LEARNING BY TRADING IN A MACRO-ECONOMIC FORECASTING GAME

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Abstract

Macroeconomic forecasts are used extensively in industry and government even though the historical accuracy and reliability is questionable. Moreover, professional forecasters lack a test environment in which they can test their forecasting ability. We design a play-money market game for economic variables that aggregates macro-economic information. We analyse participation and learning in such an online game. In our platform learning occurs on three levels. First, participants learn how to trade in a continuous double auction just as in stock markets. Second, they learn about their own macroeconomic forecasting ability in comparison to their peers. Third, by following market forecasts they learn about the current state of the economy. We show that the game successfully aggregates macroeconomic information as forecast errors fall over the prediction horizon. The game-generated forecasts compare well to the Bloomberg-surveys forecasts, the industry standard.

Keywords: Stock-market Game, Learning, Macroeconomic Forecasting, Prediction Markets.

1 Introduction

A wide and important range of policy decisions are made on the informational basis of economic forecasts such as GDP growth. It is a well established fact that traditional economic forecast models lack the necessary accuracy (Osterloh 2008; McNees 1992; Schuh 2001). Simplified, the current approaches mix expert knowledge with historic extrapolation. They are thus inadequate to capture rapid economic changes. The last financial crises exemplified the failure of economic forecasting. Weeks after Lehman Brothers filed for bankruptcy protection, the consensus still predicted a 2% rise in German GDP for 2009. In 2009 German GDP dropped by 4.5%. Yet 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 (Batchelor, 2007). In Germany forecasts are produced by numerous institutions and but released on only periodical basis. Hence even professional forecasters receive feedback about their performance late and sporadically. Internet games offer the advantage of instant information exchange. But how can online games be designed to facilitate information aggregation of macroeconomic variables? Furthermore how can we enhance learning about one’s own forecast abilities?

Over the last couple of years prediction markets as a game-like forecasting method have gained interest in the scientific world and in 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, export and unemployment figures in Germany. Separating two distinct learning types we analyse how learning takes place within the participating community. Furthermore we evaluate the effect of performance feedback mechanisms on activity 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 learning in markets and prediction markets as learning environments are discussed. Section three summarizes the research questions. The forth section presents the IS-artifact and details the field experiment setting. The subsequent section evaluates the IS-artifact from a forecasting perspective. Finally section six concludes this paper.

2 Related Work

2.1 Prediction markets as macroeconomic learning environments

A common approach to economic forecasting is to identify experts who can make a prediction. 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 macroeconomic forecasts suffer from the optimism bias (Batchelor, 2007) and imitation behavior (Osterloh, 2008). In macroeconomic forecasting performance feedback is scarce. Forecasters learn about their forecast performance only in periodic ex-post analyses.

Internet games offer the advantage of instant information exchange and peer-performance comparison that is not possible in a real-life. An arising question is how to build and maintain internet games to forecast macroeconomic variables. Furthermore how can participants learn about macroeconomic forecasting and the current state of the economy? A certain type of online games, 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).

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.

As the system works like financial markets, it offers a learning environment for trading in stock markets. Moreover, a recent study shows that prediction markets can enable active learning in large groups (Buckley et al, 2011). Participation in prediction markets changes the learning event from the passive receipt of material and recall of facts to active decision making. Thus learners are challenged to engage in the learning process. In a similar case-study a prediction market was used as a teaching tool for MBA classes (Raban and Geifman, 2009). The authors conclude that students gained valuable insight into their own decision making patterns as well as the hands-on activity helped to enhance the understanding of market and added to the lessons.

However, both explorative studies use short-lived prediction markets as a pedagogical tool in a closed class-room environment.

### 2.2 Learning in markets

Classical learning-by-doing models suggest that traders might improve their ability as they actively trade. Through their actions and provided feedback traders gain experience and thus improve over time. A second type of learning is called ‘learning about ability’. As investors trade, they might realize that their ability is low and decide to stop trading. By analysing investor records (Seru et al., 2009) separate these learning types and find most of the learning occurs as individuals learn about their own ability and low-ability investors stop trading. Contrary to these results a study on retail investor behaviour finds that excess portfolio returns improve with account tenure – a proxy for investor experience. Furthermore, they also find that trade quality significantly increases with experience (Nicolosi et al., 2008).

In prediction market literature, learning has been viewed from a forecasting perspective. Based on models of information aggregation, Adams (2006) theoretically shows that when learning is allowed, a prediction markets may aggregate information. In particular, adding learning to the model used in Manski (2006) causes the market price to converge to the mean of the distribution of beliefs. Hence the ‘market’ learns the correct outcome probability over time.

### 2.3 Markets for economic derivatives

Financial markets for macroeconomic 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 macroeconomic 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.

