Participation, Feedback & Incentives in a Competitive Forecasting Community

Completed Research Paper

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Abstract

Macroeconomic forecasts are used extensively in industry and government despite the lack of accuracy and reliability. Prediction markets as a community forecasting method have begun to gain interest in academia industry alike. An open question is how to design incentive schemes and feedback mechanisms to motivate online communities to contribute and thereby increase the predictive power of the market. We design a prediction market for macroeconomic variables that aggregates information from a cross-section of participants. We analyze participation and feedback in this online community. We show that a weekly newsletter that acts as a reminder drives participation. In public goods projects participation feedback has been found to increase participants' contributions. We find that the competition inherent in markets appears to dominate classical feedback mechanisms. We show that forecast errors fall over the prediction horizon. The market-generated forecasts compare well with the Bloomberg- survey forecasts, the industry standard. Additionally we can predict community forecast error using an implicit market measure.

Keywords: Feedback, Incentives, Macro-economic Forecasting, Prediction Markets,

Introduction

Important policy decisions are made based on the forecasts for economic variables (GDP, unemployment, exports). It is a well-established fact that traditional economic forecast models lack accuracy (Osterloh 2008; McNees 1992; Schuh 2001). The current approaches mix expert knowledge with historic extrapolation and models of the economy. They are often found to be inadequately able to capture rapid economic changes. The last financial crisis demonstrated the drawbacks of economic forecasting. Weeks after Lehman Brothers filed for bankruptcy protection, the consensus opinion was for a 2 % increase in German GDP for 2009. In 2009 German GDP dropped by 4.5%. Another issue is the reliance of the current forecasts on expert input. Experts are prone to biases and political influence and generally do not perform better than novices in forecasting future events (Armstrong 2008). Due to the reliance on personal judgments, forecasts have been found to exhibit a bias towards optimism when the trend changes (Batchelor, 2007). In Germany forecasts are produced by numerous institutions and released on a periodical basis. Thus a pure forecast consumer (e.g. decision maker) might find it difficult to aggregate the various forecasts and come to a confident appraisal. Internet communities offer the advantage of instant information exchange and group decision making that is difficult in other settings. But, how can online communities be designed to facilitate information aggregation on macro-economic variables? Further, how can incentives schemes be designed to motivate participants to contribute and share their information?

Over the last couple of years prediction markets as a forecasting method have gained interest in academia and industry. They facilitate and support decision making through aggregating expectations about events (Hahn and Tetlock, 2006). The roots of their predictive power are twofold; the market provides the incentives for traders to truthfully disclose their information and an algorithm to weight opinions (Arrow et al., 2008). We thus setup a prediction market for economic variables called Economic Indicator Exchange (EIX). The EIX play money prediction market is specifically designed to continuously forecast economic indicators such as GDP, inflation, IFO index, investments, exports, and unemployment figures in Germany. In order to build a sustainable community with continuous participation we design and test an incentive scheme for long-lasting play-money prediction markets. We also evaluate the effect of feedback mechanisms on activity level in a market-based system. Finally, by comparing market forecasts to 'Bloomberg' survey forecasts we show the potential of markets as information aggregation tools.

The remainder of this paper is structured as follows: The second section gives a brief review of previous markets for economic variables. Furthermore incentives schemes and feedback for information exchanges are discussed. The third section presents the IS-artifact and details the field experiment setting. Section four summarizes the research questions. The subsequent section evaluates the IS-artifact from a forecasting perspective. In Section six we conclude.

Related Work

Prediction markets as online communities

A common approach to economic forecasting is to identify experts to make predictions. These experts use statistical models combined with heuristics, which are based on an expert's experience and intuition. However experts are prone to biases and political influence and generally do not perform better than novices in forecasting future events (Armstrong 2008). Furthermore macro-economic forecasts suffer from imitation behavior (Osterloh, 2008). Group decision making is a technique often applied to deal with these limitations. Internet communities offer the advantage of instant information exchange and group decision that is not possible in a real-life. An arising question is how to build and maintain internet communities to forecast macro-economic variables. Furthermore how can informed people be motivated and incentivized to participate in information sharing and collaboration? A certain type of online communities, so called prediction markets have emerged as a forecasting tool for wide range of applications.

