatment so they could learn the mechanics of the trading in general and the trading system in particular. It was explained that the trial had no monetary consequences. After any questions were answered the actual trading treatment began.

The second treatment consisted of 25 periods and each period was subdivided into two decision stages. At the beginning of each period, before trading started, subjects entered the "information stage" and were shown a screen revealing their endowment, the public information with its standard deviation and were given the option of buying private information with a given standard deviation at a stated fixed cost.

The endowment consisted of cash in Experimental Currency Units (ECU) and experimental risky assets. The cash endowment was the same for all subjects at ECU 8000. The individual supply of assets was randomly allocated with a normal distribution with an average of 60 and a standard deviation of 20. To help subjects understand the implications of the random allocation the instructions showed not only the standard deviation (20) but also the 68% (40-80) and 95% (20-100) ranges for the supply distribution. The written and oral instructions explained that each asset would produce a payout at the end of the experiment. Subjects were informed that the payout would fluctuate randomly per period around an average of 200. On the information stage screen, below the endowment, all subjects were shown the public information about the payout for that period and the standard deviation of this information.

The written and oral instructions both emphasized that each period all subjects would receive the same public information and that there were five possible values for these standard deviations. For all five levels 68% and 95% probability intervals were given in a table in the written instructions.

Our treatment variable is the standard deviation of public information. Each period the program randomly drew one of five standard deviations for the public signal in succession until all five were used and the cycle was restarted. The five standard deviations were calibrated in the pilot experiments in order to achieve a wide range for the fraction of informed traders.

When deciding whether or not to buy the private signal, subjects were shown relevant information, namely (1) their cash endowment, (2) their endowment of risky assets, (3) the public information (4), the standard deviation of the public information, (5) the cost of buying private information, (6) the standard deviation of their total information combined if they bought the private signal.

The instructions made clear that their private information supplemented the public information and allowed a more reliable estimate of the payout. A table provided in the instructions showed the standard deviation of the estimate at each level of combined public and private information, along with the width of the associated 68% and 95% probability ranges. Students were explained that the standard deviation of private information is the same for all subjects that buy it, but that the actual estimate of the payout is unique to each subject and is provided once trading starts only if the subject buys private information.

After subjects had decided whether or not to buy private information, they entered the second stage in which they participated in the actual trading. The rational expectations models make no assumptions about the trading mechanism that is used to reach equilibrium. Other experimental asset markets generally use a continuous double auction. We did the same. Traders could post one bid and ask at a time, in any quantity that they could afford to buy or had to sell (see screen shot in the Appendix). 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 lasted for 150 seconds, which in most periods is enough for price movements to settle (see next section).

Displayed in the upper right hand corner of the trading screen subjects were shown the "public information" and its standard deviation and then "your information" and its standard deviation. The instructions indicate that the latter is an improvement on the former. In other words, information is combined optimally by the program so that traders know exactly the quality of all their information. This left only the market as a source of information that requires mental processing.

After trading the payout was revealed and subjects were shown the value of their holdings in ECU. The instructions also stated that earnings from one period could not be used for trading in another and that total earnings for all periods would be converted to euros at an exchange rate of 25000 ECU per euro at the end of the experiment. The exchange rate between ECU and euros was chosen so that the average payment was around €10 per hour.

For the variables we used the following calibrations: The cash endowment was set at ECU 8000 in order to be low enough to make the risky asset the most important influence on earnings, but high enough so that the probability of traders running out of money was low. Subjects actually had less than 400 units of experimental money at the end of the period only 8% of the time.

To improve the applicability of our evidence to the issue of monetary policy, other variables in the experiment were calibrated based on US fixed income asset markets in general and the fed funds market in particular. The supply distribution was calibrated using the annual inflows into fixed income mutual funds between 1995 and 2006, as reported by the Investment Company Institute (2000,2007). The standard deviation of these flows as percentage of total assets is set equal to the standard deviation for the total supply for the experimental market as a whole. With twenty subjects, the individual standard deviation is 20, which is what is actually programmed. Because the individual supply is the variable that is set, the standard deviation of total supply depends on the number of subjects (See Table 1 for the specific values). To keep the probability of an individual without sufficient assets to participate in trading low, the average of 60 is set to three standard deviations above zero. In the experiment subjects run out of assets during trading 5% of the time.

The payout per asset was calibrated using the fed funds rate. The standard deviation of the payout of 70 is equivalent to the standard deviation of yearly percentage changes in the fed funds rate between 1997 and 2007, i.e. a rate hike from 1% to 1.5% would be a fifty percent increase. The average of 200 is set to roughly three standard deviations, simply to insure that the risk of the payout hitting zero is low.

The cost of the private information was also calibrated based on US fixed income markets. We adopt the interpretation of Elton, Gruber, Das and Hlavka

(1993), that mutual fund costs are an indicator of information expenditure. While actively managed mutual funds are probably the prototype informed investors, there are clearly other costs involved. Nevertheless, this could be seen as an upper bound of empirically plausible information costs in financial markets. We use data from the Investment Company Institute (2000,2007) on the expense ratio of fixed income mutual funds to determine costs as a percentage of assets. Based thereon we set the cost of the private signal at 1% of the expected value of the endowment of risky assets (1% of 60 units $\times$ 200 ECU) Because the payout is calibrated with the fed funds rate, the standard deviation of the private signal is based on forecasts of that interest rate by private sector economists. The standard deviation of the private signal is the same as the standard deviation of one year ahead percentage forecast errors of the fed funds target rate. The source for this information is the survey of Consensus Economics.

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 deviations	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	

Table 1: Variable calibrations

Matching the Diamond (1985) model closely results in a relatively complicated laboratory market. This complexity is an innovative feature of our setup. Most other such experiments involve more stylized treatments in order to make them 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 has an important advantage, however, apart from being merely novel. It allows the most complete test of the theory possible. The main difference between the Diamond (1985) model and our setup is that it involves 16 to 20 real humans rather than an infinite number of rational traders with exponential utility. Demonstrable deviations from the predictions of the model thus result from these differences rather than simplifications in the setup imposed by the experimenter. Although using a finite number of real humans is a step towards reality, one could argue that we have a market with fewer traders that are less experienced than what we would find in reality. To address this concern we did 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 earlier sessions (including pilot sessions) in order to create an experienced group of subjects in the last three sessions, thereby aiming to further reduce the risk that subjects do not have sufficient time to understand our complex market. A little under half (47%) of the subjects in the last three sessions participated in the first three sessions, the rest of the experienced traders either participated in one of the four pilot sessions or had prior experience with another market experiment. Third, in our questionnaire we asked subjects how long they thought it took them 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. Based on this we drop the first five periods from every session.

The subjects involved in the experiment were almost all students at the Utrecht University, from a wide range of faculties. The average age was 22 and, reflecting the student population, 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 there were also 13 subjects with other nationalities.

	Subjects	Male	Female	%	Dutch	Foreign	%	Av. age	Exper.	%
Session 1	16	5	11	69%	13	3	19%	22.6	2	13%
Session 2	16	4	12	75%	10	6	38%	21.5	5	31%
Session 3	18	9	9	50%	14	4	22%	23.2	3	17%
(Weigted) Average	16.7	6.1	10.6	64%	12.4	4.3	26%	22.5	3.3	20%
Session 4	19	5	14	74%	12	7	37%	21.6	16	84%
Session 5	20	9	11	55%	14	6	30%	21	14	70%
Session 6	20	9	11	55%	17	3	15%	23.7	13	65%
(Weighted) Average	19.7	6.9	12.0	61%	14.4	5.3	27%	22.1	14.3	73%
Difference of Averages	3.0	0.8	1.4	-3%	2.0	1.0	1%	-0.4	11.0	53%
(Weigted) Average	18.2	6.6	11.3	62%	13.5	4.9	27%	22.3	9.3	49%

Table 2: Subject statistics

5 Results

5.1 Prices and market performance

An important issue in experimental asset markets is how well prices reflect the underlying fundamentals, in this case the payout. To examine this we present both graphic evidence in Figures 2a through 2f and quantitative evidence of convergence in Table 3, followed by a preliminary discussion, some of which precedes more in-depth analysis in the next subsection.

Charts of the traded prices and the payout allow quick observation of the proximity of prices to the payout. These are presented in Figures 2a - 2f. Each figure represents one of the six sessions. The figures each contain twenty charts showing price movement within the periods 6 to 25. There are five charts in each row, representing each of the five standard deviations of public information in random order. The black line in the middle represents the payout. The y-axis is in ECUs and shows values within two payout standard deviations (70 ECU) below and above the payout. This way all charts have the same range of 280 ECU, making it is easier to compare price movements across periods. The charted lines represent traded prices. They are shown in order of execution from left to right. The x-axis thus represents a trade index rather than time.

