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Forecasting Inflation via Experimental Stock Markets
Some Results from Pilot Markets

Abstract

While there are various techniques of inflation forecasting in use, none of them has proved to deliver consistently more accurate forecasts than the others. That is why most users of inflation forecasts monitor a variety of inflation indicators and forecasts and check them for consistency. This paper aims at contributing to an extension of the methods in use. We propose to conduct experimental inflation forecasting markets in order to uncover market participants' inflation expectations. While the markets directly deliver density forecasts of inflation they also allow to construct mean forecasts and a measure of forecast uncertainty. We also present evidence from a number of pilot markets underlining that the proposed method might enrich the arsenal of existing forecasting techniques.

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1. Introduction

Throughout the last decade, interest in forecasting macroeconomic variables, and especially inflation, has increased considerably. This is at least partially due to the fact that many central banks switched to inflation targeting strategies of monetary policy. An essential part of these strategies is the use of inflation forecasts as intermediate target of monetary policy decisions.[1] Thus, central banks following an inflation targeting strategy are in urgent need of high quality inflation forecasts in order to be successful in achieving their primary goal of guaranteeing a stable price level. However, due to the fact that expectations about inflation are embedded in planning decisions of all kinds, inflation forecasting is also an important matter outside central banks. The private sector is in need of inflation forecasts when corporations make investment decisions, corporations and workers (or trade unions) negotiate wages or individuals make savings decisions based on expected future real income. The public sector also cares about future inflation, e.g. when planning budgets.

The aim of this paper is to contribute to extending the conventional set of inflation forecasting techniques. We propose a new method of forecasting inflation: assessing market inflation expectations via conducting experimental stock markets. Our belief that experimental stock markets could be a useful tool is driven by the experience that experimental political stock markets have been quite successful in predicting electoral outcomes.[2] Thus, transferring the idea to forecasting macroeconomic variables like inflation might be fruitful. We therefore develop a prototype design for inflation forecasting markets in this paper. We also report and analyze the results from a number of related pilot experiments conducted in Germany.

The outline of this paper is as follows: the second section gives a brief review of conventional forecasting techniques. In the third section we develop the design of a prototype experimental inflation forecasting market and show how the market data can be used to construct both density and mean forecasts of inflation. We also show how

[1] See Svensson (1997,1999).
[2] See Berg et al. (1998), Berg, Forsythe and Rietz (1997) or Berlemann and Schmidt (2001).

the uncertainty surrounding the mean forecast can be assessed. In the fourth section we report and analyze the results of several pilot forecasting markets conducted in Germany. Section 5 summarizes the results.

2. Conventional inflation forecasting techniques

Conventional inflation forecasting techniques can roughly be subdivided into two basic approaches: the expectations and the econometric approach. Before we outline the idea of experimental macroeconomic forecasting markets we should give a brief overview on conventional concepts (see figure 1).[3]

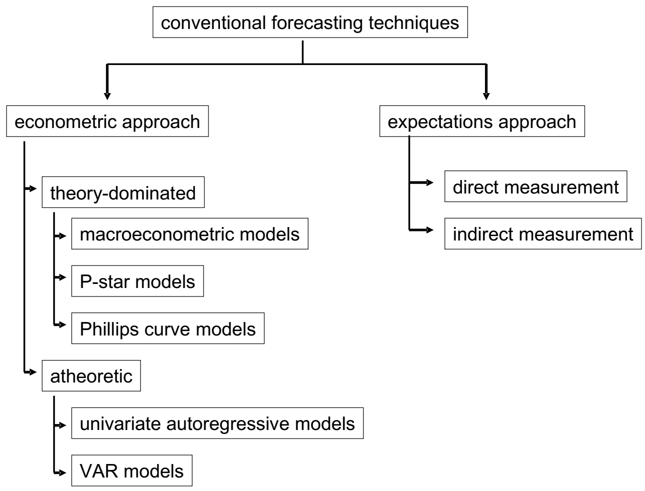

Figure 1. Conventional inflation forecasting methods.

The first of the two basic approaches to forecasting inflation is the econometric approach.[4] Econometric forecasting models use actual and historical macroeconomic data to generate forecasts. In forward-looking models even expectations on future values of some variables can enter econometric models. Econometric forecasting models can be divided into two subgroups: theory-dominated and atheoretic models.

The basic idea underlying theory-dominated econometric approaches is that there is some theoretical model explaining by which factors inflation is determined. Whenever

[3] For a brief introduction to inflation forecasting see also Tallman (1995).
[4] For a detailed description of alternative econometric inflation forecasting techniques see Bank of England (1999).

we believe to know the correct model and whenever we possess the necessary data we should be able to produce some reasonable forecast of future inflation. Due to the fact that there is a large number of theories, explaining the causes of inflation, econometric inflation forecasting models differ in as much as the underlying theoretical models differ. Large-scale macroeconometric models[5] try to give a reasonably complete account of the macroeconomy. Therefore this type of model is typically highly disaggregated. However, large-scale macroeconometric models are hard to handle. That is why often models with higher degrees of aggregation are used. Among the most often used theory-dominated small-scale forecasting models are Phillips curve models and P-star models. Phillips curve models try to exploit systematic relationships between inflation and some measure of economic activity.[6] P-star models are based on the quantity equation and relate inflation to both output and liquidity gaps.[7]

Atheoretic models of forecasting inflation make no or only minimal use of theoretical arguments. In the simplest case, inflation is forecasted on the basis of past observations of inflation itself. Due to the fact that inflation is somewhat persistent inflation forecasts based on an autoregressive model might perform quite well in the short run. While autoregressive models focus solely on past observations of inflation VAR models let the empirical data determine the forecasting model's structure. However, VAR models are not completely atheoretic but rely on only a minimum of restrictions resulting from theoretical considerations.[8]

The second basic concept of forecasting inflation, the "expectations approach", is not concerned about the question which theory, allowing to predict future inflation, is the appropriate one. The basic idea of the expectations approach is that many people care - or at least should care - about inflation. The various forms of inflation effects[9] deliver the theoretical reasoning for this argument. The expectations approach simply suggests that

[5] See e.g. Bank of England (1999), Jordan and Peytrignet (2001) or Poloz, Rose and Tetlow (1994).
[6] See e.g. Stoch and Watson (1999), Atkeson and Ohanian (2001) or Fisher, Liu and Zhou (2002).
[7] See Hallman, Porter and Small (1991), Tödter and Reimers (1994), Issing and Tödter (1995) and Gottschalk and Bröck (2000).
[8] See Doan, Litterman and Sims (1984) or Thompson and Miller (1986).
[9] See e.g. Briault (1995).

a certain subgroup of people, caring about future inflation, knows enough about the true determinants of price level changes to be able to predict future inflation well on average. Thus, it is sufficient to measure inflation expectations of an informed subgroup without knowing which methods are used for individual forecasts. Even if individual beliefs on future changes in the price level might differ heavily because of heterogenous information sets and different ways of interpreting them (i.e. individuals might use different theoretical "models" for their forecasts) the aggregate of individual expectations should be a good predictor for future inflation, provided that individual forecasts turn out to be rational.