Prediction markets facilitate and support decision making through aggregating expectations about events (Hahn and Tetlock, 2006). In most cases they allow anonymous participation, which may increase the likelihood of nonconformist to participate and reveal information. The roots of their predictive power are twofold; the market provides the incentives for traders to truthfully disclose their information and an algorithm to weight opinions (Arrow et al., 2008). Previous work showed that same principles apply in play-money prediction markets in which prizes are shuffled among top performing traders (Rosenbloom and Notz, 2006).

The most basic trading mechanism for prediction markets is based on a continuous double auction for one stock which represents the outcome of an event. The stock will pay 1 if an event has the predicted outcome and else the stock will be worthless. Market participants form expectations about the outcome of an event. Comparable to financial markets, they buy if they find that prices underestimate the event in question and they sell a stock if they find that prices overestimate the probability of an event. Thus communication in such a system is limited to the market language; bids and offers.

Markets for Economic Derivatives

Financial markets for macro-economic variables have been used since the 80s. The Coffee, Sugar and Cocoa Exchange established a futures market on the consumer price index allowing traders to hedge on inflation. The market, however, was closed due to low interest (Mbemap 2004). In 1993 Robert Shiller argued for the creation 'Macro Markets' which would allow a more effective risk allocation (Shiller 1993). In an attempt to set up a market to predict economic variables in 2002 Goldman Sachs and Deutsche Bank created the so called 'Economic Derivatives' market. It tries to predict macro-economic outcomes such as ISM Manufacturing, change in Non-Farm Payrolls, Initial Jobless Claims and consumer price index (Gadanecz et al., 2007). The traded contracts are securities with payoffs based on macroeconomic data releases. The instruments are traded as a series (between 10-20) of binary options. For example a single data release of the retail sales in April 2005 was traded as 18 stocks. In order to maximize liquidity the market operators use a series of occasional Dutch auctions just before the data releases instead of the more common continuous trading on most financial markets. Thus the market provides hedging opportunities against event risks and a short horizon market forecast of certain economic variables. By analyzing the forecast efficiency Gurkaynak and Wolfers (2006) find that market generated forecasts are very similar but more accurate than survey based forecasts[1].

In an attempt to forecast inflation changes in Germany, Berlemann and Nelson (2005) set up a series of markets. The markets feature continuous trading of binary contracts. In a similar field experiment Berlemann et al. (2005) use a similar system in order to aggregate information about inflation expectations in Bulgaria. All in all, the reported forecasts results in both experiments are mixed but promising.

Feedback & Incentive schemes in online markets

Prediction markets work by incentivizing information revelation and participation. Hence traders can be rewarded based on their performance which is directly linked to the quality of their contributions. There are two common ways to set incentives in prediction markets. In real money markets traders invest money and gain directly like in financial markets. Due to the legal restrictions on gambling, setting up a real-money market incurs huge technical and regulatory costs. As an alternative, market operators can set up play money prediction markets. Instead of real money, participants are endowed with a virtual currency. Previous research has shown that play-money markets perform as well as real-money markets predicting future events (Wolfers and Zitzewitz, 2004; Rosenbloom and Notz, 2006). In order to encourage participation and information revelation market operators shuffle prizes, according to incentives schemes. Luckner and Weinhardt (2007) study the impact of three different incentive schemes on prediction accuracy in short-term laboratory experiments. They find that a rank-order scheme outperforms a fixed payment incentive scheme and surprisingly a performance-compatible payment. It remains unclear how participants can be incentivized in long term field prediction markets.

A common way to increase participants' intrinsic motivation to contribute to public goods projects is to give user feedback and recognition. Cheshire and Antin (2008), as well as a study conducted by Ling et al. (2005), try to raise user contribution in online communities through feedback mechanisms. Many motivational theories in psychology include a feedback component such as the goal setting theory from Locke (2001). According to Cheshire and Antin (2008), there are three different feedback mechanisms which are assumed to lead to an increased contribution rate.

- *Gratitude* is a simple 'Thank you'-message displayed after a contribution. Beenen et al., (2004) find that sending a one-time 'thank-you' email can raise contributions.

- A *Historical Reminder* is a feedback mechanism, which informs the participant about the number of individual contributions. According Cheshire and Antin (2008), this may help the user to think about his own past contribution behavior.

