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**STRATEGIC COORDINATION IN
FORECASTING. AN EXPERIMENTAL
STUDY**

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GEORG-AUGUST-UNIVERSITÄT GÖTTINGEN

STRATEGIC COORDINATION IN FORECASTING. AN EXPERIMENTAL STUDY

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Abstract

Reputational herding has been considered as a driving force behind economic and financial forecasts clustered around consensus values. Strategic coordination can consequently explain poor performances of prediction markets as resulting from the distinct incentives that forecasters face. While this notion has been considered theoretically and empirically, the underlying behavioral working mechanisms have not yet been described. We thus put forth an exploratory experiment on the emergence and robustness of coordination in a forecasting setting implementing contradictory incentives for accurate forecasts and coordination. Forecasts are shown to be inaccurate and biased toward current values. This in turn has subjects aiming at coordination benefits. Predominantly, coordination is achieved through the risk-dominant equilibrium as the game proceeds. Once established, coordination is fairly stable and adds to overall welfare. Our results support the assumption of rational herding as a driving force for predictions of poor accuracy that are systematically biased towards focal points.

Keywords: coordination; incentives; laboratory experiment; reputational herding; sunspot equilibrium

JEL classification: C90; D03; D83; G17

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1. INTRODUCTION

Economic actors regularly coordinate their decisions in a broad range of settings, within which a common course of action yields higher payoffs. A widely discussed area of coordinated actions can be found on markets for economic and financial forecasting. It has been convincingly argued that prediction markets are particularly prone to rational herding, which manifests in a bias towards consensus forecasts in individual predictions. By conforming to the majority of other agents, individuals benefit from concealing their inability to provide accurate forecasts. Building on John Maynard Keynes' writings on financial markets, Scharfstein and Stein (1990) suggest in their seminal paper that forecasters generate a "sharing-the-blame" effect by strategically coordinating their predictions. Accordingly, analysts rationally decide against the truthful reporting of private information, rather adapting to a common consensus to be perceived as being more capable. In this way, the blame for false predictions can be avoided by pointing to the communities' overall inability of correctly anticipating actual developments.

The systematic, strategic overweighing of publicly available information has subsequently been modelled theoretically and investigated empirically in a considerable number of studies. Most recently, Ottaviani and Sorensen (2006b) have formalized the conception in a theory of reputational cheap talk, whereby forecasters aim at improving their reputation by pretending to principals to be well informed. This leads to a strong bias towards the overall consensus forecasts and consequently to inaccurate predictions due to the strategic non-disclosure of private information, the ultimate result being that "paradoxically, the desire of analysts to be perceived as good forecasters turns them into poor forecasters" (Ottaviani and Sorensen, 2006b, p.443). This concept has been tested empirically, yielding ambiguous results. Most prominently, Hong et al. (2000) suggest that particularly less experienced analysts seek safety in consensus forecasts, while similarly, Lamont (2002) and Clement and Tse (2005) find forecasts to be clustered around consensus values. By contrast, building upon models of anti-herding, studies such as those by Batchelor and Dua (1990), Zitzewitz (2001a; b) and Bernhardt et al. (2006) present evidence in favor of strategic differentiation in prediction markets.

While these results are contradictory, a compromising interpretation has been put forth by Marinovic et al. (2010), who argue that the lack of strong competition and ex-post evaluations of forecasting accuracy leads prediction markets to quickly deteriorate to pure beauty

contests. Thereby, herding on consensus values becomes predominant as analysts are primarily rewarded for their ability to anticipate the expectations and choices of all other participants. Forecasters then cease their predictive efforts and resort to merely guessing the actions of others, thus striving for coordination. Therefore, the distinct structure of incentives might explain why herding on consensus values is more or less pronounced in prediction markets for different economic or financial key figures.

Under these conditions, forecasting that maximizes individual reputation can be interpreted as a coordination problem in which players minimize deviations from the average prediction by agreeing upon a common focal point. While this notion has been discussed extensively in previous studies, no behavioral study to date has explored strategic coordination in a forecasting setting. Studying strategically biased forecasts experimentally could provide a useful empirical insight into the coordination patterns of independent agents in a forecasting environment. Given that underlying mechanisms of coordination are inaccessible from a purely theoretical perspective or solely through an evaluation of time series data, a controlled laboratory environment might provide additional evidence. Consequently, we run an exploratory experimental study to provide behavioral insight into analysts' coordinative behavior in a forecasting setting.

We build our investigation on two distinct strands of literature in experimental economics. Firstly, we use recent experiments on forecasting as our working horse, whereby payoff-maximization demands that subjects correctly interpret fundamentals and make accurate predictions. These settings (see e.g. Becker et al., 2008) primarily focus on showing subjects' inability to rationally process graphical or statistical information, which is interpreted as a refutation of the rational expectation hypothesis. Secondly, we implement a coordination mechanism as an alternative mode of generating payoffs. This approach follows a large body of experimental studies that consider rationality in coordination games. Based on Duffy and Fisher's (2005) seminal paper, recent studies have considered the effectiveness of random focal points, so-called sunspots¹, in fostering coordination between subjects. Connecting these two experimental approaches, we are able to study if and how subjects coordinate in forecasting games.

¹ Duffy and Fisher (2005) explain the term "sunspot" as originating from William S. Jevons, who assumed solar activity to be a considerable influence on economic activity. In the modern meaning, it is referred to as a random variable that is unrelated to the fundamentals yet nevertheless fosters coordination.

While the basic structure of our setting somewhat resembles the experimental approach to reputational herding in Bedke et al. (2009), it differs by implementing an actual forecasting task and an endogenous coordination mechanism. Subjects are asked to perform judgmental forecasting of future values based on the graphical and numerical depiction of several determinants. Due to the complexity and interaction of the underlying fundamentals determining the values to be forecast, accurate predictions – albeit the first best solution – are effectively hard to achieve. Frustration with the task might prompt subjects to increasingly consider the alternative strategy, i.e. coordination on a common focal point, which also leads to a payoff in each period. While theoretically all values within the range of possible forecasts could be used to coordinate, we implement a unique payoff and risk dominant equilibrium at the respective rounds' current value. Uniqueness of this particular efficient coordination regime is achieved by implementing costs for forecasts that deviate from the focal point. In societies of eight, all players are also randomly matched to groups of two, who are able to communicate via chat. All fundamentals, prior predictions and earnings of other players are common knowledge.

Within this framework, we investigate whether subjects succeed in agreeing on focal points, even when the task of forecasting future values is conflicting to coordination. We can thus explore four particular aspects. Firstly, we aim at analyzing forecasting accuracy and the predictive quality of the rational expectation hypothesis. Secondly, we assess whether subjects in a forecasting setting succeed in coordinating on external focal points. Thirdly, we investigate the robustness of coordination once it is established and finally, we discuss the welfare implications of our results.

Overall, we find that subjects fail to make forecasts in line with the rational expectation hypothesis. Accordingly, forecast accuracy is poor, even when subjects do not aim at coordination. However, coordination on the sunspot equilibrium constituted by current values increases strongly over periods and is fairly successful overall. The coordination is found to be efficient and quite robust, i.e. once subjects achieve coordination on the sunspot at minimal costs, they tend not to deviate from this strategy. Along with dismal performance in forecasting yet increasing cooperation, subjects' effort levels and confidence in the accuracy of their predictions decreases. It can thus be assumed that frustration with the forecasting task fosters coordination. While total welfare is considerably lower than the maximum, for a number of subjects it approaches the benchmark representing efficient coordination as the game proceeds.

The remainder of this paper is organized as follows. Section 2 reviews the literature related to our study. Section 3 presents the game and our experimental design. The results are presented in section 4, before section 5 offers a conclusion.

2. RELATED LITERATURE

The forecasting behavior of financial and economic analysts has been discussed extensively from various scientific angles.² While the sheer volume of studies precludes a comprehensive review, broad trends upon which our study builds can be outlined.

Starting in the early-1990s, two closely related strands of literature have evolved that apply the concept of analyst's rational herding. Primarily, based on the seminal contributions by Welch (1992), Bikhchandani et al. (1992) and Banerjee (1992), the concept of informational cascades has become widely discussed. These authors implement a sequential decision-making regime in which the disregarding of private information in the face of potentially conflicting public information becomes rational in certain situations. Bayesian updating has agents rationally interpreting the weights of private and public information and deciding accordingly. Thus, when aggregate public information becomes overwhelming, a cascade situation develops and the single private information is rationally discarded by all following agents in the decision sequence (Graham, 1999). The private information of these players is not revealed by their decisions and information aggregation becomes insufficient. Starting with the seminal contribution by Anderson and Holt (1997), experimental studies have documented subjects' failure to rationally make use of private and public information. Thereby, subjects display a tendency to cling to private information that systematically contradicts rational behavior derived from perfect Bayesian updating (Weizsäcker, 2010

² A generalist theoretical perspective on economic aspects of forecasting is given in Elliot and Timmermann's (2008) literature review. The authors encompass the large number of empirical and theoretical studies within several discussions on forecasting. More specifically and closer to our investigation is Devenov and Welch (1996), who offer an overview of theoretical explanations as to why herding among agents in financial markets might occur. Individual forecasting behavior is a prominent topic in experimental psychology, particularly from the perspective of heuristics and biases, leading to non-optimal results in many forecasting settings. Harvey (2007) offers a comprehensive introduction to the literature concerned with individual forecasting behavior. More generally, Assad (2012) gives an overview of the literature on experimental finance and includes aspects of forecasting. Stekler (2007) differentiates between various components regarding the process of macroeconomic forecasting and reviews the respective studies. Ramnath et al. (2008) provide an applied institutional perspective, presenting a taxonomy on the role of financial analysts in capital markets. Similarly, v. Campenhout and Verhestraeten (2010) more specifically review contributions on herding behavior among financial analysts. Another perspective of applied forecasting regarding corporate analysts is given by Lawrence et al. (2006), who review the central research of the past 25 years in judgmental forecasting.

offers a meta-study). Rational herding thus occurs less often than it is predicted by theory due to subject's reluctance to discard private information.