However, the basic problem of the expectations approaches is how to uncover market participants' inflation expectations. Direct methods of measuring inflation expectations typically rely on some sort of expectation surveys in which certain subsamples of the population are asked to reveal their personal inflation expectations.[10] While in some surveys the respondents have to make some qualitative assessment of future inflation, others ask for concrete numbers. However, in both cases some appropriate way of aggregating the individual responses has to be found. The indirect approach to asses expectations is to derive inflation expectations from market participants' behavior on real world (financial) markets. A straightforward way to do so is to use prices of CPI futures to derive market expectations.[11] However, in most countries markets for these futures did not develop.[12] Alternatively, several authors tried to gauge inflation expectations from the term structure of interest rates.[13]

Numerous studies analyzed the relative accuracy of inflation forecasts generated by the various summarized forecasting techniques.[14] However, when evaluating this literature no coherent picture can be drawn since the success of the various discussed inflation forecasting techniques seems to depend very much on the studied countries, sample periods and the frequency of the available data. Several authors come to similar results

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[10] See e.g. Croushore (1996) or Thomas (1999).
[11] Lovell and Vogel (1973) and Lioui and Poncet (2002).
[12] Horrigan (1987) provides a discussion of the reasons why the attempt to establish a CPI futures market in the United States failed.
[13] See e.g. Fama (1970) or Mishkin (1990).
[14] See e.g. the studies by Webb (1999), Stock and Watson (1999) or Kozicki (2001).

when reviewing the related literature.[15] It is therefore not surprising that no method of forecasting inflation dominates in the practice of forecasting. Even if f.ex. central banks invest a lot of resources into econometric forecasting models they often do not completely rely on these models' forecasts. In Bank of England (1999, p. V), George, the Bank of England's Governor, states in this respect:

> "The Bank's use of economic models is pragmatic and pluralist. In an ever-changing economy, no single model can possibly assimilate in a comprehensive way all the factors that matter for policy. Forming judgements about those factors, and their implications for policy, is the job of the Committee, not something that can be abdicated to models or even to modelers. But economic models are indispensable tools in that process."

Thus, individual beliefs and judgments often play an important role even in inflation forecasts that are based upon econometric models. Most central banks therefore rely on a mixture of the concepts and often decide somewhat discretionary on the appropriate forecast. Regularly, there is some kind of macroeconometric model in the heart of the forecasting system which is supplied with a number of additional smaller models that are used to generate input data for the core model and to check the validity of its forecasts.[16] In consequence, most central banks monitor a variety of inflation indicators.[17] We may interpret this procedure as some kind of distrust in conventional forecasting methods. Therefore further research in methods of measuring future inflation seems to be useful and necessary.

3. Experimental stock markets

Our proposal of conducting experimental markets to forecast inflation builds up on the earlier described expectations approach of forecasting inflation. In line with Lioui and

[15] See e.g. Litterman (1986) and Webb (1999).
[16] Compare for example the forecasting system of the Bank of England, which is described in detail in Bank of England (1999).
[17] Kozicki (2001).

Poncet (2002) we argue that markets are the most efficient means of aggregating private information.[18] However, we are less optimistic that such markets will evolve in the course of the next years in a number of countries. We therefore propose to conduct small-scale experimental markets in which well informed individuals trade state-contingent contracts thereby revealing their inflation expectations. By using an appropriate design of these contracts we are able to extract not only the mean market expectation of inflation but also some information on the expected likelihood of different inflation scenarios. In the following we outline the basic setup of an experimental inflation forecast market and show how the data, generated by the market can be used to construct density and mean forecasts.

3.1. Market admittance

Experimental markets are typically fully computerized. To be allowed to take part in a market, participants have to register in the market software via Internet. Within the process of registration the applicants are asked to provide some personal information which can later be used to analyze the generated market data.

In general, electronic markets are organized as real-money markets, i.e. all transactions in the market are based on real money.[19] In these markets participants initially have to decide on their personal investments[20] which have to be covered by the traders. Thus, each participant can win or loose money in the market, depending on his or her success

[18] Most economists nowadays believe that markets are highly efficient means of aggregating private information and revealing them via market prices (see e.g. Beckmann and Werding (1994), p. 517, Forsythe, Frank, Krishnamurthy and Ross (1995), p. 771, or Forsythe, Rietz and Ross (1999), p. 83.) According to this view it is the price mechanism through which bits of information, held by individuals who communicate by no other means, are brought together and shared with one another (see Hayek (1948,1968)). Following Smith (1982) this strong belief in the abilities of markets to aggregate and disseminate information is nowadays referred to as the "Hayek hypothesis". Experimental work substantiated this hypothesis (for reviews of the related work see Sunder (1995) or Beckmann and Werding (1994)).

[19] In virtual-money markets all participants initially get endowed with the same amount of virtual money. These funds can be used by the participants to organize market transactions. In virtual-money markets the participants with the highest returns on investment are typically rewarded by the market organizer. Thus, different from real-money markets the participants in virtual-money markets bear no risk of losing money. That is why virtual-money markets typically attract a larger number of traders. However, this obviously comes at the price of players engaging in more risky strategies, possibly leading to biased forecasts.

[20] Typically investments are restricted due to legislative restrictions.

in trading. As soon as the initial investment has been transferred to the market organizer (typically this is done via cash or bank transfer to a market account) the participant gets a trader-ID and a password to get access to the market. In addition to that a trader account for the participant is created and his initial investment is transferred to the account.

In general, there are no formal restrictions for participation in experimental stock markets. Technical precondition for taking part in an experimental market is an Internet connection.

3.2. Market design

The type of market we propose to use is called "winner-takes-all-market". In such a market a set of binary lock-in options is traded. The underlying of these options is some measure of inflation, e.g. CPI inflation as typically measured and announced by national statistical institutes. A binary lock-in option[21] has a fixed, predetermined payoff if the underlying is inside the strike range at expiration. In experimental forecasting markets this payoff is typically normalized to one currency unit. The payoff function of such an option is visualized in figure 2. Thus, the type of lock-in options traded in an inflation forecasting market is formally identical to what is called pure, Arrow or Arrow-Debreu securities in the financial markets literature.[22]

The set of binary lock-in options which is traded in the market consists of n different options. The strike ranges of these options do not overlap and cover the whole range of possible outcomes of the underlying, i.e. inflation. Since the number of unique linearly independent securities is equal to the total number of alternative states of nature we deal with a complete market.[23] Regardless of the initial distribution of securities it is thus possible to reduce uncertainty about the value of future wealth to zero. A set of options

[21] In financial literature this type of option is also called digital, simplex, all-or-nothing, bet or lottery option.

[22] See e.g. Copeland and Weston (1992) or Eichberger and Harper (1997).

[23] Copeland and Weston (1993), p. 112.

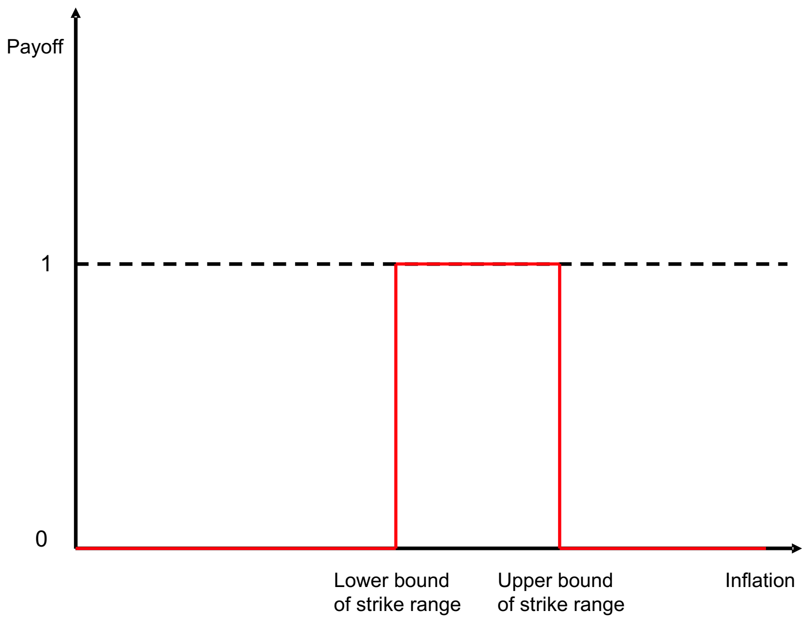

Figure 2. Payoff function of a binary lock-in option on the CPI.

defining a complete market and the related payoff rules are shown in table I. Such a complete set of options is also called "unit portfolio" or "bundle".

Table I. Complete set of n options.