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[1] One must note that the Bloomberg survey forecasts are published on Fridays before the data release, whereas the auction was run -and the forecast was generated- on the data release day.

- *Relative Ranking* displays the contribution frequency compared to peers. The knowledge about cumulative group behavior can be beneficial to the production of a public good, like contributions to a Wiki (Cheshire 2007).

Additionally one might consider using *social ranking* feedback, which illustrates a ranking within a group of users who created a similar number of contributions. One might argue that information about individuals with a similar ranking, and therefore the same amount of contributions, leads to an increase in social competition, and therefore, positively impacts the motivation to contribute. However -to our knowledge- social rankings have not been tested yet. As most work on the effect of feedback mechanisms on user participation and contribution relates to cooperative environments such as public Wikis, it remains unclear if and how the effects can be reproduced in more competitive environments such as electronic markets.

An economic indicator exchange

In October 2009 a play money prediction market was launched specifically designed to forecast economic indicators such as GDP, inflation, investments, export and unemployment figures in Germany. The goal is to forecast the indicators over longer time periods in advance and continuously aggregate economic information. The market called Economic Indicator Exchange (EIX)[2] was launched in cooperation with the leading German economic newspaper 'Handelsblatt'. The cooperation aims at reaching a wide and well informed audience interested in financial markets and economic development. We thus expect no problems understanding the indicators and the concept of trading. The market is publicly available over the Internet and readers where invited to join. The registration is free and requires besides a valid email address just minimal personal information.

Market & contract design

The market design features a continuous double auction without designated market maker. Participants are allowed to submit marketable limit orders with 0.01 increments through the web-based interface. After registration participants are endowed with 1,000 stocks of each contract and 100,000 play money units. We propose to represent continuous outcomes with one stock and define a linear payout function. Contracts for each economic indicator are paid out according to equation 1.

$$p = 100 + \alpha \times (\frac{I_{t0} - I_{t-1}}{I_{t-1}})\ with\ \alpha = 10 \qquad (1)$$

A contract is worth: 100 +/- α times the percentage change for an indicator in play money (e.g. a change of 2.1 % results in a price of 121). We set α to 10. Therefore the representable outcome ranges from -10% to infinity. To represent the whole outcome range from -100% to infinity α could be set to one. Previous work indicates that market participants find it difficult to estimate minor changes in the underlying (Stathel et al. 2009). Hence we propose to scale the minor changes to a certain level. Looking at historical data there were no events where German GDP dropped 10% per quarter. The rationale for setting α to 10 was the deliberation that participants find it more intuitive to enter integers in order to express reasonable accuracy. Additionally German statistical data releases rarely come with more than one decimal.

Table 1 summarizes the economic variables tradable on the market. Due to the payout function and the selection of the corresponding units; all stock prices are expected to roughly range between 50 and 150. Therefore participants could similarly gain by investing in specific indicators. The indicators are a mix of leading -forecasting the economy- (e.g. Investments) and lagging -describing the state of the economy- (e.g. Unemployment numbers) economic indicators. To facilitate longer forecast horizons every indicator is represented by three independent stocks each representing the next three data releases (t_1, t_2, t_3). As a consequence the initial forecast periods vary between one month for monthly released indicators and up to 3 quarters for quarterly released variables. One day before the release date the trading in the concerned

[2] www.eix-market.de

stock is stopped. Finally the stocks are liquidated according to the payout function defined in equation 1. As soon as the trading in one stock stops, a new stock of the same indicator (e.g. t_4) is introduced into the market. This means that participants received 1000 new stocks of the respective indicator. All in all participants are able to continuously trade 18 stocks at all times.

A ranking of all the traders sorted by their deposit value, i.e. the balance of their cash account plus the value of the contracts they held at the specific point in time, is not part of the trading screen but is separately displayed on the EIX web portal. Available account information for individual traders includes the number of shares held in each contract, the balance of the cash account, the total value of their deposit, a list of outstanding buy and sell orders, as well as a list of trades. The portal also provides more information on the prizes traders can win; the operational principle of the prediction market including a video tutorial and frequently asked questions, as well as up-to-date news stream related to the German economic development.