Reputational herding is closely related to discussions of herding evoked by informational cascades. However, an additional dimension of incentives is considered, which rewards imitating the choices of previous agents. Consequently, agents gain positive reputational externalities from the fact that their decisions resemble those of a reference group. Ottaviani and Sorensen (2000) discuss the similarities between both concepts and propose that an agency-based reputational model might yield superior explanatory power for a wide range of economic contexts. The seminal model for reputational herding goes back to Scharfstein and Stein (1990), who formalize Keynes' remarks on conformity in financial markets.³ Other influential models of reputational herding have been contributed by Hirshleifer (1993), Trueman (1994), Prendergast and Stole (1996) and Holmstrom (1999), who point at different sources, dimensions and consequences of reputational pressure. Froot and Scharfstein (1992) more closely discuss the beauty contest-like structure of reputational concern, which evolves due to short time horizons. Most recently, Bar-Isaac (2012) suggests a model on the interplay of career concerns, transparency and the resulting incentive for the acquisition of expertise.

Two contradictory basic notions can be identified within the theoretical discussion on the parameters of reputational herding. The first such notion emphasizes individual gains from conforming to a publicly observable consensus value. Accordingly, conformity and coordination are seen as the dominant strategy in forecasting situations. By contrast, proponents of strategic differentiation, i.e. anti-herding, point to potential reputational advantages of making forecasts that significantly deviate from consensus values. By appearing to be bold, analysts can gain competitive advantages, signaling to have access to superior private information.

Supporting the first notion, Ehrbeck and Waldmann (1996) present a model favoring the reputational gains of biased forecasts, within which agents aim at mimicking the most capable

³ The original, widely quoted citation being: "it is the long-term investor, he who most promotes the public interest, who will in practice come in for most criticism, wherever investment funds are managed by committees or boards or banks. For it is in the essence of his behavior that he should be eccentric, unconventional, and rash in the eyes of average opinion. If he is successful, that will only confirm the general belief in his rashness; and if in the short-run he is unsuccessful, which is very likely, he will not receive much mercy. Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally." (Keynes 1936, p. 157-158)

forecasters, instead of merely minimizing prediction errors. However, their assumptions of a strategic bias towards common values fail to hold empirically. Accordingly, they suggest a behavioral explanation of biased forecasts. In three related models, Ottaviani and Sorensen (2006a;b;c) argue that reputational concerns regularly fail to create appropriate incentives for the truthful reporting of private information. Thus, the role of strong incentives to herd on the mean forecasts is emphasized, particularly for the case when markets are unaware of analysts' strategic herding. In turn, if the market knows about these strategic incentives, forecasts are made honestly and necessarily deviate from the consensus equilibrium due to the full revelation of private information. Moreover, if markets for forecasts include a competition for accuracy with pre-specified rules in a winner-takes-all setting, agents' predictions become fully differentiated. Ottaviani and Sorensen (2006c) more closely discuss the conditions that preclude the realization of equilibria for truth telling. In these equilibria, relative reputational concerns that would otherwise lead to a differentiation of forecasts have no impact and competition fails to alter the resulting equilibrium.

In contrast to the models predicting a strong overall bias towards common information, numerous reputational models suggest anti-herding in forecasting. Most prominently, Trueman (1994), Zwiebel (1995), Prendergast and Stole (1996), Avery and Chevalier (1999), as well as Zitzewitz (2001b) show how reputational competition might effectively lead to differentiated forecasts. Laster et al. (1999) present a model with common information of all forecasters and thus a common expectation of future values. However, due to the structure of the demand side, forecasts cover the future value's probability distribution. Furthermore, forecasters more dependent on publicity will deviate more strongly from consensus values. Effinger and Polborn (2001) similarly point to positive reputational effects of not following predecessors, while Laux and Probst (2004) again show heterogeneity in forecasts accruing from strategic behavior. However, this only holds when past performance is perfectly evaluated by the markets. Otherwise, analysts cease their effort to become better informed and revert to herding. Kim and Zapatero (2009) argue that relative performance evaluation is the primary driver of analysts' herding. They further propose that herding is most likely to occur when the market comprises strong penalties for underperforming analysts.

Theoretical models have effectively mapped the various potential influences of reputational concerns on forecasters, with both herding and anti-herding as dominant strategies, the according equilibria crucially depending on the market structure faced by analysts.

Complementary to the theoretical work, empirical studies have investigated forecasting time series, discussing whether and under what conditions herding around common public information or signals, most prominently consensus values⁴, occurs in forecasting. Graham (1999) tests a sequential model of analysts' predictions, finding that herding behavior by contributors to investment newsletters depends on their former reputation. In laboratory studies, Cote and Sanders (1997), as well as Ackert et al. (2008) find empirical evidence for Trueman's (1994) model, as subjects with weak private information herd on the predictions made by others who are endowed with stronger private information. Welch (2000) provides empirical support for consensus herding consistent with models in which analysts coordinate based upon common information. Gallo et al. (2002), Bofinger und Schmidt (2003), Spiwoks (2004), Spiwoks et al. (2005; 2008a; b), Spiwoks und Hein (2007), Ager et al. (2009), Jegadeesh and Kim (2009), as well as Gubaydullina et al. (2011) also find empirical evidence for analysts herding around consensus values. Bizer et al. (2013) in a recent classroom experiment with inexperienced participants also find a pattern of forecasts strongly biased towards current values of the respective time series. While Clement and Tse (2005) strengthen this notion, they point to the simultaneous occurrence of bold forecasts incorporating analysts' private information. Consequently, these bold forecasts have more informational value than those resulting from herding, although such forecasts only constitute a small fraction of their data. Batchelor (2007) adds to these results by showing an overall bias towards the consensus and a resulting weak forecasting accuracy overall. However, some forecasters consistently aim at signaling ability by making distinctively optimistic or pessimistic predictions in comparison to the consensus.

A similarly large body of literature has evolved aiming at supporting the theoretical perspective of strategic differentiation in forecasting. Batchelor and Dua (1990) show that analysts systematically deviate from average forecasts in an optimistic manner, suggesting that differentiation is responsible. In a follow-up study, Batchelor and Dua (1992) find forecasters to be conservative in the sense that they cling to their past predictions. However, they are shown not to be consensus-seeking. In two separate studies, Zitzewitz (2001a; b) reports equity analysts' earnings forecasts and thereby presents strong evidence of anti-

⁴ Zarnowitz and Lambros (1987) provide an extensive discussion on potential definitions of consensus and uncertainty in economic forecasting. Gregory et al. (2001) provide a more recent contribution concerning how a consensus should be defined, as well as providing additional empirical insights.

herding in form of an exaggeration of differences with respect to the consensus. Furthermore, implementing the notion that forecasters can extract valuable information from consensus forecasts, Bernhardt et al. (2006) as well as Chen and Jiang (2006) present evidence in favor of anti-herding in forecasting. Most recently, Doern and Weisser (2011) investigate macroeconomic forecasts and find a strong dispersion of forecasts, leading them to conclude that predictions overall are informational efficient and unbiased.

Another strand of literature approaches the role of reputation in forecasting by analyzing which analysts consistently stick to consensus values or make deviating predictions on a personal level. Stickel (1992) shows that analysts with a high reputation who made it on an “all star” list tend to rely less on consensus values. Cooper et al. (2001) support this point of view, showing that earnings forecasters herd by following superior lead analysts. As superior analysts publish their forecasts earlier, timeliness is suggested as a good measure of performance. Consequently, herding on consensus values is not universal, but rather depends on the expertise of individual forecasters. Analyzing individual career paths, Hong and Kubik (2003) show that accurate, as well as generally optimistic forecasters are more likely to have favorable careers. Clarke and Subramanian (2006) investigate the connection of employment risk and deviations from consensus values, showing that analysts with both very high and very low employment risk are most likely to deviate from consensus values. Leone and Wu (2007) measure the validity of analyst rankings and argue that they correctly represent their performance in terms of accuracy. Another prominent discussion deals with experience of analysts and their tendency to herd on consensus values. Chevalier and Ellison (1999), Hong, et al. (2000), Lamont (2002), and Clement and Tse (2005) report results consistent with theoretical work by Avery and Chevalier (1999) and Holmstrom (1999), thus indicating that older analysts herd less compared to their young counterparts. By contrast, Prendergast and Stole (1996) and Graham (1999) theoretically show that older analysts and managers should herd more. These assumptions are supported empirically by Stark (1997), Graham (1999), Li (2002) and Boyson (2010) who suggest that increased experience does not lead to more extreme deviations from consensus values.

While there are numerous theoretical and empirical contributions on reputational herding in prediction markets, to the best of our knowledge no experimental study to date has attempted to reconcile forecasting and strategic coordination in a single experimental setting. We thus review the respective experimental research.

Primarily, there is a large number of empirical studies on forecasting from the perspective of experimental economics, operational research and experimental psychology, with Leitner and Wildburger (2011) providing a comprehensive review. While several aspects are considered in these fields, reconnecting the findings to the more general discussions on consensus-seeking behavior in economic forecasting remains difficult. We argue that the most accessible finding in this regard is the ubiquitous rejection of the rational expectation hypothesis. Unsurprisingly, this finding is replicated in a number of experimental studies using graphical depiction of indicators that constitute the future value to be predicted.⁵ Thus, subjects' inability to adequately process fundamentals and reconstruct the underlying models can be interpreted as asserting the notion of reputational herding by incapable forecasters.