Contract name	Pays off 1 currency unit, if
$\pi(k_1-)$	$\pi < k_1$
$\pi(k_1, k_2)$	$k_1 \leq \pi < k_2$
$\vdots$	$\vdots$
$\pi(k_{n-1}, k_n)$	$k_{n-1} \leq \pi < k_n$
$\pi(k_n+)$	$k_n \geq \pi$

There is no general rule how much options should be traded and how large the strike ranges should be. In order not to induce some kind of bias by arbitrary contract design it seems to be reasonable to center the contracts symmetrically around the last announced inflation rate. Experiences from political stock markets show that the number of traded contracts n should not be too large ($\leq$ 10) and the strike ranges should not be too small. Otherwise it will be quite hard for the participants to guess how likely it is that inflation will fall into a certain strike range. However, in order to get a forecast as precise as possible the market organizer might be interested in having the possibility to vary the set of traded options during the market period. This can easily be done by splitting options into two (or more) contracts with smaller strike ranges (given that the options do not overlap and all possible outcomes of the underlying are still covered). In order not to influence the values of the participants' portfolios by contract splits, every holder of a split contract gets one of every newly issued contract in exchange.

3.3. Trading in the market

Upon entering the market and any time thereafter participants can buy unit portfolios from the market organizer for the price of 1 currency unit until the market closes. Complete unit portfolios can also be sold back to the market organizer during the market period for the price of 1 currency unit each. Selling and buying unit portfolios from or to the market organizer are primary market transactions. Together with the earlier described payoff structure of the binary lock-in options the pricing of the unit portfolios guarantees that the market is a zero-sum-game for the market organizer. All initial investments get paid back to the participants. However, the market is typically no zero sum game for the individual participant since he can win or loose money, depending on his success in trading within the secondary market.

On the secondary market participants can buy or sell contracts from or to other participants. The secondary market is organized as a so-called "double auction market". Market participants can issue offers to buy (bids) or offers to sell (asks) contracts. When using a first type of transactions, so-called "limit orders", traders have to choose the order type (bid or ask), the contract type, the number of contracts he wants to trade, the transaction price and finally the order's expiration date. Limit orders are maintained in separate bid and ask queues ordered first by offer price and then by the time of issuance. Whenever an offer enters one of the queues it remains there until is withdrawn by the trader, reaches its expiration date or is carried out. Orders are carried out whenever bid- and ask-prices overlap. The second type of transactions, the so-called "market orders", are orders to buy or sell at current market prices which are carried out immediately.

All primary and secondary market transactions are organized via a market software.[24] Besides serving as a market platform the software provides several facilities for the traders to obtain information on the market. A trader can access personal information on his market account, current portfolio or already submitted orders. The software also delivers information about the highest bids to buy and lowest asks to sell for each traded contract type or the last prices for which a certain share was traded.

Different from real world stock markets, short sales and purchases on margin are typically disallowed to secure the zero-sum game character of experimental forecasting markets. In addition, there are typically no transaction costs levied by the market organizer for both, primary and secondary market transactions. The market participants only have to bear those transaction costs resulting from getting Internet access and opportunity costs from spending time on trading in the market.

3.4. Market liquidation

A forecasting market gets liquidated as soon as the realization of the underlying is known, i.e. the inflation rate is announced by the responsible institution. The individual payoff of each participant consists of (i) the money the trader held on his market account when the market closed and (ii) the liquidation value of the portfolio of contracts the trader held at the end of the market. We might illustrate the liquidation procedure at the example shown in table II.

Therefore, we assume that the inflation rate turns out to be in between k_2 and k_3 percent. The second column in table II shows the individual portfolio of participant j and the third column the liquidation values of the contracts. The total value of participant j's portfolio of contracts is thus 13 currency units. Adding the 3 currency units participant j is assumed to hold on his market account at the end of the market period leads to a total payoff of 16 currency units.

[24] The markets we report on in this paper were organized using two different softwares. However, their basic features were quite similar.

Table II. Portfolio liquidation for an imaginary participant j under the assumption that the inflation rate turns out to be in between k_2 and k_3

Contract/asset	Number of contracts in portfolio of participant j	Liquidation value per contract unit	Total value in curr. units
$\pi(k_1-)$	76	0	0
$\pi(k_1, k_2)$	4	0	0
$\pi(k_2, k_3)$	13	1	13
$\pi(k_3, k_4)$	2	0	0
$\pi(k_4, k_5)$	5	0	0
$\pi(k_5+)$	0	0	0
Cash on account	3	-	3
Total payoff	-	-	16

3.5. Density forecast, mean forecast and forecast uncertainty

In order to show how and why the described design of an experimental stock market should enable us to obtain a reasonable inflation forecast we argue on the basis of Arbitrage Pricing Theory.[25]

According to Arbitrage Pricing Theory[26] the equilibrium price of a pure security principally depends on three factors: the risk-free rate of return, individuals' attitudes towards risk and expectations as to the probability that a particular state will occur.[27] More precisely we can express the price at time t of any pure security as

$$p_{s,t} = \frac{E[p_{s,T}]}{(1 + r^f + r^r)^{(T-t)}}$$

with r^f being the risk-free rate of return, $E[p_{s,T}]$ the expected payoff of the contract at time T and r^r a risk premium for taking over unsystematic risk (which can not be diversified). In order to determine the equilibrium price of the binary lock-in option traded in a forecasting market we will consider these three determinants sequentially.

Let us first focus on the risk-free rate of return. There are two risk-free portfolios in an inflation forecasting market. The first one consists of holding any of the pure securities at

[25] The same results can principally be derived from Capital Asset Pricing Theory (CAPM). Since the assumptions of CAPM are somewhat more restrictive than those of Arbitrage Theory we base our expositions on the latter.
[26] Arbitrage Pricing Theory goes back to Ross (1976).
[27] Copeland and Weston (1993), p. 116.

all. Obviously, the return on this portfolio is zero. The second risk-free portfolio consists of one of each of the pure securities. Such a portfolio would deliver 1 unit of currency in every state of the nature. Such a unit portfolio can be purchased from or sold back to the market organizer at any time during the market period for the price of one currency unit. Thus, the return on a unit-portfolio is zero by construction. One might be tempted to argue that the price of a unit-portfolio could be smaller than 1 currency unit when the sum of asks to sell prices adds up to a smaller value than 1. However, such a situation can not be an equilibrium since it is not arbitrage-free.[28] One might also argue that there is a significantly positive risk-free return outside the inflation market, e.g. when investing into government bonds. However, once the decision to transfer money to the market account has been made (what is a necessary precondition to take part in an inflation market), the money can not be withdrawn during the market period. Thus, the risk-free rate of return is zero ($r^f = 0$) in an inflation forecasting market.

The second determinant of a pure security's price lies in individual beliefs concerning the relative likelihood of different states s occurring, the so-called state probabilities. For simplicity, let us assume that in equilibrium individuals agree on the probabilities $h_{\pi(k_{n-1},k_n),t}$ of the states of nature.[29] In that case we can decompose the expected price of a pure security in state $\pi(k_{n-1}, k_n)$ at time t into the probability of the state occurring and the price of an expected currency unit contingent on the state occurring. Thus, we have

$$E[p_{\pi(k_{n-1},k_n),T}] = h_{\pi(k_{n-1},k_n),t} \cdot 1.$$

In consequence, expected prices of pure securities differ to the same degree as market participants expect different states to occur with different probabilities.

The third determinant of pure securities' prices is market participants' attitude toward risk. While there are obviously no risk premia for the case of risk-neutral investors, one

[28] In the described situation one could easily make sure profits by buying unit-portfolios on the secondary market and selling them for the price of 1 currency unit to the market organizer. Realizing these transactions will quickly eliminate all arbitrage opportunities.

[29] This assumption is without effect on the line of argument. Principally, subjective beliefs concerning state probabilities can also differ (see e.g. Copeland and Weston (1993), p. 117.

might argue that risk-averse individuals will demand for such a premium in order to take over risk. However, this is only true for the case that aggregate wealth differs between the different states of nature.[30] In the market setting we suggest to use aggregate wealth is the same regardless of which state is realized (this is due to the zero-sum game character of the market). Thus, there is no non-diversifiable risk and, consequently, equilibrium prices include no risk premia, i.e. $r^r = 0$.