Overall Figures 2a - 2f suggest that, despite the complex treatment, average traded prices are close to the payout in all of the sessions. Traded prices are also in relatively tight trading ranges, and thus close to their average, for most sessions. There are nevertheless observable errors between prices and the payout, particularly in Session 2, which we discuss below. It should be noted that, as Equation (4) shows, we will always see some error in the equilibrium price because the random supply also affects the market price. Furthermore, unlike the theoretical market, there are a limited number of private signals. So, even if the private information of all subjects were perfectly impounded into the price, there would still be an error between the combination of the finite number of private signals and actual payout. Before we conduct a more detailed discussion of market efficiency, we introduce the quantitative measures presented in Table 3.

To attain a quantitative measure 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) and Noussair, Plott and Riezman (1995). The regression defined in Equation (5) is run on trade prices for each period.

(5) $P_t = b\frac{1}{t} + l\frac{(t-1)}{t} + u_t \qquad u_t = mu_{t-1} + \varepsilon_t$

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 regression estimates a convergence path to an equilibrium price. The path starts at b and progresses to the limit l, which is interpreted as the convergence or equilibrium price of the market. The moving average specification allows for some persistence in the deviations of prices from the convergence path, reflecting the likelihood that the noise in the last price will also partially affect the subsequent trade. The convergence is quite tight in the sense that the estimates of the limit, l, are highly significant, with a median T-stat of 110.