Secondarily, with regard to coordination behavior, the experimental studies on “sunspot” equilibria (SSE) are closest to our study and can be used to derive our behavioral predictions. The first experiment testing the rationality of subjects in SSE-coordination games was put forth by Marimon et al. (1993). In a simple market setting, colored squares serve as a coordination mechanism, yet no coordination on SSE resulted. In the seminal contribution on SSE, Duffy and Fisher (2005) are the first to show that extrinsic, irrelevant information fosters coordination. In their setting, salient sunspots without connection to the fundamentals influence subjects' decisions and foster coordination. Crawford et al. (2008) show that sunspots' effectiveness is limited when they are not payoff dominant. Similarly, Bosch and Vried (2013) report that the impact of focal points strongly depends on the respective payoff and time that subjects have to consider coordination choices. This result is discussed by Agranov and Schotter (2012), who find that detrimental effects of payoff asymmetries can be neutralized by implementing communication among subjects. Alternatively, Roos et al. (2010) consider SSE as a reason for coordination failure, which might lead to welfare losses, as subjects are dragged away from the payoff-dominant equilibrium by the sunspot. Fehr et al. (2011) show that the efficiency of sunspot coordination depends crucially on the precision of public information, private signals and their respective correlation. Accordingly, extrinsic information might also lead to miscoordination, which is interpreted as evidence for the considerable fragility of sunspot-coordination. Further applications of this concept are provided by Arifovic et al. (2012), who show sunspot coordination in macroeconomic

⁵ See Becker et al. (2005; 2007; 2008; 2009) for different variants of this experimental design. While parameters are changed, the basic conclusion of non-optimal forecasts, as measured by the benchmark of rational expectations, is replicated.

forecasting, as well as Shurchkow (2013), with coordination framed as speculation attacks. Finally, Bardsley et al. (2009) comprehensively discuss the working mechanisms of coordination by independent subjects, yet find contradictory evidence for the two potential explanations of team reasoning and cognitive hierarchy. Consequently, the exact behavioral mechanisms for successful coordination have not been determined to date. In a closely related experimental strand of literature, external recommendations for coordinated play are considered. Duffy et al. (2013) provide an overview, concluding that experiments so far have shown that recommendations to play a particular equilibrium are only followed imperfectly and particularly less if the recommended equilibrium is payoff-dominated by some other equilibrium of the game. We interpret these findings as pointing to the fragility of coordination on focal equilibria, given that even experimenter-given advice is only followed irregularly. Therefore, coordination on endogenously generated equilibria in forecasting might not emerge robustly.

A third strand of literature from experimental economics relevant to our study is the superior performance of groups in achieving coordination. While teamwork itself has been shown to increase overall rationality across experimental studies (see e.g. Kugler et al., 2012), coordination in particular is similarly facilitated by the cooperation of players; for instance, as in Feri et al.'s (2010) study of coordination games. These findings hold relevance in our setting, which comprises both teamwork and coordination, suggesting that coordination might be facilitated by a two-player team setting, as implemented in this study.

3. EXPERIMENTAL DESIGN AND PROCEDURE

We implement a forecasting task that is built on the experimental design by Becker et al. (2007). Additionally we introduce incentives for coordination, extending the basic setting, which primarily encourages accurate predictions. The coordination element is based on the experimental literature on sunspot equilibria (Duffy and Fisher, 2005). Under fully rational behavior, the welfare maximizing outcome is defined by all subjects making optimal forecasts and thereby automatically coordinating on the expected future values. However, this is an unlikely outcome given the high complexity of the forecasting task. Ultimately, the decision problem for all subjects comes down to choosing between the strategies of making accurate forecasts or attempting to coordinate on a common focal point. In the following, we present the specifics of the game to clarify the dual game structure.⁶

3.1 GAME SETUP

Let us first consider the forecasting task, before explaining the coordination aspect of the game and finally describing the respective payoff regime.

Forecasting task

Participants are asked to make 21 forecasts on the development of a time series x_t , which are the realizations of the simple linear equation:

$$x_t = \theta_1 a_t + \theta_2 b_t + \theta_3 c_t + \theta_4 d_t + \varepsilon_t$$

with $\theta_1 = 11$, $\theta_2 = -6$, $\theta_3 = -4$, $\theta_4 = -0.3$ and ε_t being a normally distributed random variable with $\varepsilon_t \sim N(0,15) \forall t \in T$. These weighting factors and the realizations of the random variable are unknown to participants. Weightings are chosen such that values for a_t drive x_t positively to a similar extent as b_t and c_t combined negatively. The influence of d_t is rather small, which simplifies the task, once this has been recognized by subjects. However, participants receive values for a_t, b_t, c_t, d_t in every period, henceforth denominated as determinants. All values are rounded integers. Expected future values can subsequently be derived without taking ε_t into account, given that:

$$E(x_t) = E(\theta_1 a_t + \theta_2 b_t + \theta_3 c_t + \theta_4 d_t) + E(\varepsilon_t) = \theta_1 a_t + \theta_2 b_t + \theta_3 c_t + \theta_4 d_t$$

⁶ Instructions including a screenshot of the game play are attached in appendix A and B. Original instructions were in German and can be obtained from the authors upon request.

Overall, there are $T = 30$ periods. The forecast horizon h is five periods. Let \tilde{x}_t denote the forecast at period t , which aims at x_{t+h} . This means in period $t = 5$, subjects make a forecast $\tilde{x}_{t=5}$ for $x_{t=10}$ and so on. Subjects observe determinant values and the values of x_t of the first five periods before making forecasts. Accordingly, the first forecast is given in period 5, and the last one in period 25. Thus, while subjects did not know the correct formula, they had a certain insight into the past development of the time series and could reflect upon its derivation.

Additionally, the correct value x_t is shown in each period t ; this has subjects wait five periods to assess the accuracy of their predictions. Consequently, the first feedback is given in period 10.

Figure 1 summarizes the determinant values, while Figure 2 shows the resulting time series of x_t and respective expected values for $x_t (= x_t - \varepsilon_t)$ over the course of the game.