Altogether, we end up with the following pricing formula for the binary lock-in options traded in inflation forecasting markets:

$$\begin{aligned} p_{\pi(k_{n-1},k_n),t} &= \frac{E[p_{\pi(k_{n-1},k_n),T}]}{(1+r^f+r^r)^{(T-t)}} \\ &= \frac{h_{\pi(k_{n-1},k_n),t}\cdot 1}{(1+0+0)^{(T-t)}} \\ &= h_{\pi(k_{n-1},k_n),t}. \end{aligned}$$

Thus, the prices of the pure securities traded in an inflation market are perfect predictors of the probabilities, market participants attach to the different states of nature. However, this is true only if the market is in equilibrium. It is then when all available information is reflected in the current market prices.[31] Since current market prices do not always sum up to unity in practice[32] a normalization procedure is typically applied. This is necessary in order to be able to interpret the market prices as probabilities.

While an experimental inflation forecasting market directly generates a density forecast of inflation it does not automatically deliver some form of mean inflation forecast. Whenever we are in need of mean forecasts we have to make some simplifying assumptions on the distribution of inflation expectations within the intervals as marked by the strike ranges of the option contracts. For sufficiently small intervals it seems to be reasonable

[30] See e.g. Copeland and Weston (1993), p. 118.
[31] There is still a lack of a commonly accepted dynamic model how the market participants learn from the observed market prices, i.e. how exactly the process of aggregating disseminated information works. Although one might be able to build such a model it will be hard to test it empirically since the necessary data on individual beliefs are hard to obtain. One might also be somewhat sceptic whether a formal behavioral model will be able to capture the diversities of individual learning.
[32] Note that there will be no additional trades when all market participants have the same expectation on the density function of inflation. Thus, the trading process might stop although not all information is included in the market prices. However, in markets with a large number of traders this phenomenon typically diminishes.

to assume that the market participants expect all realizations of inflation within this interval to be equally likely. In this case the interval can be represented by its class middle. However, a complete set of options includes two options with infinitely large strike ranges ($\pi(k_1-)$ and $\pi(k_5+)$ in the example in table I). To deal with this problem one might use the (upper respectively the lower) bounds of these infinitely large intervals instead of the class middles.[33] We can then calculate the mean market inflation forecast π_t^f at time t by multiplying the normalized, last observed market prices with the class middles (respective the bounds of the lowest and the highest interval) and adding up for all traded contracts

$$\begin{aligned}\pi_t^f &= \frac{p_{\pi(k_1-),t}}{P_t} \cdot k_1 + \frac{p_{\pi(k_1,k_2),t}}{P_t} \cdot \frac{k_2 - k_1}{2} + \ldots \\ &\quad + \frac{p_{\pi(k_{n-1},k_n),t}}{P_t} \cdot \frac{k_n - k_{n-1}}{2} + \frac{p_{\pi(k_n+),t}}{P_t} \cdot k_n.\end{aligned}$$

with

$$P_t := p_{\pi(k_1-),t} + \ldots + p_{\pi(k_n+),t}.$$

In the literature on political stock markets often daily volume-weighted prices are used for generating forecasts instead of last observed prices. While only marginal prices can be expected to include all available information we therefore also report forecasts which are based on normalized weighted prices.

By far most published inflation forecasts are mean forecasts. Typically these forecasts do not provide any information on the underlying probabilities of different inflation scenarios. Since one and the same mean forecast can principally be constructed by many different probability distributions information about the uncertainty surrounding a mean inflation forecast is important in addition to the forecast itself. A measure of forecast uncertainty helps to qualify a forecast and is useful to give a richer picture of the expected range of likely outcomes.[34] Inflation forecasting markets allow to assess the mean inflation forecast's uncertainty directly. Since the normalized market prices $p_{t,j}^n$ can be interpreted

[33] Doing so is obviously problematic when the observed prices for the options covering the infinitely large intervals are quite high. However the market administrator can lower the market prices of these intervals by making use of the earlier described split option of contracts.
[34] See e.g. Ericsson (2001), p. 88-89.

as the market's aggregated evaluation of the probabilities of different inflation scenarios, these probabilities can be used to calculate the empirical variance of the daily mean inflation forecast as

$$\begin{aligned}\sigma^2_{\pi^f,t} \;=\; & \frac{p_{\pi(k_1-),t}}{P_t}\cdot(k_1-\pi^f_t)^2+\frac{p_{\pi(k_1,k_2),t}}{P_t}\cdot\left(\frac{k_2-k_1}{2}-\pi^f_t\right)^2+\ldots \\ & +\frac{p_{\pi(k_{n-1},k_n),t}}{P_t}\cdot\left(\frac{k_n-k_{n-1}}{2}-\pi^f_t\right)^2+\frac{p_{\pi(k_n+),t}}{P_t}\cdot(k_n-\pi^f_t)^2.\end{aligned}$$

It should be underlined that experimental markets allow to construct forecasts and to assess their empirical variance at any point in time during the market period. Thus, experimental forecasting markets deliver time-series of fixed-event forecasts of the underlying of the traded contracts.[35]

4. Results from pilot forecasting markets

In this section we report and analyze the results from a series of 5 prototype forecasting markets conducted in Germany. While these forecasting markets differed in some respects, they all made use of the basic design developed in the previous section. The first 4 markets we report on were designed to directly forecast CPI inflation. The 5th market focusses on a policy instrument rather than a policy outcome. In this market we tried to assess market expectations on the future development of main refinancing rate (MRR) of the European Central Bank (ECB).

4.1. Market descriptions

We start out with a brief description of the pilot markets.[36] Table III summarizes the main characteristics of the 5 experimental forecasting markets.

The first market ("market I") was organized at Dresden University of Technology (Germany) in close cooperation with the Iowa Electronic Markets (United States). The

[35] The presented market design is also suitable to generate forecasts for macroeconomic variables like unemployment rates or gross national products.

[36] For a more detailed description of the market features see the appendix.

Table III. Overview on pilot forecasting markets.

Market nr.	Underlying	Market period	participants	Investment per trader
I	CPI inflation Feb 2001	20.10.00-13.03.01	44	23.22 Euro
II	CPI inflation Dec 2001	17.10.01-15.01.02	32	12.94 Euro
III	CPI inflation Jun 2002	23.4.02-11.7.02	47	17.87 Euro
IV	CPI inflation Oct 2002	26.07.02-12.11.02	36	8.00 Euro
V	ECB MRR 15.1.03	13.10.02-14.01.03	31	virtual money

market was designed to forecast the German February 2001 CPI inflation rate. It opened up on 20th October 2000 and was closed on 14th March 2001, soon after February 2001 CPI inflation was announced on 10th March. All transactions were based on real money. Altogether, 44 traders participated in the market, most of which were students of economics and business administration at Dresden University of Technology. While the market was principally open to all interested people, the market was advertised primarily in economics courses at Dresden University of Technology. The total amount of money invested was 1021.62 Euro (23.22 Euro per trader).

The second market (”market II”) was conducted by Dresden Electronic Markets (DEM) at Dresden University of Technology. The CPI inflation rate to be forecasted was the one of December 2001 in Germany. The market opened on 17th October 2001 and closed on 15th January 2002. Altogether, 32 traders took part in the market most of which were again students of economics and business administration at Dresden University of Technology. Again the market was principally open to all interested people. The sum of investments was 414 Euro (12.94 Euro per trader).

Market organizer of the third market (”market III”) was again Dresden University of Technology. The market was designed to forecast the June 2002 CPI inflation rate in Germany. The trading period begun on 23rd April and ended on 11th July 2002. A total number of 47 traders enrolled in the market most of which were again students of economics and business administration at Dresden University of Technology. However, a considerable number of people outside the university took part in the market. The sum of investments was 841 Euro (on average 17.87 Euro per trader).

The last German inflation forecasting market ("market IV") we report on was again organized by Dresden Electronic Markets. The market was designed to forecast the October 2002 CPI inflation rate in Germany. The trading period begun on 26th July and ended on 12th November 2002. A total number of 36 traders took part in the market most of which were identical to the traders in market III. The sum of investments was 288 Euro (on average 8.00 Euro per trader).