Table 1: Economic variables

Indicator	Unit	Data Release Cycle	Payout Number	Payout Function
Exports	%-Changes	monthly	12	$100 + \alpha \times (\frac{I_{t0} - I_{t-1}}{I_{t-1}})$
GDP	%-Changes	quarterly	4	$100 + \alpha \times (\frac{I_{t0} - I_{t-1}}{I_{t-1}})$
IFO Index	ABS-Changes$_{t-1}$	monthly	3	$100 + \alpha \times (I_{t0} - I_{t-1})$
Inflation	%-Changes$_{t-12}$	monthly	11	$100 + \alpha \times (\frac{I_{t0} - I_{t-12}}{I_{t-12}})$
Investments	%-Changes$_{t-1}$	quarterly	5	$100 + \alpha \times (\frac{I_{t0} - I_{t-1}}{I_{t-1}})$
Unemployment	Million (ABS)	monthly	12	$100 + \frac{ABS(Number)}{100.000}$

Trading Interface

The trading interface is displayed in figure 1. Participants have convenient access to the order book with 10 accumulated levels of visible depth (I1), the price development (I2), the account information (I3) and market information (I4) such as the last trading day. As additional information the Handelsblatt provides access to an up-to-date economic news-stream (I5) and finally the indicator's last year's performance (I6) is displayed. Participants are able to customize their trading interface individually. By clicking the small arrows the six information panels open and close. In the default setting, only the trading mask and the six headlines are visible. After each submitted order the chosen interface is saved per user. On user return the system opens the previously used interface elements on default. Moreover, a short description of the market comprising the respective payoff function is shown as part of the trading screen.

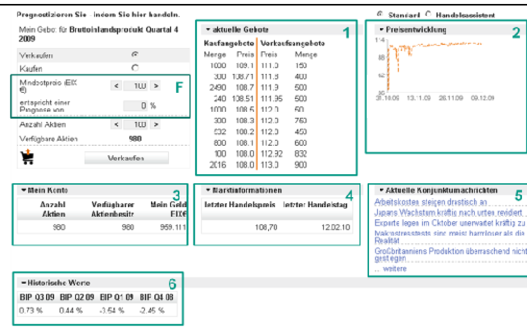

Figure 1. Trading screen with open information panels and feedback mechanism

Incentives

As mentioned, the market is a free to join play money market. In order to motivate participants intrinsically we provided two interface features; traders could follow their performance on a leader board and they could form groups with others to spur competition with friends. To increase participants' motivation and to provide incentives to contribute information we hand out prizes worth 36,000 Euro. In order to be useful, an accurate prediction must be determined well in advance of the actual outcome. It makes little sense to run a market where one obtains the prediction just before the actual outcome occurs. This sounds obvious, but it is actually quite difficult to achieve, because traders want to know how their 'investment' turned out, fairly quickly. As we try to forecast longer periods the incentive scheme has to address this problem. So the incentives are divided in two parts (a) monthly prizes and (b) yearly prizes. The 8 yearly prizes (total value 10,000 Euro) are handed out according to the portfolio ranking at the end of the market. The monthly prizes are shuffled among participants who fulfill two requirements for the respected month: (i) they increase their portfolio value and (ii) they actively participate by submitting at least five orders. Both incentives are clearly communicated through the interface. For the yearly prizes the leader board indicates the current status of all participants. The monthly winning status is displayed individually just after each login.

Feedback

In our market setting we distinguish between three types of feedback:

- Interface feedback
- Market-based feedback
- Participation feedback

The first feedback type is directly communicated through the trading interface. If participants enter a limit price another field displays the related prediction for that price. Vice versa, participants can change their prediction and see that the related price adapts automatically (See figure 1, F). This feature helps to communicate the complex contract design previously described.

Market based feedback is communicated on various levels. First of all, contract prices reflect the current aggregated belief of other market participants. Moreover, the orderbook displays (e.g. with a high spread) the current market confidence about a certain event. Finally, after contracts are liquidated, participants can easily follow their own contribution in relation to their peers. This confronts forecasters with their own forecasting performance. Additionally, as good forecasters increase their portfolio value they gain more weight over market run-time.