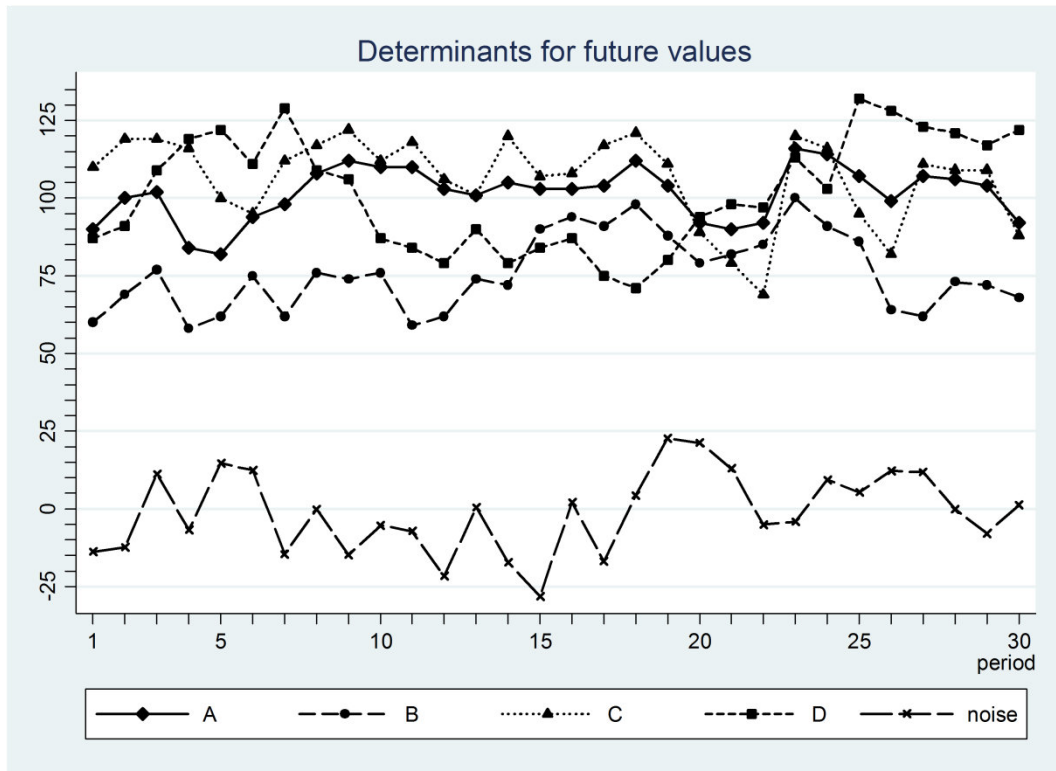


Figure 1: Time series' for determinants

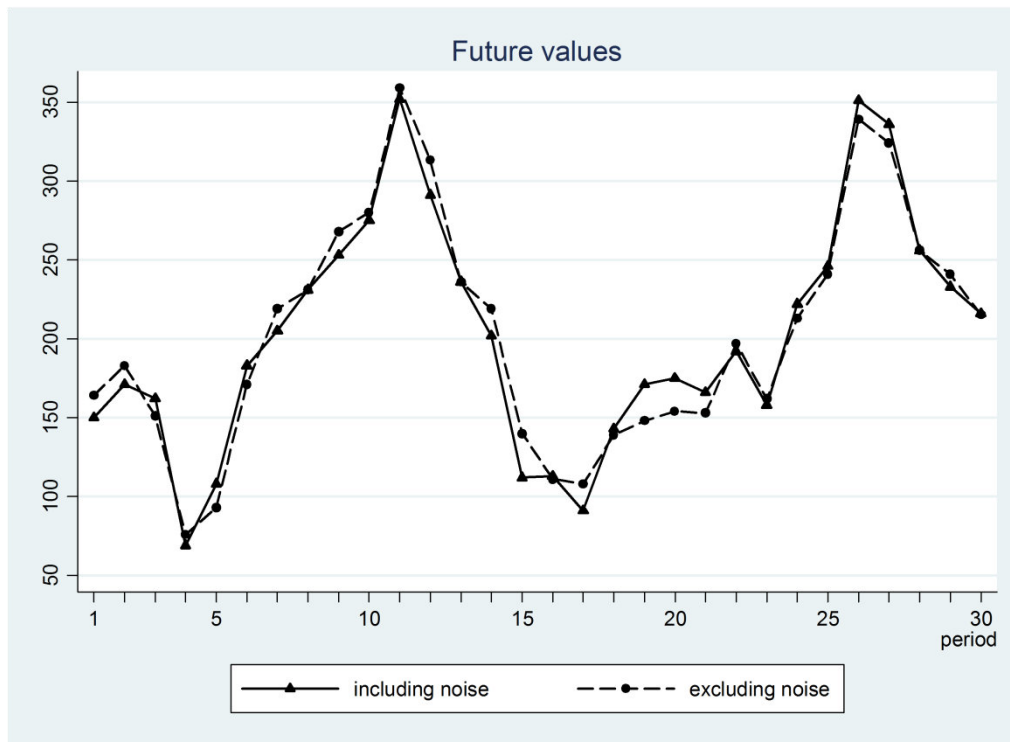


Figure 2: Time series to be forecast

Along with every forecast, subjects are asked to report a self-assessment on three questions. The first question refers to the subject's effort when making the prediction, the second question prompts subjects to assess the accuracy of the respective forecast and the third is concerned with subjects' confidence about the accuracy of the forecast given. All three questions have to be answered by noting the respective assessment on a scale from 1, representing "very low", to 7, reflecting "very high". Answering the three obligatory questions is not rewarded by an additional payoff.

Coordination task

Subjects are matched to societies of eight players. Each society consists of four teams with two members. Within a team, members are allowed to communicate using the chat implemented in zTree (Fischbacher, 2007). We thus simulate analyst communities that exchange information and potentially influence each other's decisions. However, the two group members are not obliged to give unanimous forecasts. All subjects in a society receive information about all other players' forecasts in the previous periods, as well as the respective payments achieved (costs and bonuses). This structure allows participants to coordinate by observing all others' decisions, whereby coordination can be fostered explicitly through the chat and implicitly through the forecast itself.

Payoffs

Our payoff regime incorporates three distinct aspects, as described below.

Firstly, we implement costs of forecasts equal to 1Cent times the percentage point deviation from the respective current value. According to Brown (1998), subjects are more likely to make more accurate forecasts when threatened by losses, rather than continuous positive gains. Thus, we endow each subject with €8.00, while the payoff for each period can become negative. Let C_t denote the costs of forecast denominated in € in period t and \tilde{x}_t the forecast aiming at x_{t+h} ; accordingly, we can write:

$$C_t(\tilde{x}_t, x_t) = \left| \frac{\tilde{x}_t - x_t}{x_t} \right|$$

Building on Brennscheidt (1993), we implement a punishment of extreme predictions. More importantly, these costs of forecasts ensure the existence of a unique, risk dominant sunspot equilibrium for coordination, as discussed in the subsequent section.

Secondly, each participant is paid an accuracy bonus of €2.5 for every accurate prediction, whereby we define a prediction as accurate if $0.95x_{t+h} \leq \tilde{x}_t \leq 1.05x_{t+h}$, i.e. if the interval $M_t = [0.95x_{t+h}, 1.05x_{t+h}]$ contains \tilde{x}_t . Thus, an accurate prediction deviates from the correct value by 5% at most. Let $y_{i,t}^a$ denote the function that determines the accuracy bonus payment for each player $i = 1, \dots, 8$; therefore, we can formulate:

$$y_{i,t}^a(\tilde{x}_{i,t}) = \begin{cases} 1, & \text{if } \tilde{x}_{i,t} \in M_t \\ 0, & \text{else} \end{cases} \quad \forall 9 < t < 26$$

Thirdly, there is a coordination bonus of €1 in each period, for which at least five of the eight subjects have to give forecasts in a specific interval. The range of the interval is derived from the five forecasts that are closest in relative terms in each period. The average of the highest and the lowest of these five forecasts builds the midpoint of the interval, with the lower and the upper bound again defined by a 5% deviation.

Let \tilde{x}_t^r denote the prediction in period t that is assigned rank r . Ranks are assigned to predictions sorted by their size, where $r = 1, \dots, 8$. X_t^j denotes the j^{th} vector in period t , comprising five forecasts. Thereby, vector $j = 1$ includes values from the smallest forecast ($\tilde{x}_t^{r=1}$) to the fifth smallest forecast ($\tilde{x}_t^{r=5}$). The same procedure applies to $j = 2, 3, 4$.

Therefore, we define:

$$X_t^j = (\tilde{x}_t^{r=j}, \tilde{x}_t^{r=j+1}, \tilde{x}_t^{r=j+2}, \tilde{x}_t^{r=j+3}, \tilde{x}_t^{r=j+4}) \forall j = 1, \dots, 4$$

$X_t^{j^*}$ denotes the vector with the smallest relative deviation of the upper bound from the lower bound. Let $A(X_t^j)$ denote a function that gives these relative deviations; hence:

$$A(X_t^{j^*}) = (\tilde{x}_t^{r=j^*+4} / \tilde{x}_t^{r=j^*}) \leq A(X_t^j) = (\tilde{x}_t^{r=j+4} / \tilde{x}_t^{r=j}) \forall j^* \neq j$$

The interval for deriving the coordination bonus can then be written as:

$$H_t = [0.95(\tilde{x}_t^{r=j^*} + \frac{(\tilde{x}_t^{r=j^*+4} - \tilde{x}_t^{r=j^*})}{2}), 1.05(\tilde{x}_t^{r=j^*} + \frac{(\tilde{x}_t^{r=j^*+4} - \tilde{x}_t^{r=j^*})}{2})]$$

If at least five subjects make forecasts lying within this interval, these subjects are rewarded the coordination bonus. Let $y_{i,t}^c$ denote the function to determine the coordination bonus for each subject and period; therefore:

$$y_{i,t}^c(\tilde{x}_{i,t}, \tilde{x}_{k \neq i,t}) = \begin{cases} 1, & \text{if } \tilde{x}_{i,t} \in H_t, \sum_{i=1}^8 g_{i,t} \geq 5 \\ 0, & \text{else} \end{cases} \quad \forall i, t$$

$$\text{with } g_{i,t}(\tilde{x}_t^i) = \begin{cases} 1, & \text{if } \tilde{x}_{i,t} \in H_t \\ 0 & \forall i, t \end{cases}$$

The comprehensive payoff function comprising the three components for each player and period is then given by:

$$Y_{i,t}(\tilde{x}_{i,t}, \tilde{x}_{k \neq i,t}) = y_{i,t}^a(\tilde{x}_{i,t}) + y_{i,t}^c(\tilde{x}_{i,t}, \tilde{x}_{k \neq i,t}) - C_{i,t}(\tilde{x}_{i,t}, x_t)$$

In short, subjects can receive payments by making accurate forecasts and coordinating, while they have to bear costs when deviating from each rounds' naïve forecast.

3.2 PROPERTIES OF THE GAME

This section develops the criteria for rational behavior and formulates expectations concerning subjects' behavior.

Optimal forecasts

The optimal strategy unrestricted by cognitive limitations is given by forecasts equal to the expected future values. Note that the accuracy bonus is not guaranteed by an optimal forecast due to the realizations of the random variable ε_t . However, given the actual time series of x_t forecasts equal to expected future values pay the accuracy bonus in 14 of the 21 forecasting periods. The average costs for these forecasts amount to €0.52. Thus, in the case of optimal forecasting, an average net payment of €1.15 is realized.

In this case, whether additional payments for coordination are realized depends on other players' behavior. Consider the situation in which at least five players of a society give optimal forecasts. Each of these subjects then earns the cooperation bonus, in addition to the accuracy bonus. Accordingly, the average net payment amounts to €2.15 per period.

The coordination regime

Given the forecasting task's complexity, it is reasonable to assume that subjects will fail to make optimal forecasts. In this case, they are enabled to establish a coordination regime, which pays the coordination bonus. Note that all forecasting values inducing costs smaller than €1 are Nash-equilibria for coordination. However, there is a strictly risk dominant equilibrium in coordination, which is given by the current values. Thereby, naïve forecasts can realize the coordination bonus without incurring any costs. This can be interpreted as a sunspot equilibrium, given that current values hold very little additional information for forecasting future values.

In sum, effective coordination is possible in many ways, e.g. by forecasting a simple trend or choosing a series of salient numbers like 200,300,200 etc. However, there is only one possibility of efficient coordination given by forecasting the current values. While inefficient coordination pays the coordination bonus of €1 minus the costs of deviations from current values, efficient coordination gives an average net payment equal to the coordination bonus. Nevertheless, the average net payment for efficient coordination is still lower than for making accurate forecasts without having four other players predicting optimally.

Minimizing Costs

A third potential outcome is intertwined with the attempt to establish a coordination regime. Risk-averse subjects might rely on the strategy of naïve forecasting to minimize costs,

whereby an efficient coordination might evolve. In the absence of coordination, this strategy pays €0 in each period and subjects would end up with their initial endowment of €8.

Expected behavior

Having outlined three basic strategies players can choose to pursue, it cannot be unambiguously defined which strategy ultimately defines rational behavior, given that it depends on each subject's cognitive ability and the expectation toward the other subjects' behavior within a society.⁷ Moreover, risk preferences might play a crucial role, especially since potentially negative outcomes in each period are likely to trigger loss aversion.