A natural alternative to forecasting macroeconomic outcomes as inflation rates is to forecast a central bank's use of its monetary instruments. In order to test in how far experimental markets are capable of assessing the use of monetary policy instruments we conducted an additional market on the main refinancing rate of the European Central Bank (ECB) on 15th January 2003 ("market V"). The market opened up on 13th October 2002 and closed on 14th January 2003. Different from the 4 inflation forecasting markets described earlier in this chapter the ECB market was organized as a virtual money market. Thus, all transactions in the market were done on a virtual money basis. Initially, every trader was endowed with 100 virtual Euro he could use for trading in the market. The three market participants realizing the highest returns on investment were rewarded with 75, 50 and 25 Euro. Altogether, 31 traders were engaged in the market, most of which were again students.

4.2. Mean forecasts and forecast uncertainty

As discussed earlier experimental forecasting markets allow to obtain actual density or mean forecasts at any point in time during the market period. Thus, for every of the four prototype markets we end up with a time series of forecasts $\pi^f_{T,T-t}$ of the same event, i.e. the underlying of the traded contracts π_T at time T. Thus, we deal with so-called fixed-event forecasts.[37]

While we principally can construct mean forecasts of any frequency we work on the basis of daily forecasts since new information on inflation or the main refinancing rate is typically not arriving more often than once a day, if at all. For every market we report

[37] Clements and Hendry (1998).

two types of forecasts. The first forecast, which we will call "last traded prices forecast" (LTP) is based on the prices of the last observed transaction for every contract type at midnight. The second forecast, the so-called "average traded prices forecast" (ATP) is calculated on the basis of the volume-weighted daily average price of every type of contract. When there were no transactions on a certain day, the forecast remains on the previous day's value.

Experiences with previous markets showed that it typically takes several days before trading in the markets begins. On the one hand this is due to the time lag between applying for admittance for a market and transfer of the initial investment on the market account. On the other hand the number of traders in the market is quite low in the beginning of every market, leading to relatively few and unrealistic offers placed in the market queues. We therefore report forecasts not before every contract type has been traded in the market at least once.

As an example, we report the mean market forecasts for ECB's main refinancing rate in the following.[38] During the market period the main refinancing rate was changed once. On 6th December 2002 the rate was lowered by 0.5 percent from 3.25 to 2.75 percent. In figure 3 we show the time series of fixed-event forecasts of the ECB main refinancing rate as derived from market V. It is easy to see that the market performed quite well. From the beginning of the market period on the market predicted a decreasing main refinancing rate. Initially the market predicted a decrease by some 0.25 percent. However, well before the refinancing rate was in fact lowered the market forecast further decreased to around 2.90 percent indicating that ECB might take two steps down on the ladder. After the factual change of the refinancing rate on 6th December the market forecast converged quickly to 2.75 percent and remained there until the market closed.

One of the major advantages of using experimental markets to forecast inflation is that forecasting markets deliver important information on the uncertainty surrounding the mean forecast. This is due to the fact that experimental inflation markets not only

[38] Charts for the time series of mean inflation forecasts derived from markets I-IV are included in the appendix.

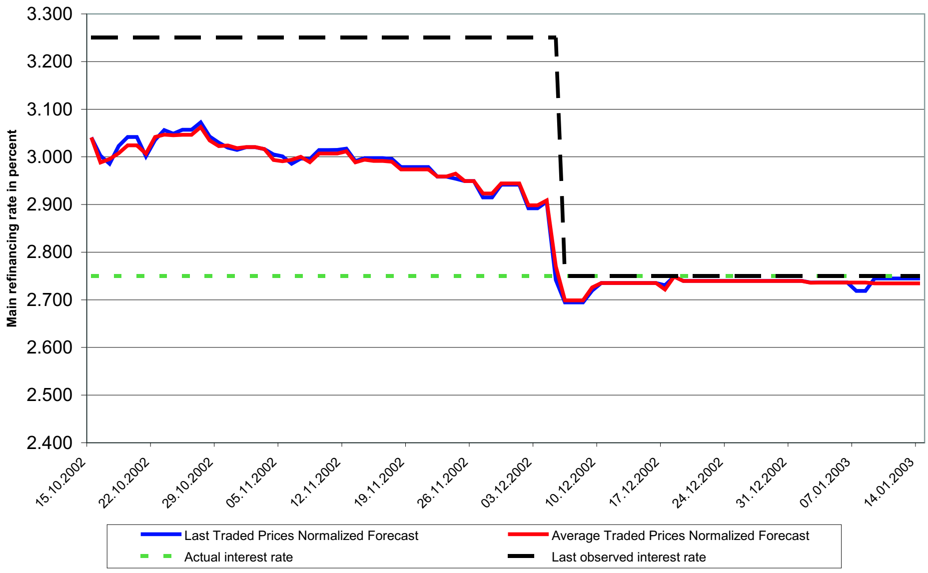

Figure 3. Mean forecast of ECB's main refinancing rate on 15th January 2003.

allow to construct mean forecasts of inflation but also deliver important information on the likelihood of alternative inflation scenarios. As explained earlier, the uncertainty surrounding the mean forecast can easily be assessed by calculating the empirical variance of the forecast.

Since inflation is a somewhat sticky variable, we should expect the empirical variance of the forecasts to decrease throughout the market period. In figure 4 we show the variances of the mean inflation forecasts (LTP) during the market periods.

In fact, there seems to be a decreasing tendency of the empirical variance during the market periods. In order to test for time trends in the forecast variances formally we run OLS-regressions of the type

$$\sigma_t^2 = c + \alpha \cdot t + \epsilon_t$$

for every market (c is the regression constant and ϵ_t the unexplained residual). The existence of a negative time trend implies the coefficient α of the time variable t to be negative. The regression results are reported in table IV. We find highly significant

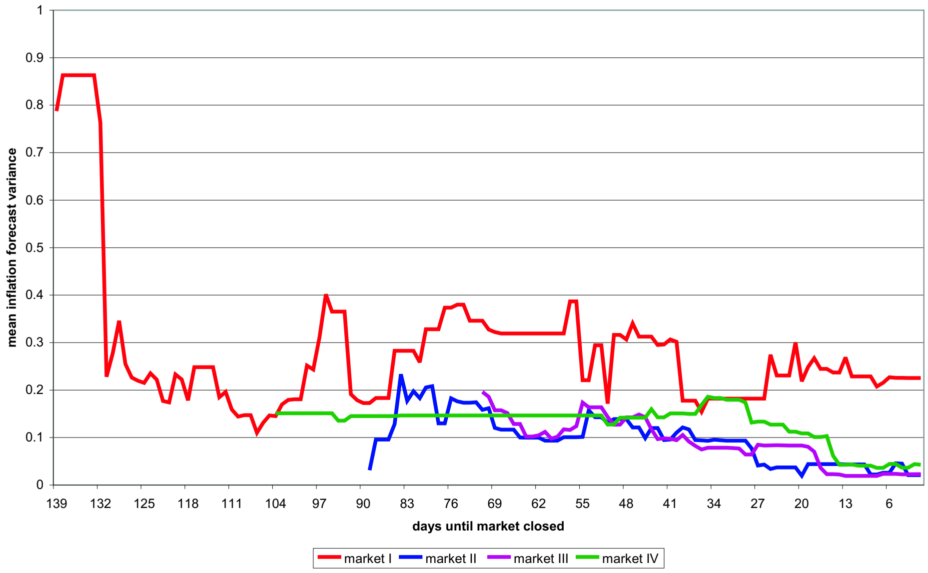

Figure 4. Variances of daily mean inflation forecast (LTP).

negative time trends of the forecast variances for all pilot inflation forecasting markets as well as for the ECB-market.[39]

Table IV. Time trends of inflation forecast variances (LTP).