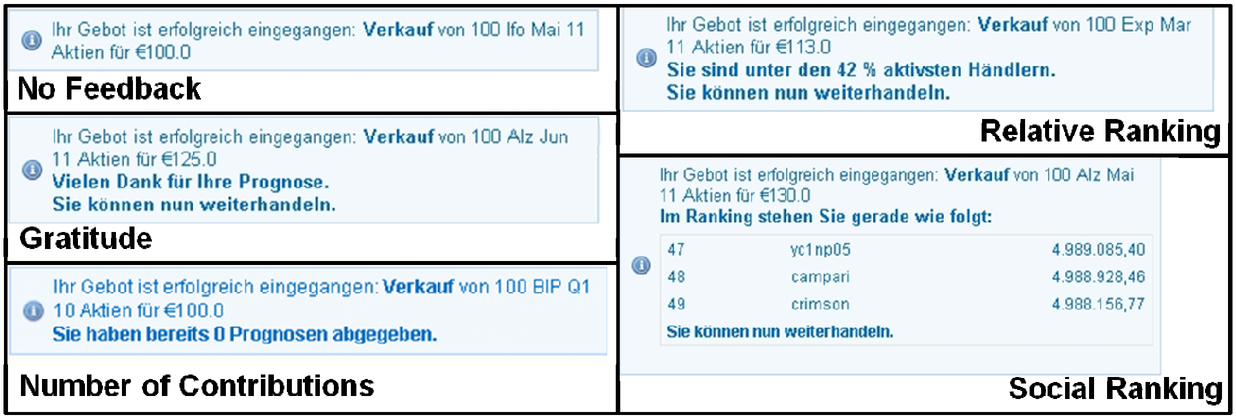

Figure 2: Participation feedback

Participation feedback is communicated directly after a user submits an order. Figure 2 depicts the different participation feedback types. The *No Feedback* type confirms the user interaction and only summarizes the offer properties. The *Gratitude* adds a Thank you for your prediction message. The third feedback just prints the number of contributions. The *relative ranking* feedback displays the contribution frequency compared to peers. Finally the last feedback type (*social ranking)* displays a short part of the overall ranking list. We created six treatment groups. We used the four feedback mechanisms described in the last section. Additionally we added a control treatment group with no feedback and a randomized treatment group, which sees randomly one of the four feedback types after each submitted bid.

Software architecture

In addition to the key design elements of the EIX prediction market described, one also has to design the web-based trading software as well as the facilities handling information about the traders' accounts, the order matching and quote updates from a technical point of view.