Overall, there is a well-defined and easily accessible risk dominant equilibrium in coordination, given by the strategy of naïve forecasting. Thereby, current values can be interpreted as sunspots facilitating coordination. We are interested in whether societies are able to establish this efficient equilibrium, i.e. a coordination regime at minimal costs, and, if so, how fast, comprehensive and stable coordination proves to be. Furthermore, we look into the dynamics of coordination and identify whether the successful cooperation of others prompts subjects to join in, dismissing their attempts at making accurate forecasts.

3.3 PROCEDURE

The experiment was conducted in the Laboratory for Behavioral Economics at the University of Göttingen. Participants were recruited using ORSEE (Greiner, 2004) and were only allowed to participate in one session. Experiments were programmed using z-Tree (Fischbacher, 2007). There were 25 sessions featuring 25 societies in December 2011 and January 2012, which gives us 200 participants in total. Prior to each session, understanding of instructions was made sure by running control questions. The sessions lasted around ninety minutes with participants earning €14.50 on average. Participants were on average 23 years old, 55% were female and 38% students of economics or business administration.

⁷ To analyze incentives and expectations in detail, one might consider a level- k approach as presented by Nagel (1995). However, a level-k based approach to individual behavior is beyond the exploratory scope of this paper.

4. RESULTS

We analyze our results with respect to prediction accuracy, the effectiveness of coordination and overall welfare. Furthermore, we are interested in subjects' self-assessment concerning their effort to make predictions, as well as the confidence in their respective accuracy.

4.1 ACCURACY OF PREDICTIONS

We begin by analyzing the accuracy of predictions. Therefore, we consider the prediction-accuracy matrix, as suggested by Andres and Spiwoks (1999). Accordingly, forecasts are classified within four categories set up by two dimensions, i.e. by the combination of *Theil's* new inequality coefficient (Theil, 1975) and the TOTA-coefficient. These two measures assess forecasting accuracy by a straightforward comparison of actual and naïve forecasts. We are thus able to reveal subjects' attempts at coordination on the risk dominant equilibrium by measuring their forecasting performance.

Theil's new inequality coefficient

To classify predictions within the prediction-accuracy matrix, we primarily need to calculate *Theil's* new inequality coefficient, which allows for an implicit comparison of actual and naïve forecasts. It is defined as the square root of the ratio resulting when dividing the mean of squared prediction errors by the actual mean of changes in the objective variable. Again, let T denote the total number of forecasts, h the forecast horizon, x_t the actual value in period t and \tilde{x}_t the forecast for period t . The coefficient is then defined as follows:

$$U = \frac{\sqrt{\frac{1}{T-h} \sum_{t=h+1}^T (P_t - A_t)^2}}{\sqrt{\frac{1}{T-h} \sum_{t=h+1}^T (A_t)^2}} \quad \text{with} \quad P_t = \frac{\tilde{x}_t - x_{t-h}}{x_{t-h}} \quad \text{and} \quad A_t = \frac{x_t - x_{t-h}}{x_{t-h}}$$

For exact predictions, U becomes 0. Predictions worse than the naïve one are indicated by $U > 1$ and better predictions by $U < 1$.

Pooled over all subjects, U 's average amounts to 1.045, whereby 33% of prediction series show a value smaller than 1, while only 2.5% achieve a value smaller than 0.9. This clearly indicates weak prediction accuracy in general.

Furthermore, we are able to decompose the prediction error by rearranging the coefficient equation. We can write:

$$\frac{\frac{1}{T-h} \sum_{t=h+1}^T (P_t - A_t)^2}{\frac{1}{T-h} \sum_{t=h+1}^T (P_t - A_t)^2} = \frac{(\bar{P} - \bar{A})^2 + (s_P - s_A)^2 + 2(1 - r_{PA})s_P s_A}{\frac{1}{T-h} \sum_{t=h+1}^T (P_t - A_t)^2} = ME + VE + RE = 1$$

$$\text{with } ME = \frac{(\bar{P} - \bar{A})^2}{\frac{1}{T-h} \sum_{t=h+1}^T (P_t - A_t)^2} \quad VE = \frac{(s_P - s_A)^2}{\frac{1}{T-h} \sum_{t=h+1}^T (P_t - A_t)^2} \quad RE = \frac{2(1 - r_{PA})s_P s_A}{\frac{1}{T-h} \sum_{t=h+1}^T (P_t - A_t)^2}$$

\bar{P}, \bar{A} denote the averages of P_t and A_t respectively. s_P and s_A denote the standard deviation of P_t and A_t ; r_{PA} gives the respective correlation coefficient. Thus, ME describes the error with respect to the mean of future values, i.e. it measures the systematic error in predictions regarding the level of future values. A systematic error in forecasts with respect to the variance of future values is captured by VE. Accordingly, RE measures the random, non-systematic component of prediction errors. Andres and Spiwoks (1999) point out that the quality of predictions crucially depends on their ability to correctly assess the variance and levels of future values. If forecasts fail to capture the two aspects, this indicates the inability to forecast the general development of the objective time series. Better forecasts are indicated by prediction errors that are driven by the random component.

Across all forecast series, we find the median share of the random component to be 51%, while the variance component is about 32% and the miscalculation of the future values' level is 16%. Hence, only half of the total prediction error can be ascribed to the random component.

TOTA-coefficient

In order to more appropriately assess prediction accuracy, we additionally calculate the second dimension of the prediction-accuracy matrix: the Topically Oriented Trend Adjustment (TOTA)-coefficient (see Andres and Spiwoks, 1999; Bofinger and Schmidt, 2003). This coefficient represents the ratio of forecasts and correct values correlation, as well as the correlation of forecasts with current values at the time the forecast was made.

For a forecast that is orientated at future values, we can write in short:⁸

$$TOTAL - coefficient = \frac{R_{forecats, future values}^2}{R_{forecasts, current values}^2} = \frac{R_{\hat{x}_t, x_{t+h}}^2}{R_{\hat{x}_t, x_t}^2} > 1$$

Where R^2 is the coefficient of determination, i.e. the squared correlation in a simple linear OLS regression without an intercept when regressing forecasts on future or current values. A TOTA-coefficient < 1 indicates topically oriented trend adjustment, i.e. forecasts more heavily rely on current values than future values. Essentially, topically oriented trend adjustment represents overestimation in case of a downward trend in the course of the objective value and an underestimation if there is an upward trend of future values.

Table 1 summarizes the results for the TOTA-coefficient pooled for all subjects.

	Mean	std. dev.	min	max
<i>TOTAL – coefficient</i>	0.6	0.02	0.49	0.73
<i>R_{forecats, future values}²</i>	0.18	0.012	0.12	0.23
<i>R_{forecasts, current values}²</i>	0.30	0.02	0.19	0.32

Table 1: The TOTA-coefficient

Overall, the correlation of forecasts and future values is weaker than the correlation between forecasts and current values. Given that no subjects achieve a TOTA-coefficient greater than 1, all subject are prone to a topically trend adjustment by considerably relying on current values, which points to a coordination or cost minimizing strategy. The results are very homogenous, as can be seen by rather low standard deviations, as well as the minimum and maximum values of the coefficient.

Prediction-accuracy matrix

The prediction accuracy matrix allows us to categorize forecasts according to the TOTA-coefficient and a selected goodness of fit measure, using *Theil's new inequality coefficient* (Andres and Spiwoks, 1999). The first category captures quasi-naïve forecasts, which can be characterized by the existence of topically oriented trend adjustment and a lower accuracy, which could have been achieved by naïve forecasts. Forecasts of the second category, denominated as false forecasts, similarly show low accuracy yet no topically oriented trend adjustment. The third category, direction forecasts, comprises forecasts showing topically oriented trend adjustment yet a higher accuracy than naïve forecasts. Finally, the fourth

⁸ For the comprehensive derivation of the TOTA-coefficient, we refer to Andres and Spiwoks (1999).

category, denominated as optimal forecasts, is achieved if forecast are better than the naïve forecasts and do not show topically oriented trend adjustment.

Figure 3 shows the distribution of mean individual forecasts over the four categories described.

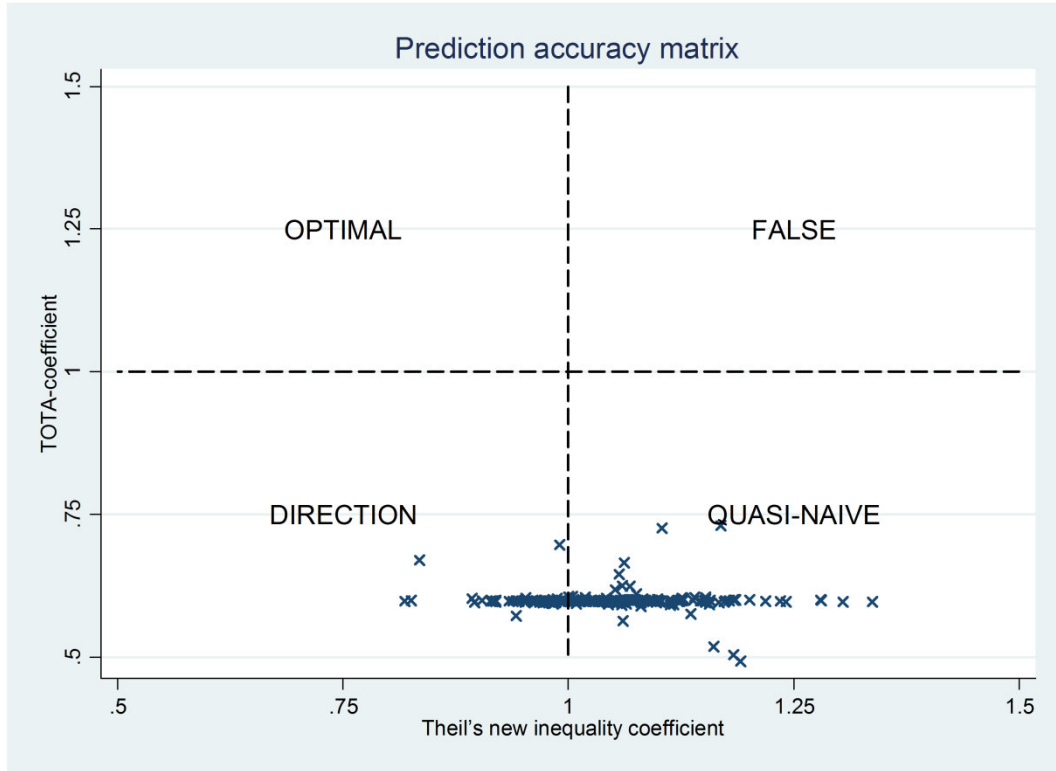


Figure 3: Prediction accuracy matrix for all subjects.