Market	Constant	T-statistic	Probability	Trend	T-statistic	Probability	Obs.
market I	0.377	15.28	0.00	-0.001	-4.29	0.00	138
market II	0.169	25.25	0.00	-0.002	-12.35	0.00	83
market III	0.165	31.17	0.00	-0.002	-16.32	0.00	72
market IV	0.173	28.75	0.00	-0.001	-8.28	0.00	111
market V	0.102	27.25	0.00	-0.003	-9.23	0.00	90

4.3. Forecast efficiency

Of course, the kind of anecdotal evidence from our pilot markets reported in the previous subsection is insufficient to prove that forecasts generated by experimental forecasting markets are of sufficiently high quality to be used in practice. In order to be able to study the forecasting accuracy of inflation forecasts derived from experimental markets we are

[39] We should note that the results for market I are primarily driven by the excessively high variance in the first days of the active trading period. When excluding the first week of market activity the time trend is still negative but insignificant.

obviously in need of a larger number of cross-section observations which are presently not available.[40] However, forecasting markets can be expected to deliver high quality forecasts only if the markets incorporate newly arriving information in an efficient manner. Thus, instead of analyzing the accuracy of the market forecasts we study in how far the time series of fixed event forecasts as derived from the pilot markets are efficient.

In order to answer this question we make use of the concept of testing for weak efficiency proposed by Nordhaus (1987). Up to now, this concept has rarely been applied to inflation forecasts. One might suggest this to be due to the fact that most existing time series of inflation forecasts are not fixed but rolling event forecasts. One of the rare tests for efficiency of a fixed event time series of price forecasts was conducted by Nordhaus (1987) himself. When analyzing a time series of oil price forecasts collected by Data Resources Inc. he finds significant autocorrelation of forecast revisions. Nordhaus also reports the results of weak efficiency tests of 3 additional time series of fixed event forecasts (forecasts of nuclear capacity, energy forecasts and real GNP forecasts). Similarly, the forecast revisions turn out to be autocorrelated. Nordhaus interprets his finding that most of the significant autocorrelations are positive as an indication that the hypothesis of social psychologists that people tend to hold on to prior views too long (see Tversky and Kahneman (1981)) might be correct.

Recently Bakhshi, Kapetanios and Yates (2003) studied the efficiency of 7 time series of fixed event inflation forecasts. The forecasts were constructed by Meryll Lynch from a survey of about 70 fund managers. Respondents had to predict the annual increase in the U.K. Retail Price Index at December 1994, 1995, 1996 and 1997 and the annual increase in the U.K. RPIX index at December 1998, 1999 and 2000. The surveys were conducted monthly providing a database of 23 forecasts per event. Bakhshi, Kapetanios and Yates reject the hypothesis that the forecast errors are uncorrelated with past revisions for 5 out of 7 time series of fixed event forecasts. Similarly 2 of the time series exhibit autocorrelation of forecast revisions.

[40] For a study of forecasting accuracy of political stock markets see Berlemann and Schmidt (2001).

The major problem of the studies by Nordhaus (1987) and Bakhshi, Kapetanios and Yates (2003) is the relatively low number of observations per time series of fixed event forecasts. The time series generated by experimental forecasting markets are considerably longer since they principally allow to generate continuous inflation forecasts. Thus, these time series provide an excellent database to study the efficiency of the forecasts.

We start out with analyzing in how far the forecast errors constructed by market prices are correlated with past forecast revisions. We therefore run the OLS regression

$$x_\tau - x_t^f = \alpha_0 + \alpha_1 \cdot (x_{t-1}^f - x_{t-2}^f) + \alpha_1 \cdot (x_{t-2}^f - x_{t-3}^f) + \epsilon_t, \tag{1}$$

with x being the variable to be forecasted. The results are shown in table V. For all markets and all forecasts we find a highly significant constant indicating that the forecasts are biased. However, different from tests on rationality of rolling event forecasts, such a bias is no sign of inefficiency of fixed event forecasts. None of the forecasts shows significant first- or second-order correlation with past forecast revisions. Thus, they all pass the first test on efficiency.

In a second test of efficiency we study in how far the forecast revisions are autocorrelated. We therefore run the OLS regression

$$x_t^f - x_{t-1}^f = \beta \cdot (x_{t-1}^f - x_{t-2}^f) + \epsilon_t. \tag{2}$$

The results for both LTP and ATP forecasts are reported in table VI. For none of the forecasts we find significant positive[41] first-order correlation, indicating that the market forecasts incorporate newly arriving information in an efficient manner.

Altogether, the results indicate that the markets were quite efficient in disseminating information. One might be somewhat optimistic therefore that experimental markets are capable of generating high quality inflation forecasts.

[41] We should note that we found a significantly negative coefficient for the ATP forecast in market 1. However, since the coefficient is negative the reason for this can hardly be that traders stick to their expectations for too long.

Table V. Correlation between forecast errors and past forecast revisions.

Market	Forecast ype	Constant (t-value)	$x_{t-2}^f - x_{t-1}^f$ (t-value)	$x_{t-3}^f - x_{t-2}^f$ (t-value)
Market I	LTP	-0.45	0.45	0.31
		$(-48.62)^{**}$	(2.32)	(1.63)
Market I	ATP	-0.44	0.38	0.14
		$(-46.20)^{**}$	(2.13)	(0.83)
Market II	LTP	0.29	0.69	0.64
		$(11.20)^{**}$	(1.44)	(1.36)
Market II	ATP	0.28	0.95	0.91
		$(11.62)^{**}$	(1.48)	(1.46)
Market III	LTP	0.59	0.42	0.40
		$(16.95)^{**}$	(0.50)	(0.47)
Market III	ATP	0.60	0.45	0.49
		$(16.76)^{**}$	(0.48)	(0.52)
Market IV	LTP	-0.24	0.54	0.50
		$(-16.18)^{**}$	(0.98)	(0.90)
Market IV	ATP	-0.24	0.55	0.49
		$(-16.30)^{**}$	(0.96)	(0.86)
Market V	LTP	0.19	-1.22	-1.54
		$(6.83)^{**}$	(-1.01)	(-1.27)
Market V	ATP	0.17	-1.18	-1.53
		$(6.11)^{**}$	(-0.85)	(-1.10)

** significant on a 99%-confidence-level
* significant on a 95%-confidence-level

4.4. Forecast distribution and further applications

It was already shown that experimental inflation forecasting markets allow to calculate a mean forecast and its variance (or standard deviation) at any point in time during the market period. In addition, for any point in time we can visualize the market's actual evaluation of the probability of different inflation realizations in a histogram. We might illustrate this at the example of data from the February 2001 inflation market. In figure 5 we show the empirical distribution of the February 2001 LTP inflation forecast of 12th December 2000. For every contract we have one observation which refers to the last observed transactions.

An inspection of the histogram suggests that inflation expectations might be normally distributed. When extending the inspection to a larger number of days at different points

Table VI. First-order autocorrelation of forecast revisions.

Market	Forecast type	$x^f_{t-2} - x^f_{t-1}$	T-value	Significance
Market I	LTP	0.12	1.39	0.17
Market I	ATP	-0.18	-2.22	0.03*
Market II	LTP	0.12	1.10	0.27
Market II	ATP	-0.03	-0.32	0.75
Market III	LTP	-0.06	-0.49	0.63
Market III	ATP	-0.14	-1.18	0.24
Market IV	LTP	0.04	0.40	0.69
Market IV	ATP	0.05	0.51	0.61
Market V	LTP	0.12	1.23	0.22
Market V	ATP	0.17	1.67	0.09

** significant on a 99%-confidence-level
* significant on a 95%-confidence-level

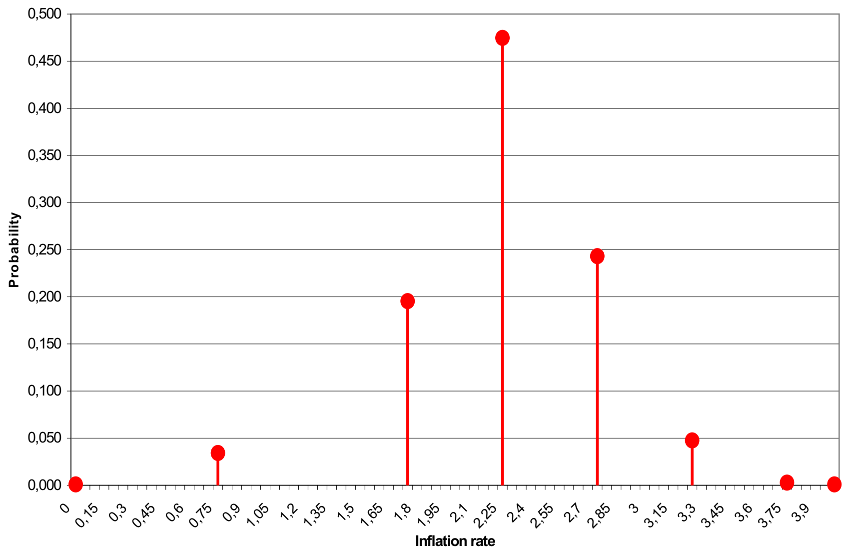

Figure 5. Distribution of February 2001 inflation forecast on 12th December 2000.

in time during the market period and to the other markets this suggestion is substantiated. However, because of the relatively low number of observations per forecast we are not able to test for this hypothesis formally.