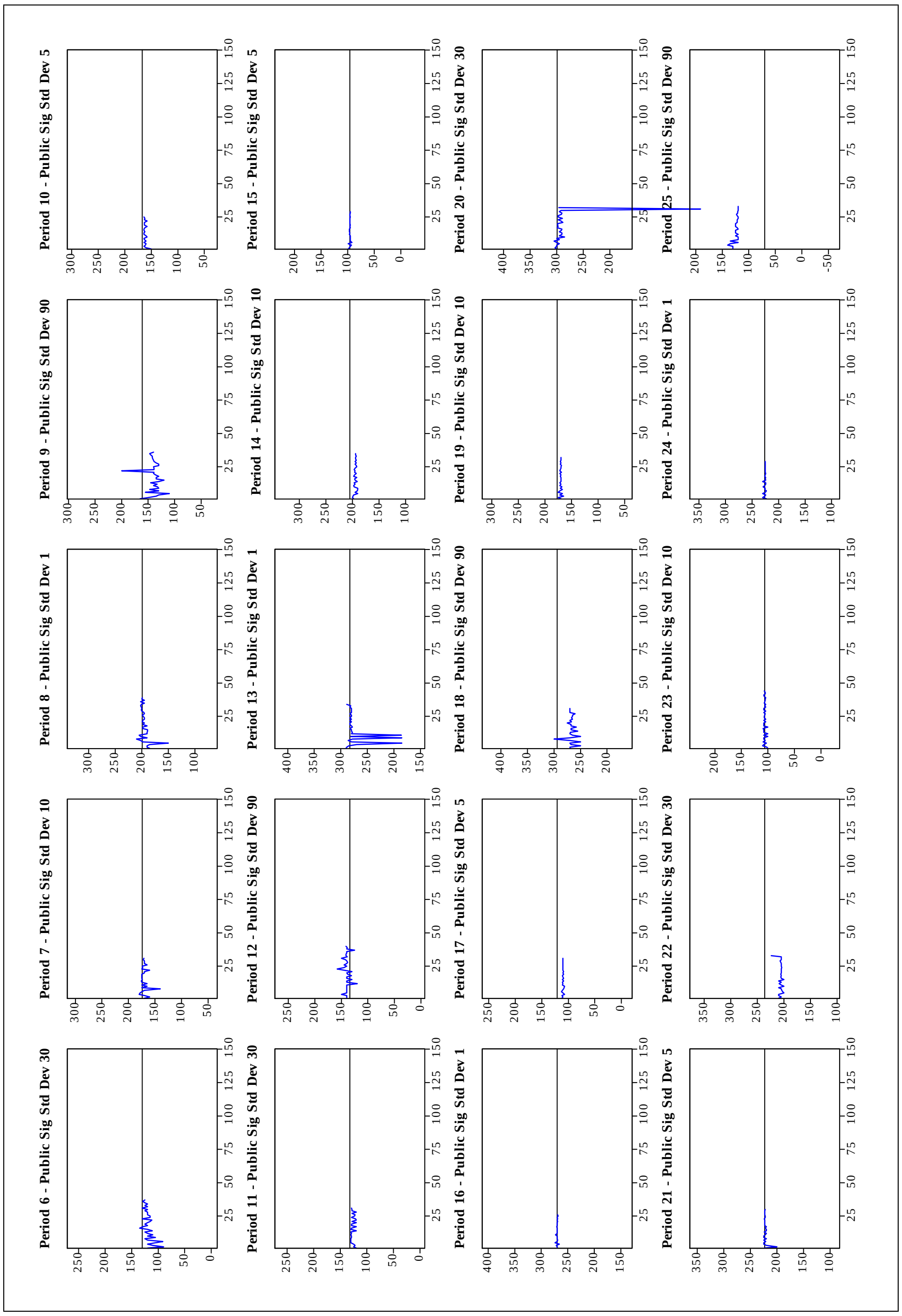

Figure 2a: Trade prices and payout Session 1

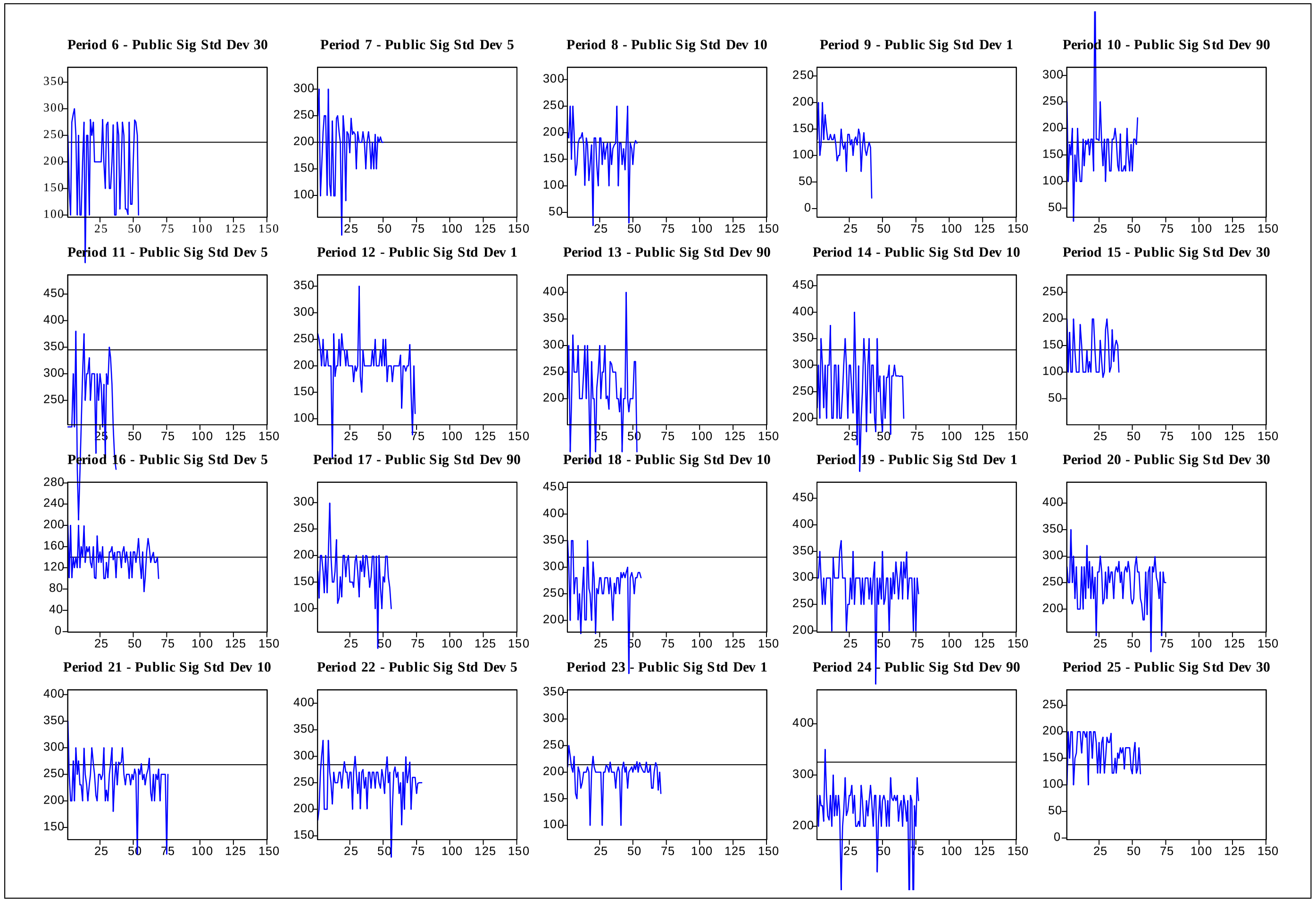

Figure 2b: Trade prices and payout Session 2

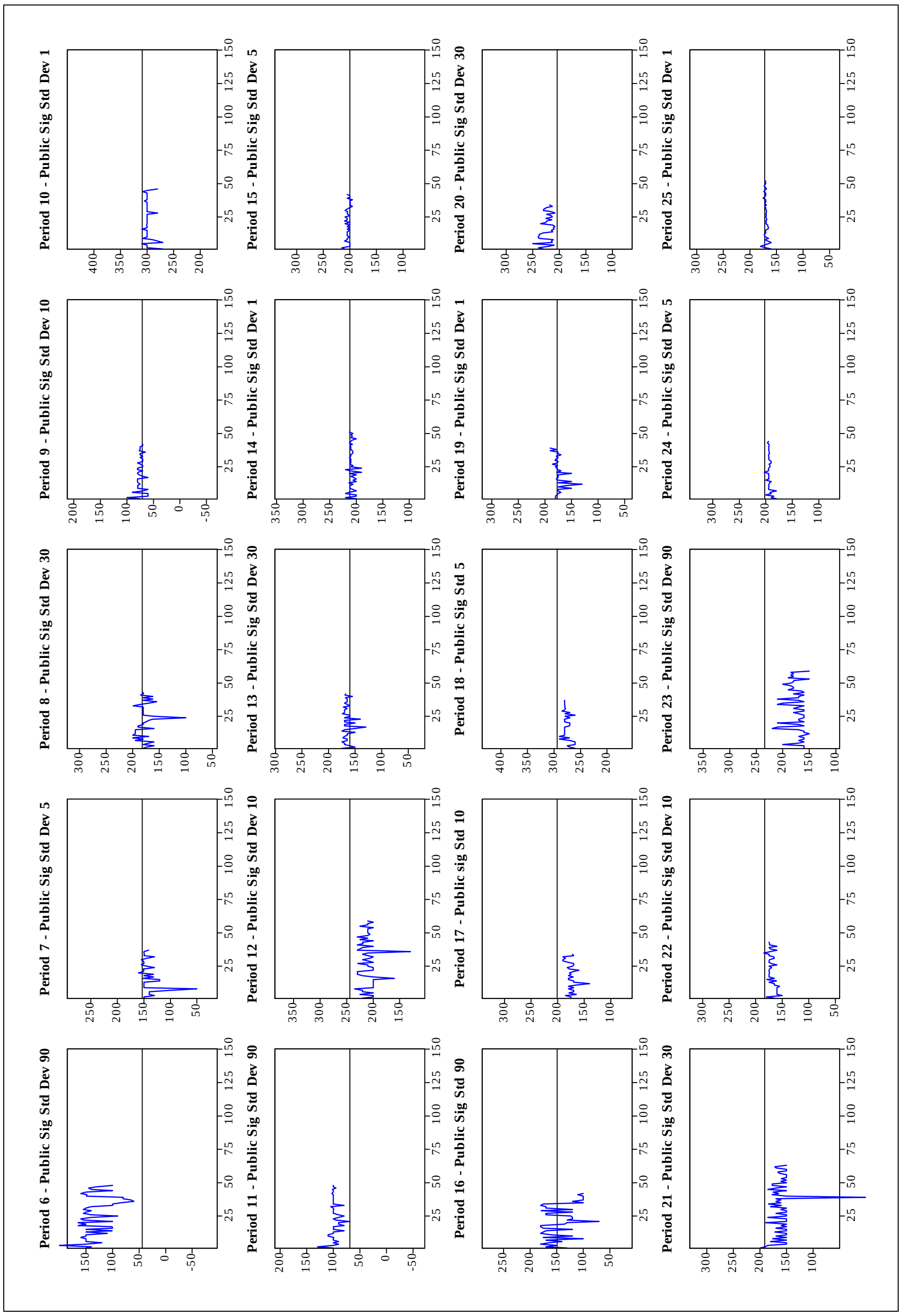

Figure 2c: Trade prices and payout Session 3

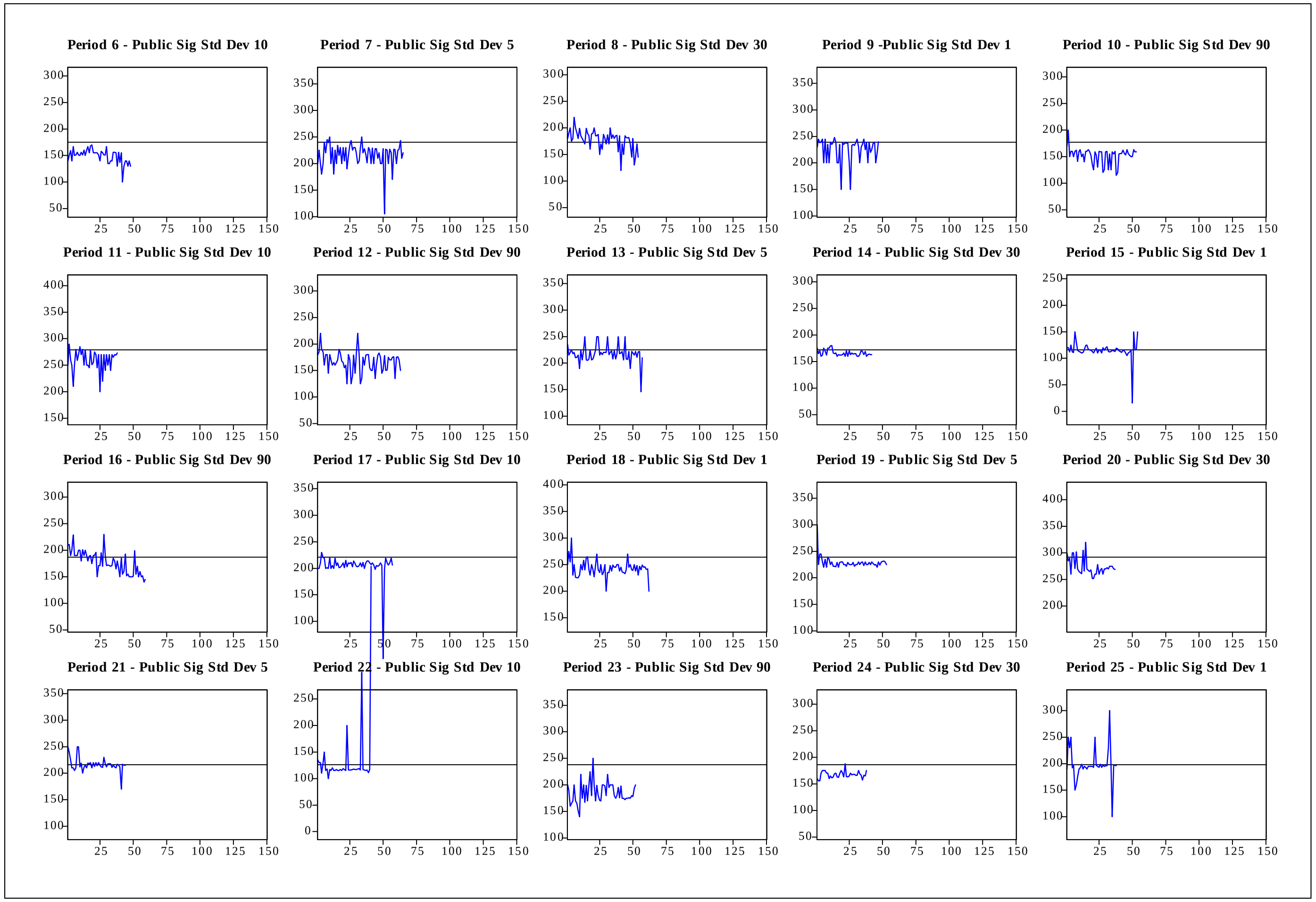

Figure 2d: Trade prices and payout Session 4

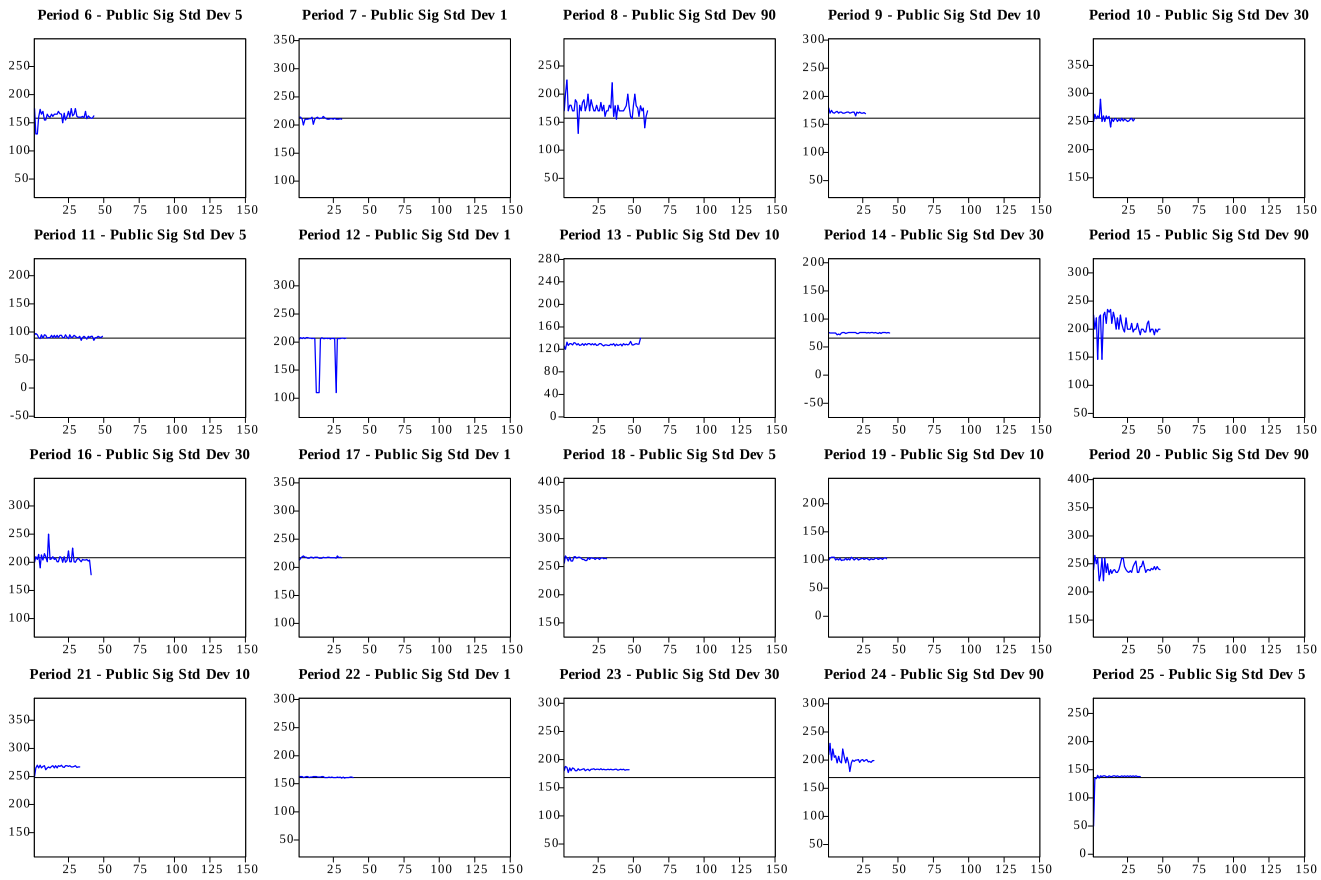

Figure 2e: Trade prices and payout Session 5

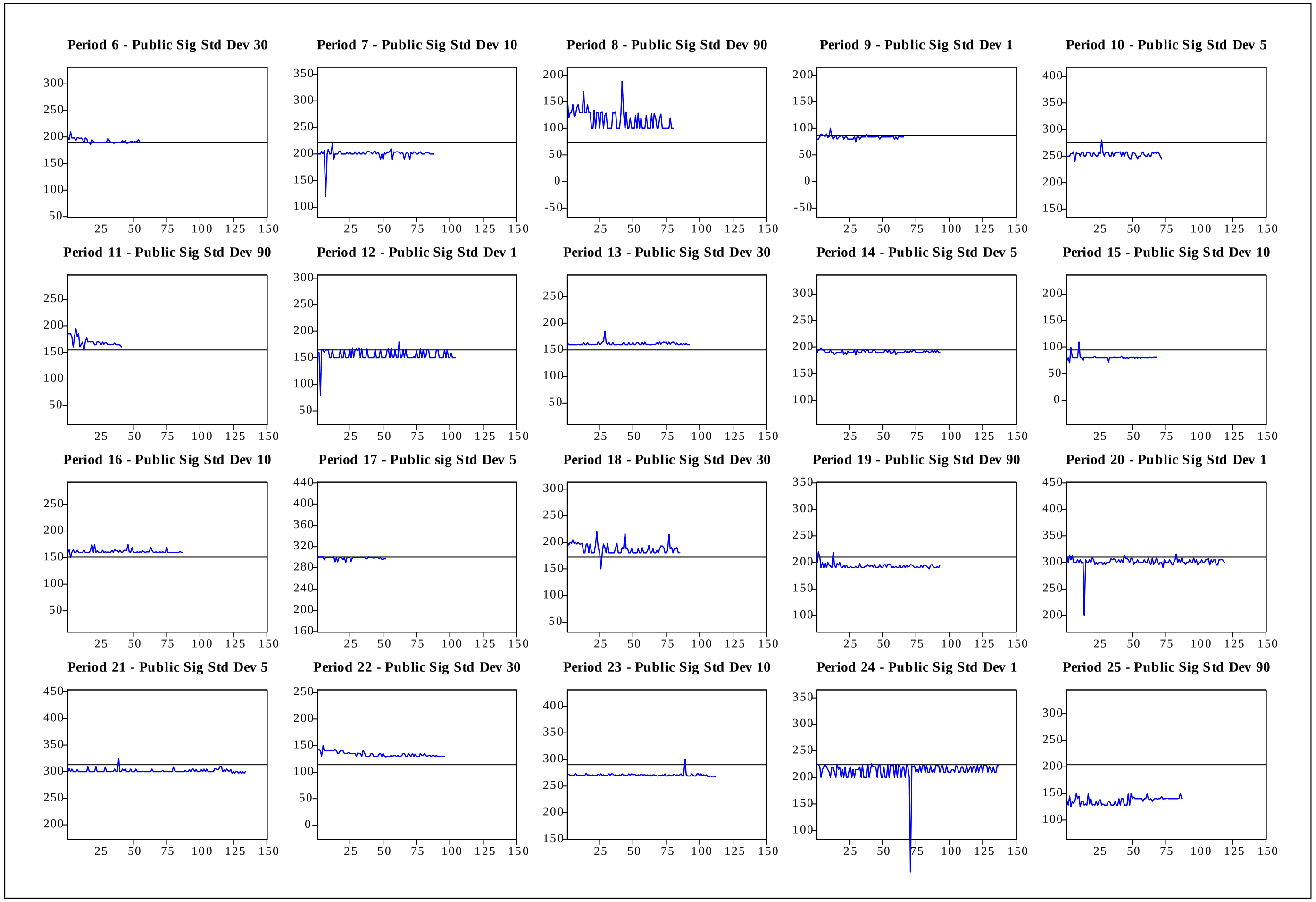

Figure 2f: Trade prices and payout Session 6

Table 3 gives some additional insight into the functioning of the experimental asset market. It shows several aggregate statistics per session and per public signal. The rows show average statistics per session and the overall average for the entire experiment. The first column on the left is the absolute error of public information, which for a normal distribution is simply $\sqrt{\frac{2}{\pi}}$ times the standard deviation. The second is the average absolute difference between the above defined limit price and the payout, which is a measure of how well overall prices reflect fundamentals. The third shows the median T-stat of the estimates of the limit, which indicates their significance. The fourth is the average of the absolute difference between the mean unit trade price per period and the payout, which is an alternative convergence measure. Throughout this paper average prices are weighed by the number of assets transacted, ensuring larger transactions are weighed more heavily. As a result prices are average per unit rather than per transaction. The fifth column contains the average standard deviation of trade prices within the periods, which reflects the volatility of prices. The sixth is the average volume, which is the total number of traded assets per period, averaged over the session. The seventh is the median percentage of traders that bought private information. Finally, the median number of periods that subjects said it took them to understand the experiment is shown in the far right column (in this case the "All" average in the bottom row is not the straight average of the session statistics because some periods have more subjects than others).