As can clearly be seen, the vast majority of forecasts fall within the category of quasi-naïve forecasts (67%), whereas only 33% are direction forecasts. All of the subjects forecast series are prone to the topically oriented trend adjustment. We can thus formulate our primary result.

RESULT 1: Subjects fail to make accurate forecasts and rely considerably on current values.

4.2 COORDINATION

We have shown that subjects are incapable of making accurate predictions, i.e. predictions that are equal to the expected future values. However, this might not reflect irrational behavior, given that participants could have chosen the alternative strategy of establishing a coordination regime. The effectiveness and stability of coordination is analyzed in the following, where we turn to the society level of aggregation to analyze our results.

Figures 4 to 6 offer representations of different aspects of coordination for each society, whereby we distinguish between effective and efficient coordination. The former merely demands subjects to successfully establish a coordination regime, whereas the latter requires the coordination to minimize costs, i.e. using the respective naïve forecasts.

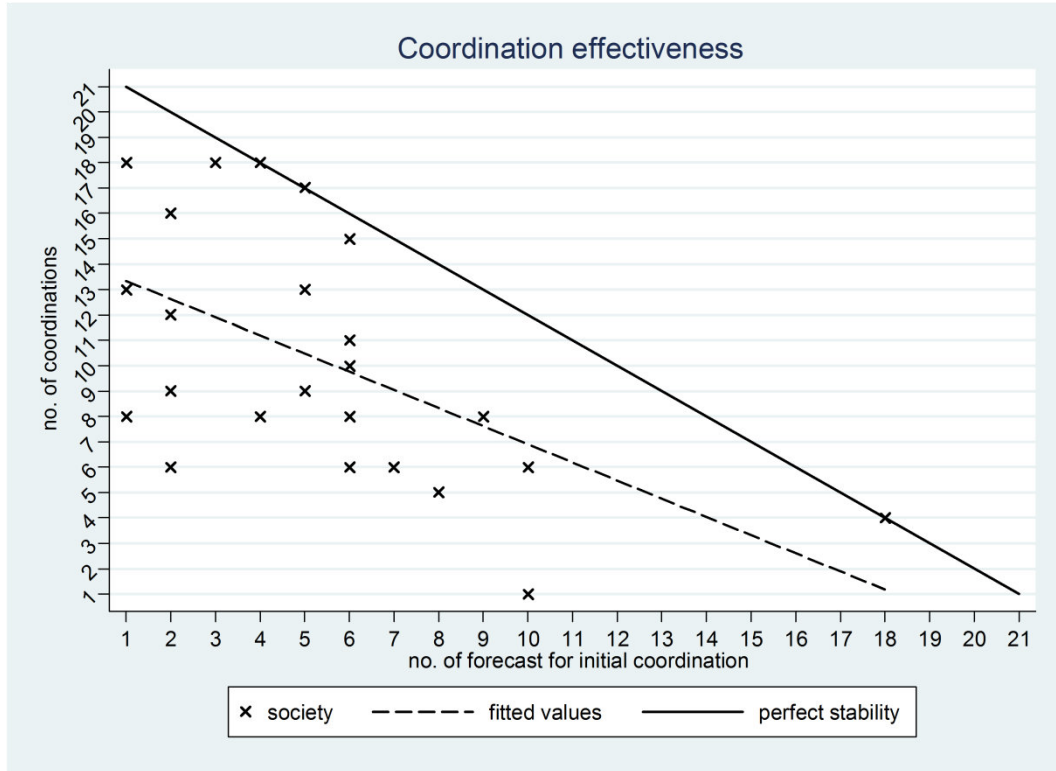


Figure 4: Coordination effectiveness.

Note: one society never managed to coordinate and is therefore not included. The number of coordination does not discriminate with respect to the number of subjects coordinating if at least the threshold of five players is met.

Figure 4 graphs the total number of successful coordination in relation to the initial period of successful coordination as an intuitive measure of effectiveness. As can be seen, the occurrence of a coordination regime within the first periods determines the subsequent course of coordination to some extent. Although there is a negative correlation of the initial period of coordination and the number of periods with successful coordination, only three societies manage to establish a perfectly stable regime, as indicated on the line presenting perfect stability. Thus societies achieving a successful coordination relatively early are likely to coordinate more often, but only few are able to coordinate in all subsequent periods. Although not perfectly stable, once established coordination regimes prove rather robust throughout the rest of the game. There is only one society that never coordinates.

Moreover, it can be expected that a successfully established coordination regime attracts the remaining subjects within a society. Figure 5 gives a more detailed perspective on the dynamics of coordination by showing the average share of subjects coordinating within a society. Additionally, the share of societies featuring coordination in the respective period is graphed. Lastly, we present the share of subjects playing the risk-dominant and cost-minimizing coordination equilibrium. We define a subject as playing this strategy if her respective forecast does not deviate by more than 5% from the naïve forecast.

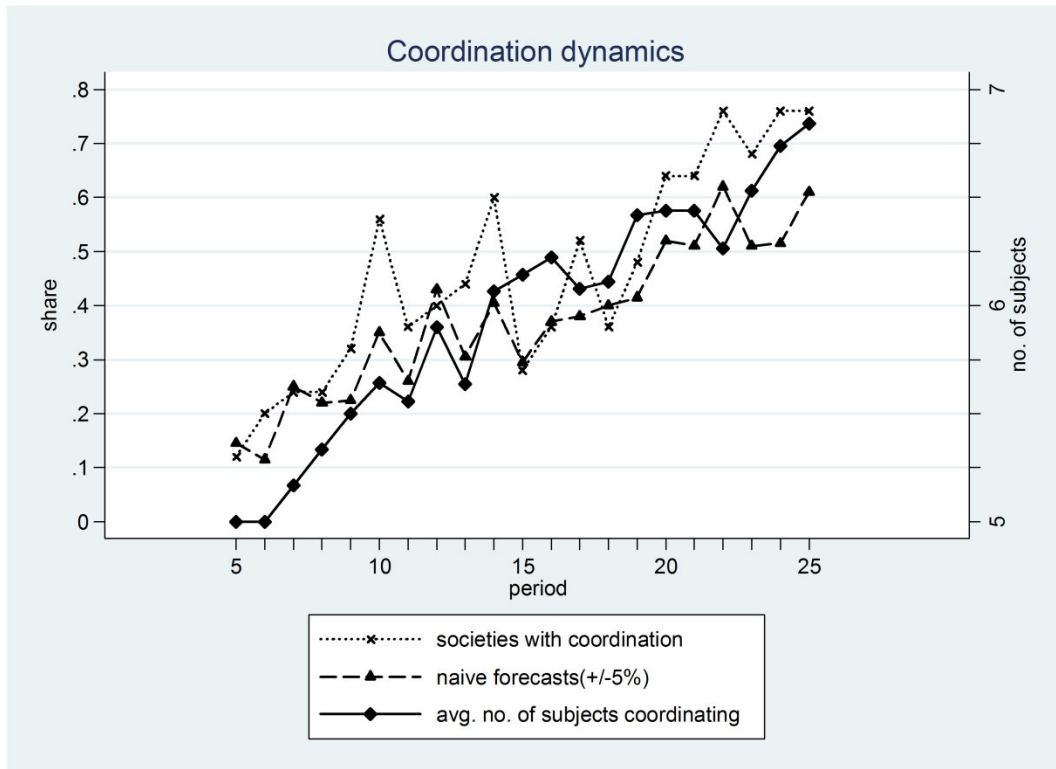


Figure 5: Coordination dynamics.

Note: share of coordinated societies with respect to all societies, naïve forecasts with respect to all forecasts and number of subjects coordinating.

Obviously, the share of societies achieving coordination is increasing over periods, which is driven by the rising share of subjects playing the risk dominant coordination equilibrium, i.e. make naïve forecasts. Also, the size of the coordination groups within societies increases throughout the game, which supports the notion of successful coordination attracting subjects that otherwise aim at accurate forecasts. However, only 22.63% of periods with successful coordination comprise all eight subjects of a society. In most cases (38.27%), only the minimum threshold of five players for the realization of the coordination bonus is reached. The coordination group is formed by six players in 32.1% of the times, and by seven players in 7%. Thus, a considerable number of subjects do not adjust to the majority within the

society following a coordination regime. They thereby forego considerably high payments by sticking to the strategy of attempting to forecast accurately.⁹

Considering efficiency of coordination, evidently naïve forecast are the predominant mechanism of coordination as the presentation of costs of forecasts in Figure 6 shows.