### 3 Research Questions

The main research question is how to design an online game to facilitate information aggregation of macroeconomic variables. This subsequently leads to question of how participants can learn about their contribution and improve their forecast performance over longer time horizons. Given that participants learn to improve their forecast ability, do market generated forecasts improve over time? 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. Furthermore we display two types of ranking; one highlighting the overall trading performance, one more directly aimed at displaying forecast performance. How well do these artefacts work? How well did learning take place in this setting?

Secondly if we find any learning effect, does this improve the macroeconomic forecasts? This leads to the question of forecast accuracy in general. From a forecasting perspective over time, if learning about the outcome occurs, the flow of information reduces outcome uncertainty and hence results in decreasing forecast errors over time. How does a gaming community perform in comparison to an expert panel?

### 4 A stock market game for economic variables

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

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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.

\(^2\) [www.eix-market.de](http://www.eix-market.de)
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.

4.1 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.

\[ p = 100 + \alpha + \left( \frac{I_{t0} - I_{t-1}}{I_{t-1}} \right) \quad \text{with } \alpha = 10 \]  

A contract is worth: 100 +/- \( \alpha \) 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 \( \alpha \) to 10. Therefore the representable outcome ranges from -100% to infinity. To represent the whole outcome range from -100% to infinity \( \alpha \) 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 \( \alpha \) 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 (\( I_1, I_2, I_3 \)). 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 stock is stopped. Finally the stocks are liquidated according to the pay-out function defined in equation 1. As soon as the trading in one stock stops a new stock of the same indicator (e.g. \( I_4 \)) is introduced into the market. This means that participants received 1,000 new stocks of the respective indicator. All in all participants are able to continuously trade 18 stocks at all times.

The web portal features more information such as available account information for individual traders which 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>
<thead>
<tr>
<th>Indicator</th>
<th>Unit</th>
<th>Data Release Cycle</th>
<th>Payout Number</th>
<th>Payout Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exports</td>
<td>%-Changes&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>monthly</td>
<td>25</td>
<td>100 + α × (\frac{I_{t} - I_{t-1}}{I_{t-1}})</td>
</tr>
<tr>
<td>GDP</td>
<td>%-Changes&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>quarterly</td>
<td>8</td>
<td>100 + α × (\frac{I_{t} - I_{t-1}}{I_{t-1}})</td>
</tr>
<tr>
<td>IFO Index</td>
<td>ABS-Changes&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>monthly</td>
<td>16</td>
<td>100 + α × (I_{10} - I_{t-1})</td>
</tr>
<tr>
<td>Inflation</td>
<td>%-Changes&lt;sub&gt;t-12&lt;/sub&gt;</td>
<td>monthly</td>
<td>25</td>
<td>100 + α × (\frac{I_{t} - I_{t-12}}{I_{t-12}})</td>
</tr>
<tr>
<td>Investments</td>
<td>%-Changes&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>quarterly</td>
<td>8</td>
<td>100 + α × (\frac{I_{t} - I_{t-1}}{I_{t-1}})</td>
</tr>
<tr>
<td>Unemployment</td>
<td>Million (ABS)</td>
<td>monthly</td>
<td>25</td>
<td>100 + \frac{ABS(Y_{t-1})}{100×10^6}</td>
</tr>
</tbody>
</table>

*Table 1. Economic variables*

### 4.2 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 (1-6) and feedback mechanism (F).](image-url)
4.3 Incentives

As mentioned the market is a free to join play money market. Previous work has shown that play-money markets perform equally well as real-money markets at predicting future events (Rosenbloom and Notz, 2006). Note also that due to legal restrictions on gambling the EIX prediction market has to rely on play money. 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. 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.

4.4 Feedback

An assumption underlying current models of learning in games is that learning takes place only through repeated experience of outcomes (Weber, 2003). In our market setting we distinguish between three types of feedback:

- Interface feedback
- Market-based feedback
- Forecast performance 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.

In order to separate between trading performance and forecasting performance the platform offers a third feedback type the so-called “EIX-score”. It is calculated based on the observed outcome, i.e. the fundamental value of each stock. If an order moved the price in the right direction with respect to the final outcome of the stock, it is informed; whereas an order moving the price in opposite direction to the final outcome price, it is uninformed. Therefore we can ex-post measure the information content of
each order. Combining the information content with the size of an order and aggregating all individual contributions, enables us to calculate a forecast based performance ranking.

4.5 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.

The EIX prediction market software is an advancement of two previously run (Statthel 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. The system can be described 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.

4.6 A two-staged experiment

The EIX-market-game was setup as a one year field-experiment. As we received positive feedback and promising forecast results, we decided to continue the experiment for a second year. We started the second market period on October 1st 2010. As the first market closed on October 31st 2010, we had a smooth transition. Every market participant who registered for the first version was automatically transferred to the second round. No new registration was required and the website layout, web-address and institutional setting remained the same. In order to continuously improve our platform, we added some minor features and slight changes to the market design. E.g. the price for ifo index stocks is
directly related to the underlying ($P = ifo index (points)$). The intuition was to make it easier for participants to translate a prediction into a limit-price. Due to a lower number of sponsors, the amount of prize money was reduced. We handed out three prizes worth 1,030 Euro per month – 12,360 Euro overall.