Session	|Error of public info| Average	|Limit Price - Payout| Average	T-Stat Limit Median	|Av. Price - Payout| Average	St. Dev. Price Average	Volume Average	%Informed Median	Periods to Understand Median
1	15.8	11.1	315.9	12.8	8.1	412.1	34.4	3
2	15.8	38.8	37.6	36.4	46.2	709.3	12.5	5.5
3	15.8	18.6	84.2	19.2	12.8	578.4	16.7	3.5
4	15.8	16.4	67.7	13.4	19.4	536.9	26.3	1
5	15.8	9.1	308.5	9.3	7.4	492.0	40.0	1
6	15.8	16.1	287.1	16.6	6.8	570.8	17.5	2
All	15.8	18.3	110.1	17.9	16.8	549.9	25.7	2
Standard deviation public signal	**|Error of public info| Average**	**|Limit Price - Payout| Average**	**T-Stat Limit Median**	**|Av. Price - Payout| Average**	**St. Dev. Price Average**	**Volume Average**	**%Informed Median**	
1	0.8	9.7	138.1	8.1	15.5	538.4	8.1	
5	4.0	12.1	267.7	13.7	14.5	538.6	19.9	
10	7.9	19.1	119.9	17.7	16.5	545.8	19.4	
30	22.0	15.7	115.8	15.8	16.5	533.6	52.5	
90	44.1	35.0	64.7	34.3	20.8	593.2	69.4	
27.2	15.8	18.3	110.1	17.9	16.8	549.9	25.7	

Table 3: Overview statistics per session and public signal

One way to see if the experimental asset market is incorporating private information into the price is to compare the error of public information (first column) to the market error measures (columns two and four). If the market price is better able to predict the payout than public information, then this must be due to the incorporation of private information. The top of Table 3 shows that all but Sessions 1 and 5 have errors higher than that of public information. Apparently, on average, market prices are less informative than the public information that all traders receive. Examining the errors per standard deviation of the public signal, which are shown in the bottom of Table 3, gives a little more insight into when this is happening.[6] Prices do outperform public information for standard deviations of the public signal of at least 30, demonstrating that the market is able to incorporate private information. When public information becomes very precise, however, errors do not decline proportionally. Indeed between public signal standard deviations of 30 and 10, errors actually rise (from 15.7 to 19.1 for the limit price error and from 15.8 to 17.7 for the average price error), which we shall discuss in detail in the next subsection.

While prices that outperform public information show that private information is being impounded into the prices, the reverse is not true. As mentioned above, supply will always contribute to market errors. Even when the market price reflects both public and private information, the effect of the random supply can still result in prices that are less predictive of the payout than public information alone.

Another reason that the decline in errors does not keep pace with the improvement in public information is due to the declining percentage of informed traders. As Equation (3) shows, this is a rational reaction to the increase in the precision of public information. It means that very little private information is available in the periods with strong public information, so that, combined with the effect of the random supply, the precision of the market price is lower than that of public information.

The observed decline in the fraction of informed traders is, of course, no accident. As mentioned above, the periods with very precise public information were calibrated in the pilot sessions precisely to attain a wide range of private information acquisition. This was possible precisely because Diamond (1985) is correct in predicting that more precise public information crowds out private information acquisition. The drivers of information acquisition in the model are examined in Middeldorp and Rosenkranz (2011) using panel data econometrics. It shows that Diamond (1985) correctly identifies the drivers of information acquisition, including the negative effect of public information. Although the level of information acquisition in the experiment is higher than theory suggests, information acquisition does respond to changes in the variables as predicted.

[6] Note again that the we make a distinction between the public *signal* with precision Δ and all public *information* with precisions h+Δ. Accordingly in Table 3 "Standard deviation public signal" refers to $\sqrt{\frac{1}{\Lambda}}$ while "|Error of public info|" refers to $\left(\sqrt{\frac{2}{\pi}}\right)\left(\sqrt{\frac{1}{h+\Lambda}}\right)$.

The top of Table 3 shows that, independent of public information, more private information acquisition is accompanied by improved market efficiency. Sessions with a higher fraction of informed traders (Column 7) tend to have lower price errors (Columns 2 and 4). Because the average precision of the public signal is the same across sessions, this indicates that more informed traders lead to better market efficiency. The same can be shown more formally with a panel regression for periods 6 - 25, with the six sessions in the cross-section and fixed effects for both sessions and periods. The limit error is the dependent variable, which is regressed on the fraction of informed traders, with the standard deviation of public information and per capita supply as control variables. The coefficient for the fraction of informed traders is significant with a p-value of 0.0221.

Data from Session 2 stand out in Figures 2a - 2f and Table 3. Limit and average prices show errors that are about twice as high as the average for all sessions. The T-stat of the limit estimate is a third of the average for all sessions (though still significant). The standard deviation of prices is roughly between twice and seven times that of other sessions while the volume is between about a quarter and two-thirds higher. The percentage of informed traders is approximately half of the average for all sessions. The last column gives a hint to what may be going on, subjects in Session 2 said that it took them longer to understand the experiment. Indeed, five of the sixteen traders thought it took them ten or more periods. Furthermore, unlike similar subjects in other sessions, these traders were clearly more active, together representing almost forty percent of the trading volume. It appears that these traders didn't understand the experiment very well but were nevertheless active. The regression analysis below relies on dummies to identify session specific effects like these, rather than neglecting the second session outright.

To sum up our overview of the data, evidence from Figures 2a - 2f and our AE model estimates of the price limits suggest that the market reflects fundamentals. The statistics in Table 3, show that prices outperform public information if there are sufficient informed traders and public information is not so precise that errors are largely driven by supply effects.

5.2 Crowding out of private information and predictability

Analysis presented in this subsection looks more closely at the core prediction of the theoretical model, namely that more accurate public information can crowd out private information to such an extent that the market's ability to predict monetary policy deteriorates. Roughly speaking the results confirm the theoretical model. Information acquisition is crowded out as public information becomes more precise. This effect, however, is not uniform, crowding out is sharper in a specific range. It is precisely there that we find a detrimental effect on the ability of the market to predict the payout.

5.2.1 Graphic evidence of rising errors

The focus here is on the impact of public information on a financial market's ability to predict future monetary policy, represented in this case as the payout of the experimental assets. Table 3 shows that crowding out of private information does take place and also presents some preliminary evidence of rising errors. To further examine the evidence of crowding out and the market's predictive ability, we chart the errors versus the standard deviation of public information. Figure 3 is analogous with Figure 1 from the theoretical model, except that we use the absolute value of the errors instead of their precision and standard deviations of the public signal instead of its precision. We also provide the percentage of informed subjects. The individual points are measurements from each of the periods 6-25 in all six session (120 points per variable). The lines represent a neighborhood fitted linear regression which fits the closest fifth of the sample, to match the five standard deviations of public information.

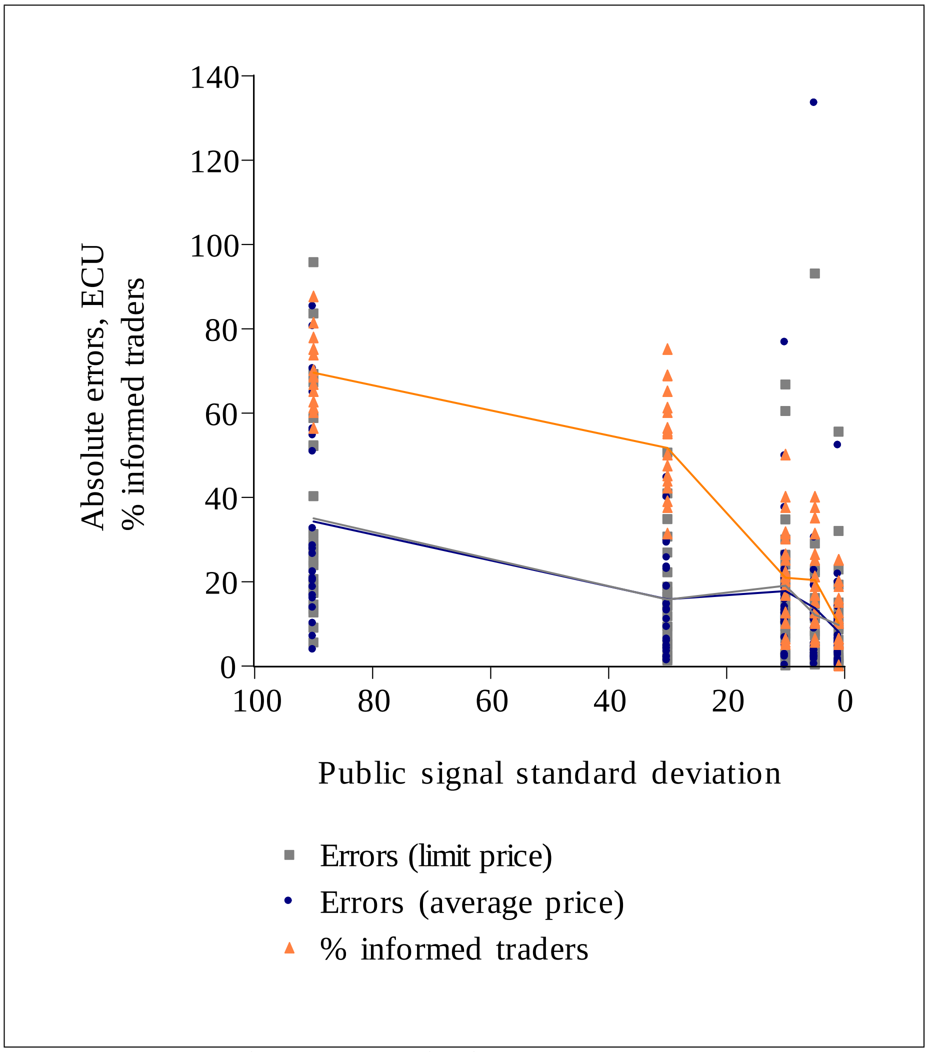

Figure 3: Public signal and errors

As expected, the overall trend is that as the standard deviation of public information declines (from left to right in Figure 3) the number of informed traders also 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 limit measure of the errors. Crowding out of private information acquisition appears to lead to a deterioration of the predictive ability of the market.