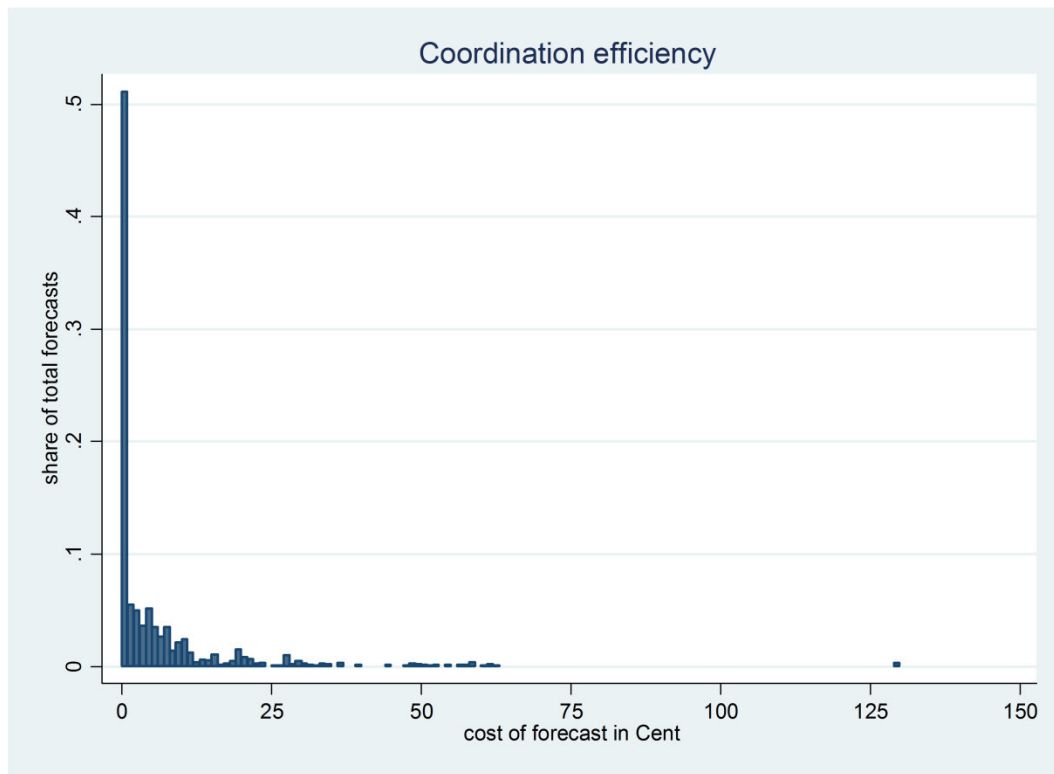


Figure 6: Coordination efficiency.

Note: only costs of forecasts yielding the coordination bonus are considered.

It can be seen that coordination is very efficient as the risk and payoff dominant equilibrium is used for a coordination regime most often, i.e. player coordinate on current values. More than 50% of forecast yielding the coordination bonus are exactly equal to current values, and the vast majority is not deviating more than 10% resulting in costs of less than 10 Cent. Coordination effectiveness is clearly fostered by the salient risk dominant equilibrium of making forecasts equal to current values. In none of the situations featuring successful coordination players manage to coordinate on the expected future values, abstaining from the cases where current values and future expected values happen to be similar. Thus the optimal

⁹ Another explanation might be seen in subjects' incapability of understanding the coordination mechanism. However, since they are able to communicate with one group member and there is full information about all other players' payments and forecasts this seems less likely.

solution of coordination on the expected future values is not achieved. We can formulate our second main result accordingly.

RESULT 2: Overall, coordination increases as the game proceeds and attracts subjects within societies, but attempts at forecasting are not universally discarded in favor of the coordination regime. However, subjects coordinate efficiently once they abstain from attempting to forecast accurately.

4.3 SELF-ASSESSMENT: EFFORT AND CONFIDENCE

Note that forecasts show poor quality (see Figure 3) even in the very first periods in which coordination is not established. Thus, it seems reasonable to assume that subjects fail to make correct forecasts and subsequently turn to a coordination strategy as indicated by the dynamics of coordination. This perspective is supported by the reported self-assessments.

As described above, subjects answered three questions in each forecasting period. These questions refer to self-assessments regarding subjects' effort in forecasting, as well as their confidence in forecasting accuracy. Figure 7 provides an overview of the respective results.



Figure 7: Overview of additional forecasting self-assessments

Not surprisingly, given increasing coordination, reported effort and confidence levels deteriorate as the game proceeds. Subjects' effort is quite high for the first five periods, i.e. before subjects receive feedback, as indicated by an average reported effort level of 4.1. In periods 6-15, the average deteriorates to 3.4 and ultimately to 2.9 for the last ten predictions, for which 50.2% of subjects report a value smaller than three. Thus, if a stable coordination regime is established, the effort for each additional forecast is rather low.

In line with this finding, there is a trend towards more pessimistic self-assessments with respect to the accuracy of forecasts, which is reflected in decreasing reported levels for the second and third question. For both questions, the median is equal to one in the last 10 periods, which is the lowest possible self-assessment. However, given that reported confidence levels start off lower than the effort levels, the downward trend is weaker.

In sum, there is more successful coordination as the game proceeds, which lowers the effort for making predictions, as well as the confidence in the accuracy of forecasts. Although there might be some bias in the self-assessments as they were not incentivized, the results are consistent with the findings presented in subsection 3.1 and 3.2.

RESULT 3: As effective coordination increases, subjects' *forecasting efforts deteriorate*. Accordingly, reported confidence levels decrease, given that subjects aim at coordination rather than accurate forecasts.

4.4 WELFARE ANALYSIS

For a comprehensive welfare analysis, we use the structure of actual payoffs. Beforehand, we define four benchmarks to evaluate the payoffs achieved.

For the first-best strategy, i.e. deriving the correct formula from the first five periods and predicting the expected future value, an average payoff of €1.15 can be achieved as derived in section 3.2. We consider this case as our first benchmark. Optimally, at least four other subjects also forecast the expected values, which pays an additional €1 as a coordination bonus in each period. This gives us our second benchmark of €2.15. The third benchmark is formed by an efficient coordination at minimal costs for forecasts, i.e. by coordination on the risk dominant equilibrium. Thus, in each period, subjects would receive €1. The last benchmark is given by the cost minimizing strategy, which is realized if subjects give strictly naïve forecasts without an effective coordination. Given that costs of forecast are zero and there are no bonuses, the respective payoff amounts to €0. Recall that subjects were given a

budget of €8 and payoffs for each period could become negative. On average, subjects earned €14.50, showing that they yielded a positive amount on average, but less than the 29€ accruing from efficient coordination in all periods.

Figure 8 summarizes the average costs, bonuses and total payoffs for all periods, as well as future values.

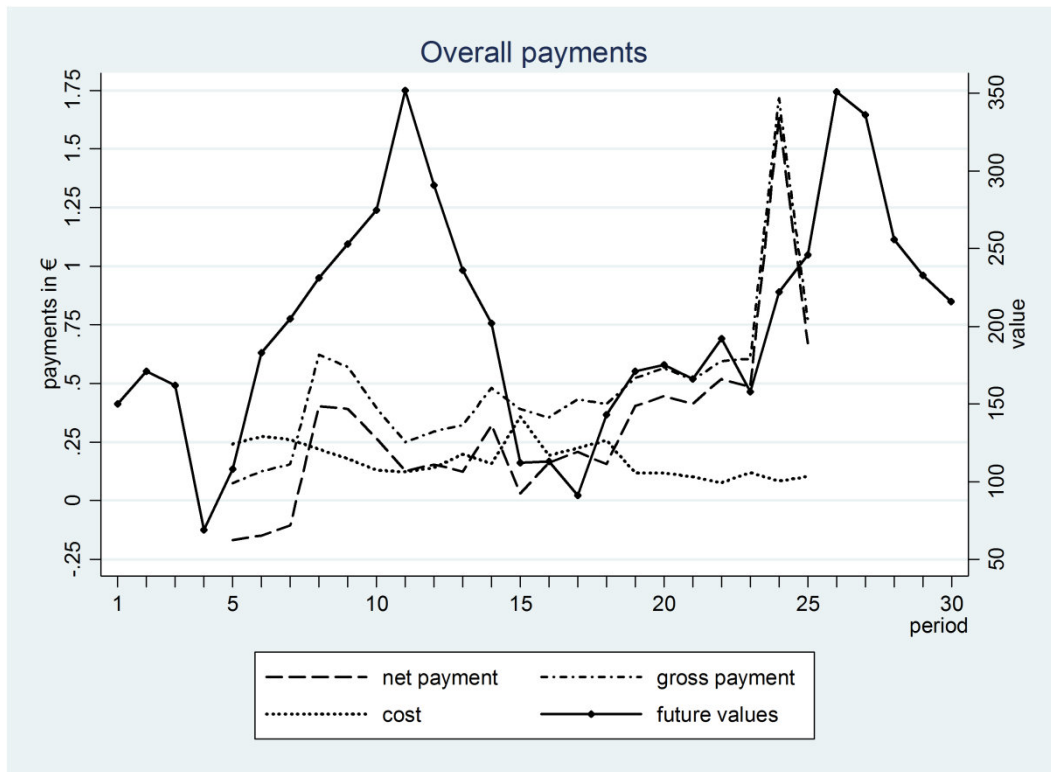


Figure 8: Overview of payoffs, costs of forecasts and future values.

It can be seen that subjects overall start off worse than the lowest benchmark given at €0. Subjects in the first periods unsuccessfully try to make accurate forecasts, thus bearing substantial costs. As the game proceeds, they increasingly coordinate effectively, which increases average payoffs. Net payments tend to go down for relatively low current values as attempts for accurate forecasts induce higher costs since relative deviation from the naïve forecast increases. However, subjects on average never reach the benchmark of efficient coordination, which would yield €1 on average. Although costs tend to decrease during the game, narrowing the gap between gross and net payments, efficient coordination is not realized ubiquitously.

There are some salient events in our time series of actual values to be forecast that warrant further discussion to explain the pattern of payoffs. Within the first periods, payments tend to

increase until period 8, at which point they reach a local maximum, before subsequently decreasing for several periods. This can be explained by some correct forecasts by “accident” in period 8 and 9 (37 of 200 in period 8; 28 of 200 in period 9). For period 8, the future value to be forecast amounts to 236, which is close to the current value of 231. In period 9, the future value is 202, which was correctly predicted by some subjects relying on salient numbers: in this case, 200. Additionally, there is an extraordinary high number of payments for group coordination, given that many subjects oriented their forecasts at the value of 200 (91 subjects received the coordination bonus). Moreover, many subjects gained the extra €2.5 in period 24 merely by sticking to the naïve forecast.