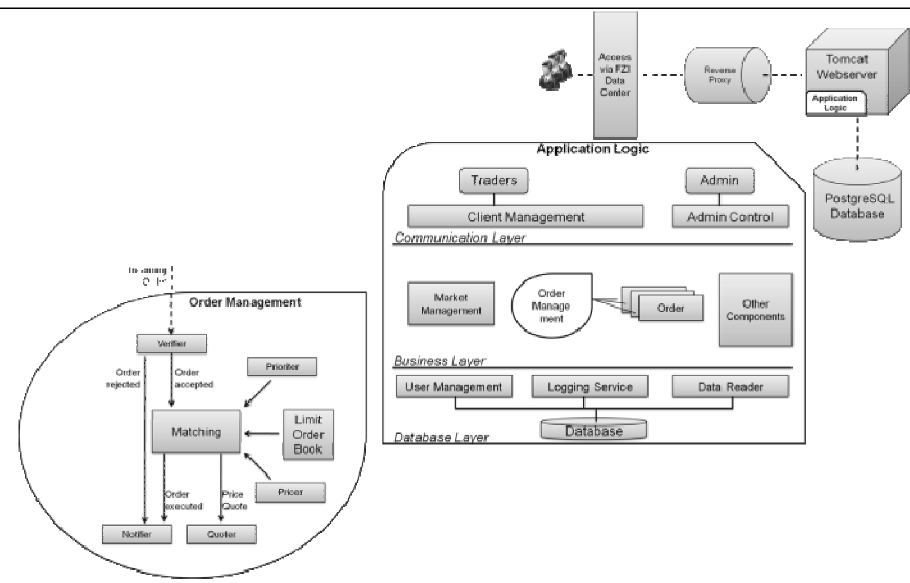

Figure 3: Software system

The EIX prediction market software is an advancement of two previously run (Stathel et al. 2009). The system is implemented in Grails. It features a modularized architecture in order to keep it easy to maintain and expendable by services and functionality. Due to the previously unknown number of users the software platform has to be scalable. Figure 2 summarizes the whole system from three perspectives; IT-infrastructure, application logic and the core order management. The *IT-infrastructure* is provided by the Forschungszentrum Informatik, Karlsruhe (FZI), it consists of three physical servers; a Squid reverse proxy -caching the static pages, a designated PostgreSQL server for the database and a tomcat application server -running the application logic. The *application logic* has been set up following the model-view-controller concept. Therefore it is separated in three layers; one handling the external communication e.g. the website presentation, one for the internal database querying and finally one running the core order processing. As the core element the *order management* processes all incoming orders. The EIX market employs the commonly used trading mechanism; the continuous double auction (CDA). In a CDA known e.g. from the Deutsche Börse system Xetra, traders submit buy and sell orders which are executed immediately if they are executable against orders on the other side of the order book (Madhavan 1992). If orders are not immediately executable, orders are queued in an order book and remain there until they are matched with a counter-offer, or are actively deleted by either the market operator or the submitting participant. Orders are executed according to price/time priority, i.e. buy orders with a higher limit and vice versa sell orders with a lower limit take priority. In case several orders were placed with the same limit price, the orders which were submitted earlier are executed first. One of the main advantages of using a CDA is the fact that markets with a CDA pose no financial risk for market operators as they are a zero-sum game. Moreover, the CDA allows for continuous information incorporation into prices and consequently traders are capable of quickly reacting to events.

Research Questions

The main research question is how to design an online community to facilitate information aggregation of macro-economic variables. This subsequently leads to question of how participants can be motivated to contribute and share their information for longer time horizons. We try this by first implementing a specifically designed market environment. Secondly we design a play-money incentive schemes which rewards participants according to their performance. How well does this incentive scheme fulfill the goal of keeping participants active and contributing? It is especially interesting how good this incentive system works for longer time horizons.

In order to further motivate participants intrinsically we use feedback mechanisms. The first question is which of the feedback types works best at motivating contributions. Secondly if we find any differences in the activity level, do the additional contributions improve the community forecast? This leads to the question of forecast accuracy in general. How does a community of novices perform in comparison to an expert panel? Additionally if we analyze user interactions can we deduce user forecast confidence?

Results

The following section first presents some descriptive market statistics and then evaluates the market generated forecasts. We show that the level of participation is mainly driven by a weekly newsletter which acts as a reminder. Furthermore we find that the induced competitiveness of market environments seem to superpose classical feedback mechanisms. Turning to the community generated forecasts we find that forecast accuracy improves constantly over time and that generated forecasts performed well in comparison to the Bloomberg-survey forecasts. Additionally we can show that the market has a supplementary benefit by implicitly providing a measure for forecast confidence.

Participation, Feedback & Incentives

The following data includes the time span from 30th October 2009 till 31st of October 2010. In total 1006 participants registered at the EIX market, of those 680 submitted at least one order. Altogether participants submitted 45,808 orders resulting in 22,574 executed transactions. Figure 5 shows the market activity over time. In the respected time frame 47 stocks were paid out. In order to keep participants active and informed we sent out a weekly newsletter summarizing the up-to-date economic news. The sending days varied during the week. Analyzing the impact of the newsletter, we find an increased activity measured as orders per day (on average +60 orders on sending days; t-value: 3.23, $p-value \leq 1\%$). The peak activity on sending days is followed in almost linear decreasing activity in subsequent five days.

As described in the previous section, we implemented five feedback treatments. We used the following OLS regression: $log(orders) = i + \beta * ML + \sum_{i=1}^{5} \alpha_i * F_i$ to test the influence of each feedback treatment on each individual activity level. In the baseline treatment no special feedback is given. As the number of orders is power-law distributed, following (Raban 2008) we use a logarithmic transformation of the *orders* variable. The results are depicted in Table 2. The model is dominated by the newsletter effect. Participants receiving the newsletter submit significantly more orders. As all feedback treatments show no significant effect, we conclude that feedback mechanisms do not induce any additional motivation to contribute in competitive market environments. It seems that different individual competitiveness levels superpose any feedback effect.