A look at the data per session gives a clearer picture. The figure below is similar to the one above except that now we show separate neighborhood fitted regression per session. The errors are based on the equilibrium prices according to the AE model limit prices.

All of the sessions except Session 1 show an increase in errors as the standard deviation of the public signals declines from 30 to 10. The size of the increase varies 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 sessions reduces the risk that this phenomenon is spurious.

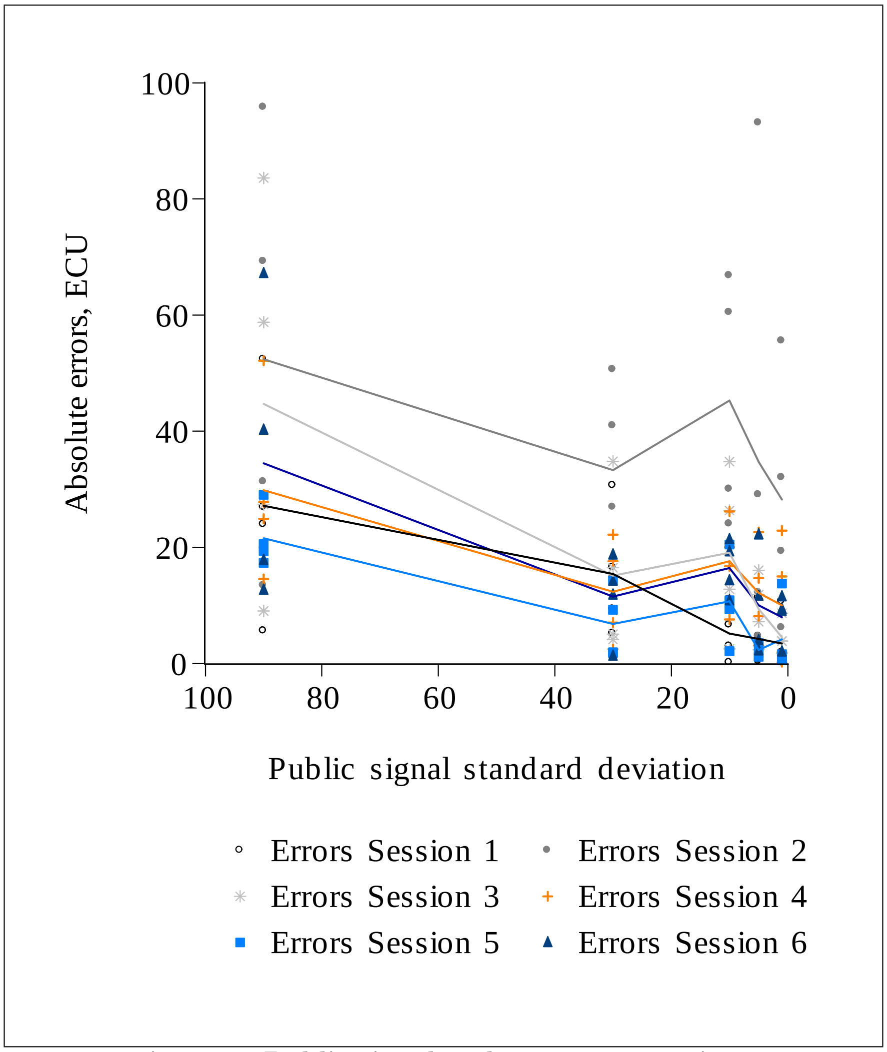

Figure 4: Public signal and errors per session

5.2.2 Session panel evidence of rising errors

Although the graphs clearly show rising errors precisely when the crowding out of private information is sharpest, they cannot be used to test for statistical significance. To do such testing, we run panel regressions, with the six sessions as the cross-section, each with data running from period six to twenty five. We regress the price error unto dummies for the different standard deviations of the public signal. The coefficients represent the different average price errors for each precision of the public signal. 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. We run separate regressions for both average prices and limit prices. Per type of error we run three different regressions, one where we pool all the sessions, one where we look at only the last three experienced sessions and one where we look at all sessions but the first.

The motivation for the breakdown is the differences in experience across sessions. As indicated above, we asked the subjects if they had experience with a previous market experiment. Clearly, by design, the last three sessions had more experienced subjects. As Table 2 shows, within the first three sessions some subjects also have trading experience from other market experiments. Experienced subjects initiate a higher percentage of their trades, about $12\frac{1}{2}$%-point more[7]; that is, more of their trades are a result of bids and offers they posted themselves, which other traders subsequently accepted. Experienced subjects are thus more often the market makers, who provide the liquidity needed for efficient markets. Considering the importance of experience, we examine the last three sessions separately.

We also examine the consequences of removing Session 1, to see how the fact that errors do not increase in this session affects the overall results.

We use fixed session and period effects in each of the regressions. We cannot use random effects because there are more coefficients than cross-sections in the restricted sample regressions. The errors data are all positive and skewed resulting in an asymmetrical distribution, to address this we take natural logs.

The coefficients of the signal dummies and associated robust standard errors are reported in Table 4. The main element of interest is the Wald test on the difference between the coefficients for public signals with standard deviations of 30 and 10. Despite the lower standard deviation, the latter also exhibits higher errors.

[7] This is based on a panel regression (with subject random and period fixed effects) of the share of individual trade volume initiated by the subject on a dummy, which indicates if the subject had experience with any previous market experiment (both our own or that of others). The experience dummy has a coefficient of 0.1269. With robust standard errors corrected for cluster correlation within sessions, the p-value of the coefficient is 0.005.

		LN average price error					LN limit price error				
	Public sig st. dev.	**Coeff.**	**St. error**	**Increase**	**Wald**		**Coeff.**	**St. error**	**Increase**	**Wald**	
	5	0.442	0.354				0.446	0.341			
All	**10**	0.957	0.450	0.032	0.942		1.145	0.347	0.199	0.536	
Session 1-6	**30**	0.926	0.344				0.946	0.335			
	90	2.027	0.327				2.068	0.339			
	5	0.840	0.529				0.821	0.592			
Experienced	**10**	2.000	0.454	0.607	0.134		1.734	0.441	0.861	0.044	**
Session 4-6	**30**	1.393	0.461				0.873	0.517			
	90	2.295	0.497				2.250	0.549			
	5	0.564	0.346				0.437	0.338			
All ex. Session 1	**10**	1.455	0.344	0.580	0.048	**	1.293	0.310	0.565	0.032	**
Session 2-6	**30**	0.875	0.328				0.728	0.315			
	90	1.980	0.342				1.860	0.334			

Table 4: Session panel regression results

The decline in standard deviation from 30 to 10 is reflected in an increase in errors in all of the subsamples reported, but it is not significant in the complete sample. The increase is largest for the experienced sessions. The significance of the effect, however, is most evident when Session 1 is excluded. For the other sessions both the average and limit errors show a significant increase between a public signal standard deviation of 30 and 10. The experienced sessions only show a significant result when using the limit price error.

5.2.3 Subject panel results confirm evidence of rising errors

To improve the "resolution" of the data we use our subject panel, with individual subjects in the cross-section rather than sessions, allowing us to control for individual effects. To do this we need to calculate prices per subject per period. The disadvantage of such an approach is that we step away from the idea of an equilibrium price that the market as a whole converges to. However, anything that affects prices on a market level can only do so by affecting individual prices, as the former is constructed from the latter.