Obviously, knowing the distributional form of the market inflation forecasts would be highly valuable since we would be able to make more precise statements about the probability of different inflation scenarios. Knowledge on the distributional form of the forecast together with our empirical assessment of its mean and variance would enable us (i) to calculate the probability for every inflation scenario that might be of interest, even if no contract in the market has been traded for the referring interval and (ii) to construct forecast confidence intervals.

5. Summary and outlook

Altogether our experiences with the reported pilot forecasting markets reinforced our initial expectation that experimental markets are a highly useful forecasting tool not only for political events as elections but also for realizations of macroeconomic variables like inflation. Given the relatively low number of participants with comparably low degrees of information the markets performed quite well and delivered not only reasonable mean forecasts of inflation but also valuable information on the probability of different inflation scenarios. However, to substantiate our view that experimental markets can fill a gap in existing forecasting techniques many additional markets have to be conducted and evaluated.[42]

It would be an interesting task to run and evaluate experimental forecasting markets with longer time-horizons, such as one or even several years. However, to organize and conduct medium- or long-term inflation forecasting markets is not too easy because of at least two reasons. First, the markets can not be liquidated before the event, the market is conducted on, has realized. Thus, when running a forecasting market on the two-year ahead inflation rate, what is technically possible, the market participants receive their payoffs after the same period of time. While the market organizer could invest the initial investments in some interest bearing asset and pay some interest on the payoffs it is nevertheless not easy to motivate participants to take part in a market with such a long time horizon. Second, when running medium- but especially long-term markets a high

[42] We should remind of the fact that it took about ten years of experimental markets research before first empirical cross-section studies of the relative performance of political stock markets could be conducted. See e.g. Berlemann and Schmidt (2001) and Berg, Forsythe and Rietz (1997).

degree of confidence between the market organizer and the market participants is necessary. Thus, there has to be some institutional background guaranteeing the liquidation procedure.

In order to motivate traders to engage even in medium-term markets one could combine short-term markets with medium-term ones. First experiences with such a staggered system of forecasting markets have been made in a series of markets conducted throughout 2002 in Bulgaria.[43] The fact that almost all traders engaged in the short-term markets, also took part in the medium-term markets is quite promising. Thus, building up a regular forecasting system allowing for both short-term and medium-term forecasts seems to be a fruitful task. Doing so would allow to evaluate the forecasts constructed from experimental forecasting markets in a more systematic way.

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[43] See Berlemann, Dimitrova and Nenovsky (2003).

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Appendix

A. Unit portfolios

Table VII shows the unit portfolio used in market I. There were initially eight binary lock-in options in the market. On November 22, the contract "$\pi(2.0-2.5)$" was split into two contracts "$\pi(2.0-2.25)$" and "$\pi(2.25-2.5)$". Therefore, each participant who held former "$\pi(2.0-2.5)$"-contracts in his portfolio was endowed with the same number of the two new contracts. Thus, the expected value of the participants' portfolios was not influenced by the contract split. The contract split was done because it was observed that the former "$\pi(2.0-2.5)$"-contract had been traded for quite high prices, thus indicating that the participants attached a high probability to the event that the inflation rate would have been in between 2.0 and 2.5 percent.

The unit portfolios of markets II-IV are shown in tables VIII-X.

Table VII. Traded contracts in market I.

Contract number	Contract name	Interval middle/limit	Pays off 1 Euro, if
1	$\pi(0.0-)$	0.000	$\pi < 0.0$
2	$\pi(0.0-1.5)$	0.750	$0.0 \leq \pi < 1.5$
3	$\pi(1.5-2.0)$	1.750	$1.5 \leq \pi < 2.0$
4	$\pi(2.0-2.5)$	2.250	$2.0 \leq \pi < 2.5$
5	$\pi(2.5-3.0)$	2.750	$2.5 \leq \pi < 3.0$
6	$\pi(3.0-3.5)$	3.250	$3.0 \leq \pi < 3.5$
7	$\pi(3.5-4.0)$	3.750	$3.5 \leq \pi < 4.0$
8	$\pi(4.0+)$	4.000	$4.0 \leq \pi$

Table VIII. Traded contracts in market II.

Contract number	Contract name	Interval middle/limit	Pays off 1 Euro, if
1	$\pi(1.0-)$	1.000	$\pi < 1.0$
2	$\pi(1.0 - 1.5)$	1.250	$1.0 \le \pi < 1.5$
3	$\pi(1.5 - 1.75)$	1.625	$1.5 \le \pi < 1.75$
4	$\pi(1.75 - 2.0)$	1.875	$1.75 \le \pi < 2.0$
5	$\pi(2.0 - 2.5)$	2.250	$2.0 \le \pi < 2.5$
6	$\pi(2.5 - 3.0)$	2.750	$2.5 \le \pi < 3.0$
7	$\pi(3.0 - 3.5)$	3.250	$3.0 \le \pi < 3.5$
8	$\pi(3.5+)$	3.500	$3.5 \le \pi$

Table IX. Traded contracts in market III.

Contract number	Contract name	Interval middle/limit	Pays off 1 Euro, if
1	$\pi(1.0-)$	1.000	$\pi < 1.0$
2	$\pi(1.0 - 1.25)$	1.125	$1.0 \le \pi < 1.25$
3	$\pi(1.25 - 1.5)$	1.375	$1.25 \le \pi < 1.5$
4	$\pi(1.5 - 1.75)$	1.625	$1.5 \le \pi < 1.75$
5	$\pi(1.75 - 2.0)$	1.875	$1.75 \le \pi < 2.0$
6	$\pi(2.0 - 2.25)$	2.125	$2.0 \le \pi < 2.25$
7	$\pi(2.25 - 2.5)$	2.375	$2.25 \le \pi < 2.5$
8	$\pi(2.5 - 3.0)$	2.750	$2.5 \le \pi < 3.0$
9	$\pi(3.0 - 4.0)$	3.500	$3.0 \le \pi < 4.0$
10	$\pi(4.0+)$	4.000	$4.0 \le \pi$

Table X. Traded contracts in market IV.

Contract number	Contract name	Interval middle/limit	Pays off 1 Euro, if
1	$\pi(0.0-)$	0.000	$\pi < 0.0$
2	$\pi(0.0 - 0.5)$	0.250	$0.0 \le \pi < 0.5$
3	$\pi(0.5 - 0.75)$	0.625	$0.5 \le \pi < 0.75$
4	$\pi(0.75 - 1.00)$	0.875	$0.75 \le \pi < 1.00$
5	$\pi(1.00 - 1.25)$	1.125	$1.00 \le \pi < 1.25$
6	$\pi(1.25 - 1.75)$	1.500	$1.25 \le \pi < 1.75$
7	$\pi(1.75 - 2.25)$	2.000	$1.75 \le \pi < 2.25$
8	$\pi(2.25+)$	2.250	$2.25 \le \pi$

Table XI. Traded contracts in ECB market.