Table 2: Trading activity and feedback mechanism

(N=410) log(Orders)	Newsletter	Thanks	Social ranking	Relative ranking	Number of trades	Random
Estimate	0.26	-0.001	-0.32	-0.22	-0.14	0.09
(t-value)	3.23	-0.03	-1.22	-0.9	-0.56	0.36

As described previously we designed an incentive scheme that aims at keeping participants' motivation high over the market run-time. Figure 4 presents the number of active participants on a monthly basis. We find a clear novelty effect, which is evident in the high activity levels in the first two months. While the number of active participants decreases we find that the percentage of participants fulfilling the monthly incentive requirements stays at the same level. The slight drop in the last month is due to the fact that we started the second market round in parallel. We conclude that the incentive structure worked well for such a long running experiment.

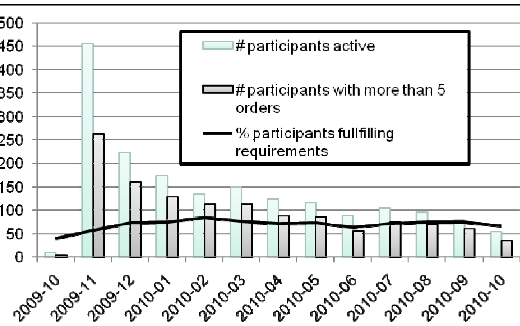

Figure 4: Participants staying active

Community forecasts

In binary markets the prediction market prices typically provide useful (albeit sometimes biased) estimates of average beliefs about the probability an event (Manski 2006; Wolfers and Zitzewitz 2006). In our linear outcome market prices do not reflect the probability of an outcome but the market participant's aggregated belief about the fundamental value of the underlying indicator. Thus the interpretation of the price is directly linked to the outcome value. In our case there are various ways to generate an economic forecast from market prices. For example participants can either infer that the $mid_{i,t}$ or the last trading price are the forecast for stock i at time t. In the following sections a market $forecast_t$ refers to the average transaction price on day t. A first indication about the market outcome is given by the deviation between market prices and fundamental values. In the following the difference between the fundamental value of the stock i (fv_i) and the market $forecast_{t,i}$ represents the $error_{t,i}$. One would expect market prices to converge to the final outcome and thus a reduction of forecast error over time.

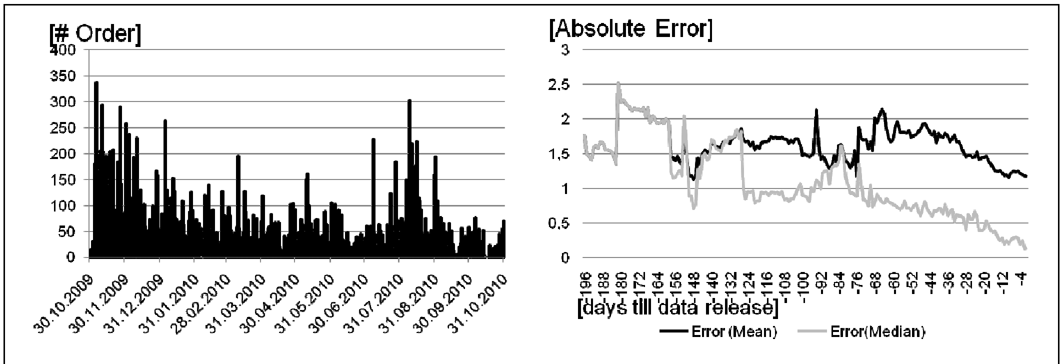

Figure 5: Number of orders and absolute forecast error over time

Forecast error reduction over time

An important question is whether the market continuously aggregates information. In Figure 5 the average absolute error over time is depicted. One can see a steady decreasing absolute error in the last 70 days. We run an OLS-regression analysis to quantify the error reduction per day. In order to control for indicator effects we add the indicator dummies $I_1 - I_5$.

$$AE = i + \alpha \times days + \sum_{j=1}^{5} \delta_j I_j \qquad (2)$$

In the last 70 days the average error is reduced by 0.011 per day (t-value 6.27, $p - value \leq 0.1\%$). We conclude that forecast uncertainty was reduced over time, information aggregation took place and hence the absolute error was reduced. In table 3 (last column) the error reduction per day is presented for each indicator separately.