Individual prices are calculated as the natural log of the difference between the average price per unit bought or sold (i.e. the price per period per subject is a quantity-weighted average) and the final payout. The regression is comparable to the one presented above with a few variations. Below we use random effects to control for individual unobservables. Because we do not use individual fixed effects, we can also control directly for observable characteristics of the subjects. We control for three such variables. First, "statistics", indicates whether or not the subject had taken a statistics course; we would expect a grasp of statistics to contribute to a better understanding of the experiment and thus possibly result in lower errors. Second, "market experiment", is a dummy for previous experience with a market experiment (either in one of the earlier sessions or another market experiment), which could also contribute to lower individual errors. Third, "risk acceptance", is the risk tolerance measure from the beginning of the experiment, with a number from 10 to 140 (with 70 as risk neutral); where the theoretical impact is indeterminate due to the contrasting ways risk acceptance is present in Equation (3). Finally, we include the individual supply of risky assets endowed to the subject per period; a larger supply should push prices down and away from the true value of the payout, thus increasing errors. Besides individual controls we also include session and period dummies, which are comparable to the fixed effects used in the regressions above. Furthermore, we use Rogers standard errors, which are consistent for correlation within the session clusters.

		LN individual price error				
	Public sig st. dev.	**Coeff.**	**St. error**	**Increase**	**Wald**	
	5	0.642	0.151			
All	**10**	1.140	0.316	0.056	0.8226	
Session 1-6	**30**	1.084	0.211			
	90	1.685	0.313			
	statistics	-0.110	0.054		0.041	**
	market experiment	-0.144	0.087		0.097	*
	risk acceptance	0.011	0.007		0.115	
	supply	0.001	0.002		0.455	
	5	1.033	0.268			
Experienced	**10**	1.607	0.284	0.327	0.042	**
Session 4-6	**30**	1.280	0.384			
	90	1.791	0.349			
	statistics	-0.043	0.071		0.545	
	market experiment	-0.104	0.104		0.315	
	risk acceptance	0.005	0.011		0.666	
	supply	0.001	0.002		0.706	
	5	0.754	0.162			
All ex. Session 1	**10**	1.264	0.282	0.262	0.013	**
Session 2-6	**30**	1.002	0.203			
	90	1.630	0.285			
	statistics	-0.066	0.054		0.078	*
	market experiment	-0.137	0.087		0.174	
	risk acceptance	0.008	0.007		0.232	
	supply	0.000	0.002		0.997	

Table 5: Subject panel regression results

Results are comparable to those in Table 4. The Wald test for the increase in the error is not significant for all six sessions combined but is at the 5% level for both the experienced sessions and Sessions 2-6. The additional control variables are of some interest. "Statistics" is significant for the Session 1-6 sample, while "market experiment" is weakly significant, suggesting that these are factors that contribute to lower error through a better understanding of the market. Neither of these variables are significant in the experienced Sessions 4-6 and "statistics" only weakly significant for Sessions 2-6. These factors are apparently not a significant advantage for traders in the experienced sessions where they are more common and overall prices better reflect fundamentals. The additional control variables do not detract from the main conclusion. The subject panel data confirm the session panel by showing evidence in most sessions of rising errors when the standard deviation of the public signal declines from 30 to 10.

5.2.4 Declining information acquisition and rising errors

The results from the regressions presented in Tables 4 and 5 clearly show that in most sessions there is an increase in errors as the standard deviation of the public signal declines from 30 to 10. From a monetary policy perspective, there is thus evidence that more precise signals from the central bank may result in a market that is less able to predict monetary policy. One could still wonder, however, whether this is a direct consequence of crowding out.

Certainly, the model we replicate in the experiment predicts that rising public information crowds out private information acquisition, which will push up errors. Therefore, observing these three developments in the experiment strongly suggests that this mechanism is at play. There are three more direct indications, however, that crowding out is the reason for the spike in errors.

First, we know that higher public information is associated with less private information in the experiment from Table 3 and this is also demonstrated by econometric analysis in Middeldorp and Rosenkranz (2011). We also know from the results presented in the previous subsection that, controlled for the public signal, lower information acquisition is accompanied by higher errors.

Second, we manipulate only the public signal (in random order across periods). Apart from the price itself, the only variable subjects influence is the acquisition of the private signal. Under the assumption that a decline in the standard deviation of the public signal (only in the range from 30 to 10) does not push up errors by itself, the reduction in information acquisition is the only variable that could explain the increase in errors.

Third, the increase in errors corresponds with the sharpest decline in information acquisition.

5.3 Relevance of our results

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. Our results do allow us to say something about these issues because we have different numbers of subjects (between 16 and 20) and levels of experience. Overall the only session in which there is no evidence of rising errors during the area of sharpest crowding out is Session 1, which is furthest removed from real world markets because it has least experienced and fewest number of traders. Indeed, the closer we get to real world markets the stronger the evidence becomes. The sessions with more subjects and the most experienced traders also show the largest increase in errors.

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. As Svensson (2006) points out, it is plausible that a central bank can produce more precise information regarding future monetary policy than any individual market participant (as we've pointed out, this is not the same as saying they should be better than the market as a whole, which can aggregate information from a diverse set of participants). Indeed even regarding general macroeconomic variables there is evidence, presented by Romer and Romer (2000), that the Fed 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 empirically calibrated private signal of 40, is plausible and relevant.

6 Conclusion

Our experimental research partially confirms the note of caution delivered by the theoretical evidence. A more precise public signal from a central bank can crowd out private information acquisition, which reduces the amount of private information that the market can aggregate and thus can lead to a deterioration of the ability of the market to predict future monetary policy. However, in our laboratory asset market, which is closely based on the original theoretical model, we only find rising errors between the market price and the fundamental value of the traded asset where the crowding out of private information is sharpest. 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 markets. Sessions with more numerous and experienced subjects produced a stronger effect. Furthermore, we calibrate our experiment with empirical measurements to improve its applicability and show that crowding out takes places for plausible levels of public information.

References

Ackert, L., Church, B. and Gillette, A.: 2004, Immediate disclosure or secrecy? the release of information in experimental asset markets, *Institutions and Instruments* **13**(5), 219–243.

Barner, M., Feri, F. and Plott, C. R.: 2005, On the microstructure of price determination and information aggregation with sequentialand asymmetric information arrival in an experimental asset market, *Annals of Finance* pp. 73–107.

Bauer, A., Eisenbeis, R., Waggoner, D. and Zha, T.: 2006, Transparency, expectations and forecasts. Federal Reserve Bank of Atlanta Working Paper 2006-3.

Berger, H., Ehrmann, M. and Fratzscher, M.: 2006, Forecasting ECB monetary policy: Accuracy is (still) a matter of geography? ECB Working Paper No. 578.

Bernanke, B.: 2004, Central bank talk and monetary policy. Speech, 7 October.

Blinder, A., Ehrmann, M., Fratzscher, M., de Haan, J. and Jansen, D.-J.: 2008, Central bank communication and monetary policy: A survey of theory and evidence. CEPS Working Paper.

Campbell, J. Y. and Shiller, R. J.: 1991, Yield spreads and interest rate movements: A bird's eye view, *The Review of Economic Studies* **58**(3), 495–514.

Carlson, J., Craig, B., Higgins, P. and Melick, W.: 2006, FOMC communications and the predictability of near-term policy decisions. Federal Reserve of Cleveland Review.

Cochrane, J. H. and Piazzesi, M.: 2005, Bond risk premia, *American Economic Review* **95**(1), 138–160.

Consensus Forecasts G-7 Countries and Western Europe: 2007, Consensus Economics. 1996-2006, www.consensuseconomics.com.

Copeland, T. E. and Friedman, D.: 1992, The market value of information: Some experimental results, *Journal of Business* **65**(2), 241–266.

Coppel, J. and Connolly, E.: 2003, What do financial market data tell us about monetary policy transparency? Reserve Bank of Australia Working Paper.

Dale, S., Orphanides, A. and Osterholm, P.: 2008, Imperfect central bank communication - information vs. distraction. IMF Working Paper 08/60.

Demertzis, M. and Hoeberichts, M.: 2007, The costs of increasing transparency, *Open Economies Review* **18**, 263–280.

Diamond, D. W.: 1985, Optimal release of information by firms, *The Journal of Finance* **40**(4), 1071–1094.

Ehrmann, M., Eijffinger, S. and Fratzscher, M.: 2010, The role of central bank transparency for guiding private sector forecasts. ECB Working Paper No. 1146.

Elton, E. J., Gruber, M. J., Das, S. and Hlavka, M.: 1993, Efficiency with costly information: A reinterpretation of evidence from managed portfolios, *The Review of Financial Studies* **6**(1), 1–22.

Fama, E. F. and Bliss, R. R.: 1987, The information in long-maturity forward rates, *The American Economic Review* **77**(4), 680–692.

Fischbacher, U.: 2007, z-tree. toolbox for readymade economic experiments, *Experimental Economics* **10**(2), 171–178.