Contract number	Contract name	Interval middle/limit	Pays off 1 virtual Euro, if
1	$r(2.25-)$	2.250	$r \leq 2.25$
2	$r(2.50)$	2.500	$r = 2.50$
3	$r(2.75)$	2.750	$r = 2.75$
4	$r(3.00)$	3.000	$r = 3.00$
5	$r(3.25)$	3.250	$r = 3.25$
6	$r(3.50)$	3.500	$r = 3.50$
7	$r(3.75)$	3.750	$r = 3.75$
8	$r(4.00)$	4.000	$r = 4.00$
9	$r(4.25+)$	4.250	$r \geq 4.25$

The contracts traded in market V are shown in table XI. The contracts were designed symmetrically around the main refinancing rate prevailing when the market opened up (3.25 percent). To understand the design of contracts it should be noted that the main refinancing rate is varied only by multiples of 0.25 percent.

B. Mean forecasts

Figures 6, 7, 8 and 9 show the mean inflation forecasts constructed from market I, II, III and IV.

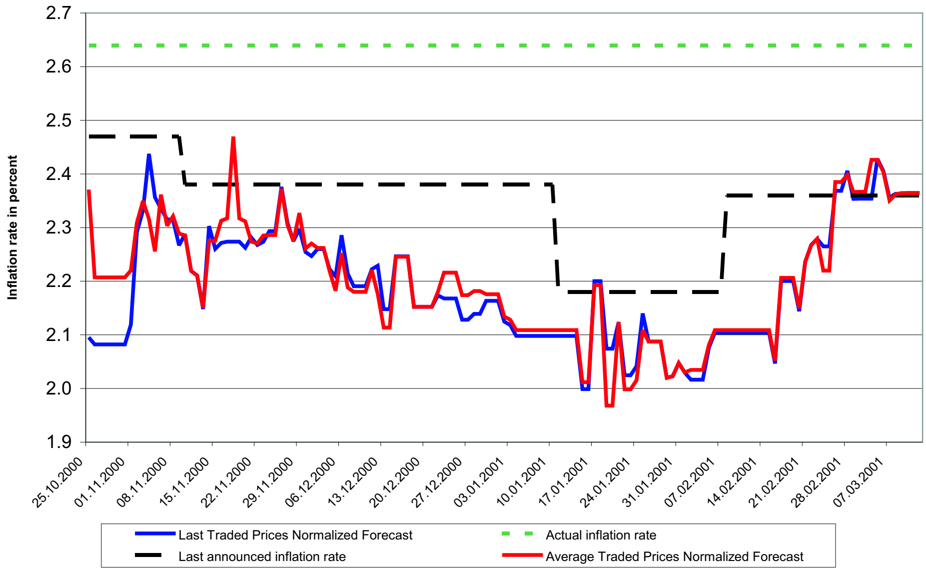

Figure 6. Mean inflation forecast for February 2001.

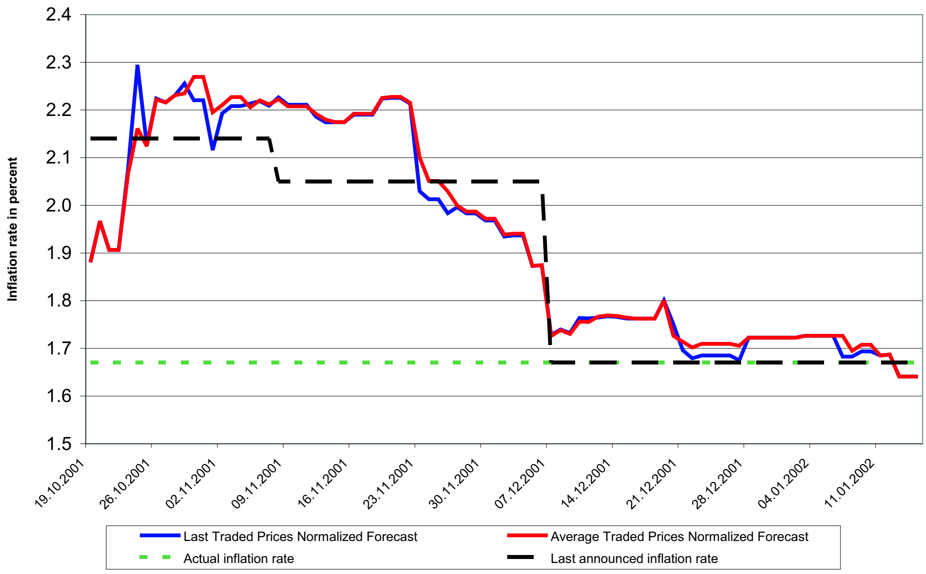

Figure 7. Mean inflation forecast for December 2001.

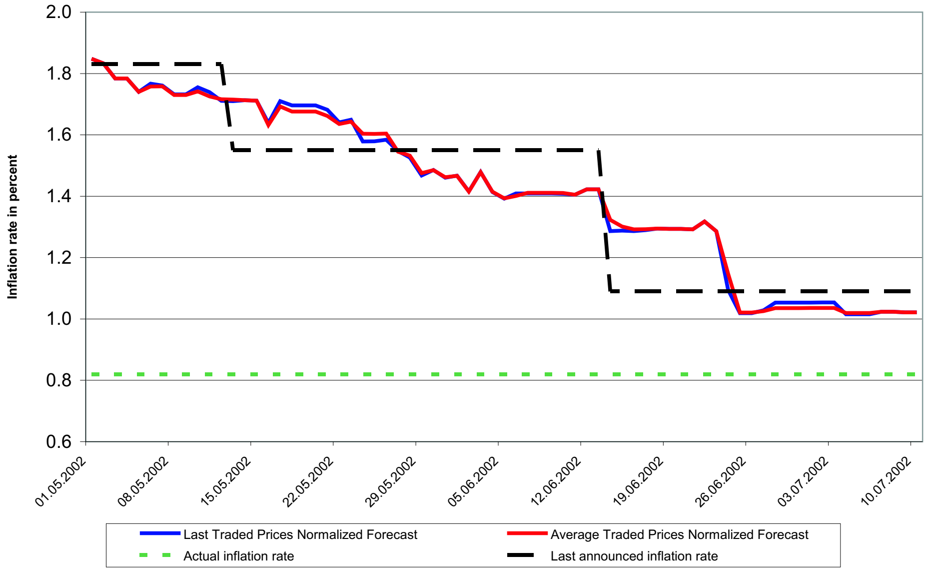

Figure 8. Mean inflation forecast for June 2002.

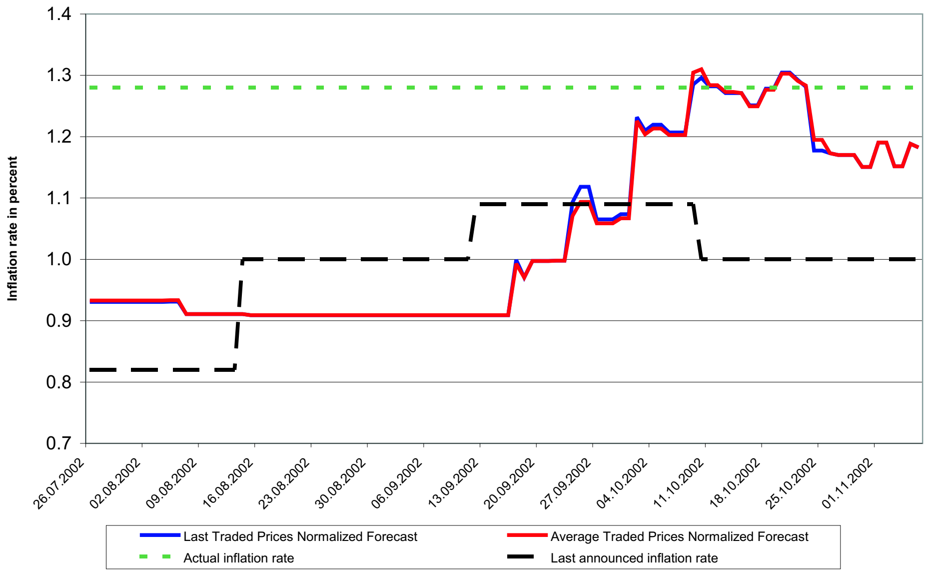

Figure 9. Mean inflation forecast for October 2002.

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