Error per indicator

On an aggregated level we compare the market-generated forecasts ten days before the data release ($forecast_{10,i}$) to the fundamental value. Table 3 summarizes the findings. We find that the market overestimates the fundamental values slightly (2.069 vs. 1.734; t-value 0.69, n.s.). When comparing standard deviations we find that the forecasts are significantly less volatile than the fundamental values (1.41 vs. 2.92; f-value 4.29, $p \leq 0.1\%$) over the period. We see that market forecasts are more stable than outcomes. This is in line with forecasts from other methods (Vajna 1977). A reason for this is that forecasters regularly tend to publish moderate, conservative estimates rather than extreme values.

To evaluate the forecast performance we compare the market forecasts to Bloomberg survey forecasts. For Bloomberg forecasts the time between the forecast and the data release varies as the forecast is made public on Fridays before the release. The direct comparison of these two show that they perform at least equally well. One must note that the Bloomberg survey forecasts are published on Fridays before the data release, whereas we use the market generated forecasts 10 days before the data release. Hence market prices could not have been influenced by the Bloomberg estimate.

Table 3: Comparing market and Bloomberg forecasts						
		Market Error		Bloomberg Error		Comparison
	N	Median	Mean	Median	Mean	EIX vs. Bloomberg
Exports	12	2.31	3.44	1.95	2.88	7 vs. 5
GDP	4	0.73	0.64	0.2	0.34	2 vs. 2
IFO Index	3	0.55	0.52	-	-	-
Inflation	11	0.24	0.26	0.2	0.35	5 vs. 4 (5 draws)
Investments	5	1.14	1.27	-	-	-
Unemployment	12	0.06	0.06	-	-	-

Predicting community forecast error

Another important question for interpreting point forecasts is the uncertainty attached to the forecast. Neither Bloomberg nor market forecasts provide explicit uncertainty information. However one might interpret implicit market properties as proxies for the underlying uncertainty. One possible implicit market measure for market confidence is liquidity. A measure for the liquidity is an asset's ability to be sold rapidly, with minimal loss of value, any time within market hours (Harris 2002). Quoted spreads are the simplest and most common measure of trading costs and can easily be calculated using trade and orderbook data. Let $Ask_{i,t}$ be the ask price for a stock i at time t and $Bid_{i,t}$ the respective bid price. $Mid_{i,t}$ denotes the mid quote then the quoted spread is calculated as follows:

$$Quoted\ Spread_{i,t} = \frac{(Ask_{i,t} - Bid_{i,t})}{2 * Mid_{i,t}}$$

Another proxy for market uncertainty could be a high price variability which indicates the traders' disagreement about the fundamental price of an asset. Finally, the higher the number of traders active in one stock, the higher the chance that all available information has been incorporated. We run an OLS regression to analyze if the three factors predict the forecast error magnitude. Table 4 presents the results. An increase in the quoted spreads by one point increases the forecast error by 3 points on average (*p-value* < 1%). This seems reasonable as the market participants acknowledge the underlying high uncertainty and set the spreads accordingly. Both other implicit market measures have to explanatory value.

Table 4: Predicting community forecast errors		
Variable	Estimate	t-statistic
$Quoted\ Spread_i$	3.37	2.68
$Var(price_i)$	-0.00	-0.10
$unique\ traders_i$	-0.01	-0.18

Conclusion

Internet communities offer the advantage of instant information exchange and group decision that is not possible in a real-life. We designed an online community facilitating information aggregation of macro-economic variables. Furthermore we presented an incentives scheme well suited to motivate participants contributing their information for longer time horizons. Investigating the level of participation, we find that a weekly newsletter, which acts as a reminder, drives activity. Assuming that classical feedback mechanisms would lead to different participation levels, we find that the induced competitiveness of market environments seem to superpose classical feedback mechanisms. Turning to the community generated forecasts we find that forecast accuracy improves constantly over time and that generated forecasts performed well in comparison to the Bloomberg-survey forecasts. Additionally we can show that the market has a supplementary benefit by implicitly providing a measure for forecast confidence. We hope our approach will positively impact the market design community and forecast results will eventually influence economic policy making in Germany by providing continuous information about the state of the economy.

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