Grossman, S. and Stiglitz, J.: 1980, On the impossibility of informationally efficient markets, *The American Economic Review* **70**(1), 393–408.

Hayford, M. and Malliaris, A.: 2007, Transparent monetary policy. Loyola University Chicago Working Paper.

Hayo, B. and Neuenkirch, M.: 2009, Does FOMC communication help predicting federal funds target rate changes? MAGKS Joint Discussion Paper Series in Economics, No. 25-2009.

Heinemann, F., Nagel, R. and Ockenfels, P.: 2008, Measuring strategic uncertainty in coordination games, *The Review of Economic Studies* . Forthcoming.

Hellwig, M. F.: 1980, On the aggregation of information in competetive markets, *Journal of Economic Theory* **22**, 477–498.

Holmsen, A., Qvigstad, J. F., Øistein Røisland and Solberg-Johansen, K.: 2008, Communicating monetary policy intentions: The case of Norges Bank. Norges Bank Working Paper 2008-20.

Investment Company Factbook: 2000, Investment Company Institute. www.icifactbook.org.

Investment Company Factbook: 2007, Investment Company Institute. www.icifactbook.org.

Jansen, D.-J. and de Haan, J.: 2009, Has ECB communication been helpful in predicting interest rate decisions? an evaluation of the early years of the economic and monetary union, *Applied Economics* **41**(16), 1995–2003.

Kool, C., Middeldorp, M. and Rosenkranz, S.: 2010, Central bank transparency and the crowding out of information in the financial markets, *Journal of Money, Credit and Banking* . Forthcoming.

Kwan, S.: 2007, On forecasting future monetary policy: Has forward-looking language mattered? Federal Reserve Bank of San Francisco Economic Letter 2007-15.

Lange, J., Sack, B. and Whitesell, W.: 2003, Anticipations of monetary policy in financial markets, *Journal of Money, Credit and Banking* **35**(6), 889–909.

Lildholdt, P. and Wetherilt, A. V.: 2004, Anticipation of monetary policy in UK financial markets. Bank of England Working Paper 241.

Mariscal, I. B.-F. and Howells, P.: 2006a, Monetary policy transparency in the UK: The impact of independence and inflation targeting. University of West England, Bristol Working Paper.

Mariscal, I. B.-F. and Howells, P.: 2006b, Monetary policy transparency, lessons from Germany and the Eurozone. University of West England, Bristol Working Paper.

Middeldorp, M.: 2010, FOMC communication policy and the accuracy of Fed funds futures. Working Paper.

Middeldorp, M.: 2011, Central bank transparency, the accuracy of professional forecasts and interest rate volatility. Working Paper.

Middeldorp, M. and Rosenkranz, S.: 2011, Information acquisition in an experimental asset market. Working Paper.

Mizen, P.: 2009, What can we learn from central bankers' words? some non-parametric tests for the ECB, *Economic Letters* **103**, 29–32.

Morris, S. and Shin, H. S.: 2002, Social value of public information, *The American Economic Review* **92**(5), 1521–1534.

Morris, S. and Shin, H. S.: 2005, Central bank transparency and the signal value of prices, *Brookings Papers on Economic Activity* (2).

Murdzhev, A. and Tomljanovich, M.: 2006, What is the color of Alan Greenspan's tie? how central bank policy announcements have changed financial markets, *Eastern Economic Journal* **32**(4).

Noussair, C., Plott, C. and Riezman, R.: 1995, An experimental investigation of the patterns of international trade, *American Economic Review* pp. 462–491.

Piazzesi, M. and Swanson, E.: 2008, Futures prices as risk-adjusted forecasts of monetary policy, *Journal of Monetary Economics* **55**, 677–691.

Plott, C. R.: 2000, Markets as information gathering tools, *Southern Economic Journal* **67**(1), 1–15. Distinguished Guest Lecture.

Rafferty, M. and Tomljanovich, M.: 2002, Central bank transparency and market efficiency: An econometric analysis, *Journal of Economics and Finance* **26**(2), 150–161.

Romer, C. D. and Romer, D. H.: 2000, Federal Reserve information and the behavior of interest rates, *American Economic Review* **90**(3), 429–457.

Sack, B.: 2004, Extracting the expected path of monetary policy from futures rates, *The Journal of Futures Markets* **24**(8), 733–754.

Stambaugh, R. F.: 1988, The information in forward rates, *Journal of Financial Economics* **21**, 41–70.

Sturm, J.-E. and de Haan, J.: 2009, Does central bank communication really lead to better forecasts of policy decisions? new evidenced based on a Taylor rule model for the ECB. KOF Working Paper 2009 No. 236.

Svensson, L. E.: 2006, Social value of public information: Morris and shin (2002) is actually pro transparency, not con, *The American Economic Review* **96**(1), 448–452.

Swanson, E.: 2006, Have increases in Federal Reserve transparency improved private sector interest rate forecasts, *Journal of Money, Credit and Banking* **38**, 792–819.

Tomljanovich, M.: 2004, Does central bank transparency impact financial markets? a cross country econometric analysis, *Southern Economic Journal* .

van der Cruijsen, C. and Eijffinger, S.: 2007, The economic impact of central bank transparency: A survey. CEPR Working Paper No. 6070.

Verrecchia, R. E.: 1982, Information acquisition in a noisy rational expectations economy, *Econometrica* **50**(6), 1415–1430.

7 Appendix

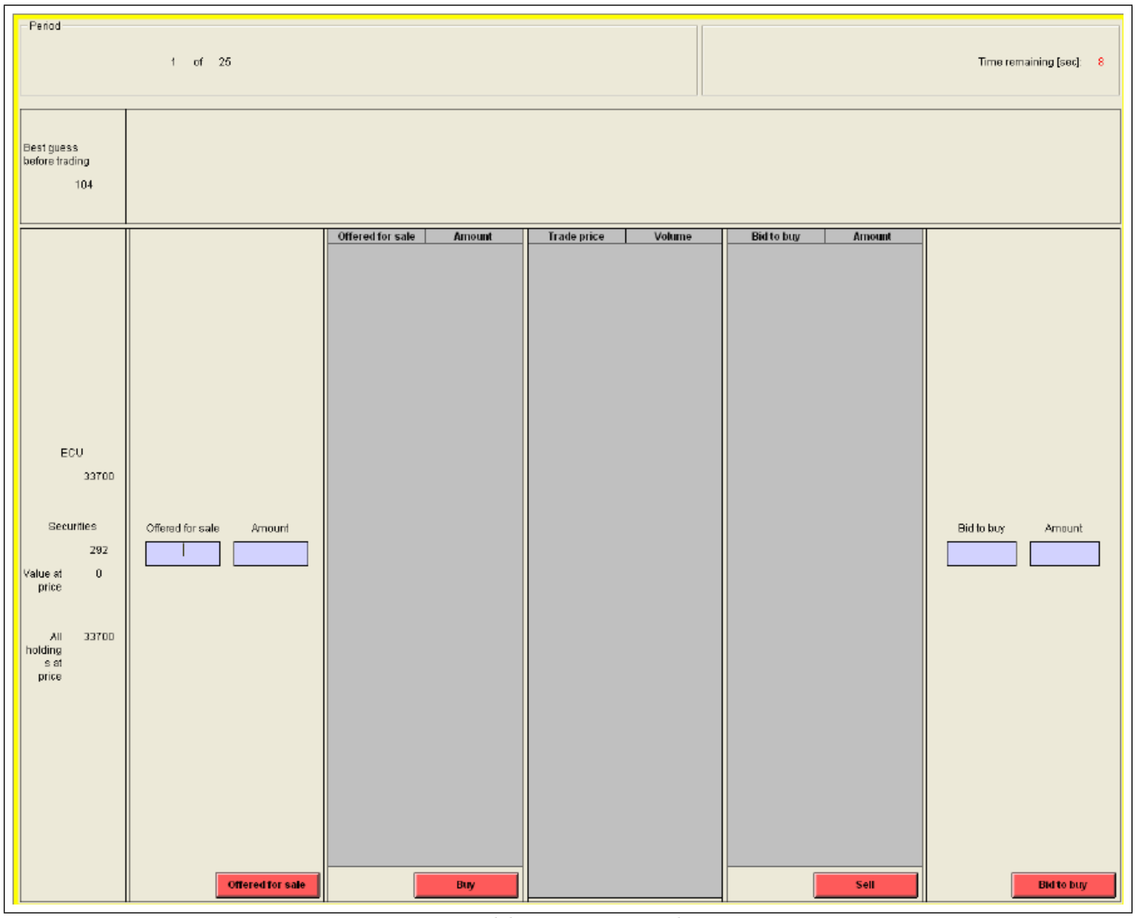

Figure 6: Double auction market screen