5 Results

The following section first presents some descriptive market statistics and then evaluates the market generated forecasts. We find that learning takes place as participants who submitted more orders are more likely to submit an additional profitable order. Previous work shows that game forecasts accuracy improves constantly over time and that generated forecasts performed well in comparison to the Bloomberg-survey forecasts (Teschner et al. 2011).

5.1 Participant activity

The following data includes the time span from 30th October 2009 till 31st of October 2011. In total 1235 (1006 in the first round) participants registered at the EIX market, of those 809 (680) submitted at least one order. Altogether participants submitted 79,334 (45,808) orders resulting in 34,028 (22,574) executed transactions. Figure 5 shows the market activity over time. In the respected time frame 107 (47) stocks were paid out. In order to keep participants active and informed we sent out a weekly newsletter summarizing up-to-date economic news.

The sending days varied during the week. Analysing 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 < 1%). The peak activity on sending days is followed in almost linear decreasing activity in subsequent five days.

Figure 2. Activity over the game period (left) and forecast error over time (right)

5.2 Learning

As previously detailed, learning might take place on two levels. First by actively trading, participants might gain experience and hence improve over time. Secondly, by observing their performance participants might realize their low-ability and consequently leave the market. Using the number of past orders as a proxy for experience we test the first idea of “learning by doing”. We run following OLS regression:

$$profit_o = \alpha + \beta_0 \cdot NumOrders_{t,u} + \sum_{i=0}^{7} \gamma_i C_i$$  (2)
\( \text{NumOrders}_{t,p} \) denotes the number of orders a user \( u \) has submitted before the specific order \( o \). We add five indicator control variables to control for indicator effects and two variables for trading behaviour. We find the experience (numOrders) variable positively correlated (estimate: 1.62, t-value: 3.51, p-value < 1%) with profits. Hence a longer in-game experience seems to help participants to perform better.

Assuming that participants learn about their ability, we expect them to stop trading if their performance is below average. As mentioned we implemented and displayed two ranking versions, one displaying the overall portfolio value, and one aimed at showing the peer forecasting performance. When correlating the two rankings we find them to differ substantially (\( \rho = 0.11, p < 5\% \)). In order to test “learning about ability” we use performance data from the first round to predict activity in the second round. We test if a participant was active (submitted at least one order) in the second round, dependent on if the participant’s ranking was below average (Logit-regression, equation 3). As the newsletter has a substantial effect in keeping participants active we add a control for that (ML). We find no significant effect for the overall portfolio ranking. However, if we recode the low-variable to reflect the forecast performance based ranking, we find that the below average performing participants are less likely to continue trading (odds ratio: -1.95, \( \chi^2 =20.23, p\text{-value} < 0.1\% \)). A reason for the difference might lie in the presentation, as the forecast-ranking is higher in the browsing menu structure.

Combining these results we conclude that participants gain experience over the time and with increasing experience submit more profitable orders. Turing to the learning about ability we find that the forecast performance-based but not the portfolio-based ranking predicts if participants stay active.

### 5.3 Continuous information aggregation

In the following sections a market-game forecast 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 \( i \) and the market (\( \text{forecast}_{i,t} \)) represents the error \( \text{error}_{i,t} \). One would expect market prices to converge to the final outcome and thus a reduction of forecast error over time (Figure 2, right side).

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 (AE) 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 \( I_1-I_5 \) (equation 4).

\[
active_{u,2} = \alpha + \beta_0 \cdot \text{low}_{u,1} + \beta_1 \cdot \text{ML}_u \quad (3)
\]

\[
AE = \alpha + \beta \cdot \text{days} + \sum_{i=0}^{5} \gamma_i I_i \quad (4)
\]
In the last 70 days the average error is reduced by 0.011 per day (t-value 6.27, p-value < 0.1%). We conclude that forecast uncertainty was reduced over time, information aggregation took place and hence the market learnt about the correct outcome.

On an aggregated level we compare the market generated forecasts ten days before the data release \( (\text{forecast}_{i,10}) \) to the fundamental value. We find that the market overestimates the fundamental values slightly (2.069 vs. 1.734; \( t \)-value 0.69, n.s.). However comparing standard deviations we find that the produced forecasts are significantly less volatile than the fundamental values (1.41 vs. 2.92; \( f \)-value 4.29, p-value < 0.1%). in the respected period. Thus we conclude that market forecasts are more stable than the outcome values. 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.

In order 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.

### 6 Conclusion

Internet games 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 macroeconomic variables. Furthermore we presented an incentives scheme well-suited to motivate participants contributing their information for longer time horizons.

Our semi-anonymous game enables naïve and professional forecasters to test their forecast ability compared to their peers. We show that participants gain experience over time indicating that the active engaging environment fosters learning. Testing if participants are able to learn their forecasting ability, we find that a specifically designed forecasting ranking provides the necessary feedback.

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.

### References