As shown in Figure 9, payoffs on the society level are very heterogeneous, which can be explained by the varying effectiveness and dynamics of coordination. Thus, some societies even approach average payoffs amounting to the benchmark of efficient coordination, while others achieve very low average payoffs due to unsuccessful coordination and weak forecasting accuracy.

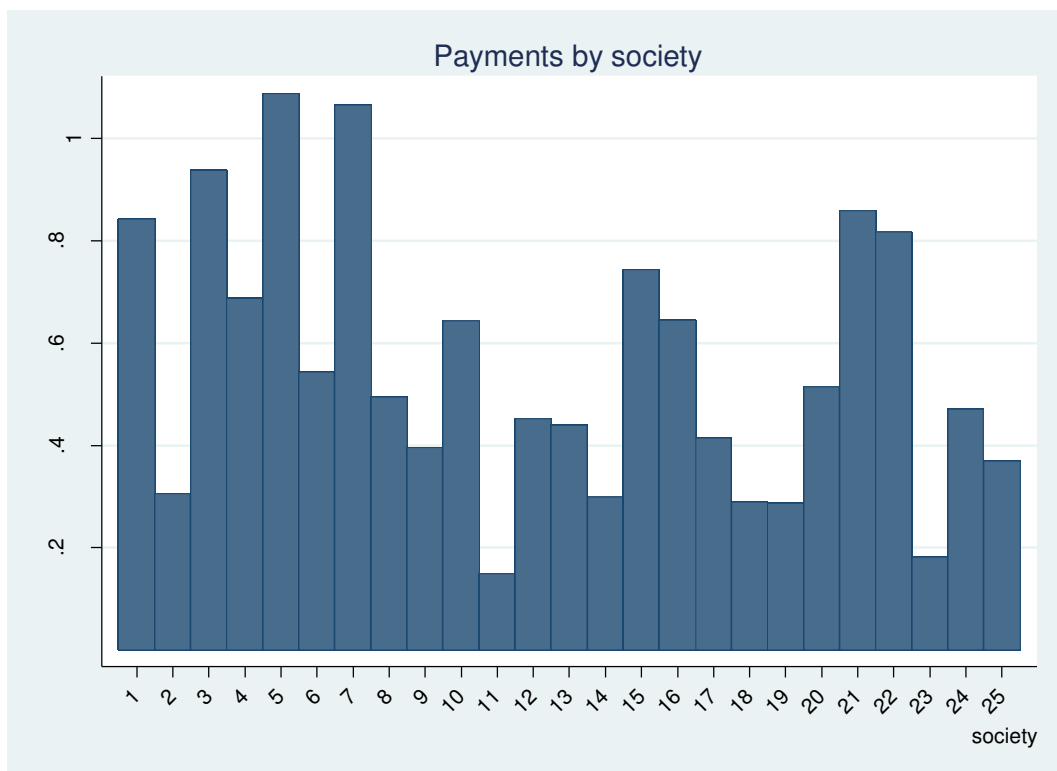


Figure 9: Average (net) payoffs per period on the society level

Overall, the welfare analysis shows that subjects fail to obtain the payoffs associated with perfectly rational forecasting. Also, coordination is not achieved universally, thus limiting the respective payoffs. However, on the society level, results are quite heterogeneous with overall

welfare depending on subjects' ability to learn to play the coordination equilibrium. We can formulate our forth core result.

RESULT 4: Subjects fail to achieve maximal payoffs through rational forecasting. Coordination is not perfectly efficient, given that it takes some time for subjects to establish a coordination regime, which subsequently fails to be perfectly stable. Coordination considerably increases payoffs, yet not to the full extent possible. In addition, individual payments crucially depend on the society-specific dynamics.

5. CONCLUSION

While the notion that analysts' "desire [...] to be perceived as good forecasters turns them into poor forecasters" (Ottaviani and Sorensen, 2006a, p.443) has been described theoretically and investigated empirically, the behavioral mechanisms of reputational herding remain largely unexplored. An empirical study in a controlled laboratory setting might thus reveal the behavioral processes involved in the interplay of forecasting accuracy and coordination among forecasters. In this paper, we aimed to experimentally investigate subjects' ability to coordinate on sunspot equilibria in a forecasting environment. Our study connects two separate strands of literature, one concerned with the efficiency of judgmental forecasting and the other discussing coordination on external focal points. Determining the occurrence, speed and stability of coordination on external signals adds to the understanding of reputational herding in forecasting settings from a behavioral perspective.

We provide results on subjects' behavior regarding the interplay of forecasting and coordination. While strong incentives for accuracy lead to initial efforts for achieving correct predictions, overall prediction accuracy is considerably low. As in previous experiments, we can reject the hypothesis of rational expectations for our forecasting task. Frustration with the task leads subjects to start playing the efficient coordination equilibrium, to which a majority of subjects conforms within a few periods. Sunspots are predominantly used to establish a simple coordination regime, while only few attempts to coordinate are made by relying on other salient numbers. Coordination on sunspot equilibria proves to be fairly robust once it is established. Overall welfare approaches but rarely reaches the benchmark payoff of efficient coordination. However, given subjects' inability to make correct forecasts, they forego significant payments rewarded for accurate predictions.

Presenting these results, we have illustrated a forecasting setting with conflicting incentives for accurate forecasts and coordination to show the effectiveness of payoff dominant SSE in fostering reputational herding. This provides additional empirical evidence for reputational herding through external signals, as outlined by Spiwoks (2004). Accordingly, forecasters evade the responsibility of making accurate forecasts that correctly reveal their private information and coordinate on consensus values instead. This effectively conceals their inability to make correct predictions. Analysts who fail to coordinate and continue to pursue correct predictions in our setting gain comparably low payoffs, which in a real-world setting would translate to the loss of reputation. Accordingly, in a more dynamic setting, only forecasters capable of coordination would succeed. Those attempting to forecast honestly would ultimately lose their occupation. On a more general level, our results emphasize that once prediction markets are structurally incapable of providing incentives for forecasts that reveal the analyst's insight about the future state, it can be assumed that they will quickly resort to herding on extrinsic focal points. While this assessment might not be applicable to all prediction markets, the empirical results suggest that numerous financial and economic predictions can be characterized by herding on consensus values. Therefore, further experimental studies should focus on investigating parameters that succeed in reducing herding in forecasting by introducing incentives for the revelation of private information and thus fostering anti-herding.

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APPENDIX A

Instructions for the experiment. The original instructions were in German and are available from the authors upon request.

General Information

In this game, you and other participants will make predictions for the development of a price. This price results from the development of different determinants. You know the four most important determinants (called A-D). Additionally, you know all prices up to the point of prediction. Based on this information, all participants make a prediction in every period. Your payoff depends on your own and your co-players' predictions. You may communicate via chat with another participant, who is randomly assigned to you at the beginning of the game. The chat messages and all other data are recorded in an anonymous form. Every participant has the same instructions and information.

The course of the game (see figure 1)

The game has 30 periods. In every period, you will make a prediction for the price in five periods. You will make your first prediction in period 5. In every period, you will see three consecutive screens:

The “Information and Chatscreen” (see: figure 2)

What you see: Development of prices up to the current period

Overview of the forecasts of all other participants

Development of the determinants (A-D)

Overview of the payoffs of all other participants

Additionally, you can use the chatbox to communicate with your group member and a calculator, which is active with a click on the respective symbol.

What you do: You make a prediction for the price in five rounds. To become accustomed with the game, you have 5 minutes to make your prediction in the first round, 3 minutes for the next five periods and 2 minutes for the rest of the game. You will see the time you have left for your prediction on the upper right side of your screen. You can reach the next screen by clicking “to the input screen”.

The “Input Screen”

What you see: You will see an input box and three questions about your prediction.

What you do: You enter your forecast within 30 seconds, answer the three questions and click “end period”. **Please note the time constraint:** If you allow the 30 seconds to pass without clicking “end period”, the game proceeds automatically. Your prediction for this period would be zero.

The “Payoff Screen”

What you see: Your current and overall payoff will be shown to you for 15 seconds.

What you do: No input is required.

Your Payoff

You start the game with a starting payment of 8€. You gain payoffs depending on your predictions, but also have to bear prediction costs. Thus, your payoffs for a single period can become negative. The payoff for all periods will be summed up and paid to you after the game. For the payoff, your prediction-costs, prediction accuracy and forecasts of other participants will be considered as follows.

Prediction costs: You will bear prediction costs in every round. They are estimated by the deviation of your prediction from the current price. You will be deducted 1Cent per percentage point deviation.

Prediction accuracy: All prices are the result of a fixed formula and the four determinants in the respective round, which determines 95% of the future price. 5% of the price is random. If your prediction is accurate, you will receive 2,50€ as an accuracy bonus. Accurate means that your prediction does not deviate by more than 5% from the actual price. You will learn if your prediction was correct in the period for which your prediction was made. For example, in period 10, you will learn whether your prediction in round 5 for period 10 was correct.

Example: The price in the current period is 100. Your prediction is 120; thus, you have immediate prediction-costs of 20. 5 periods later, you learn that the actual price was 125. Your prediction (120) does not deviate by more than 5% from the actual price. Thus, you receive a *2,50€ accuracy bonus for your prediction from 5 periods earlier*.

If you do not predict accurately, you will not receive an accuracy bonus and have to bear prediction costs.

The predictions of other participants

If the predictions of 5 (or more) participants do not deviate by more than 5% from a common price, each of the 5 participants receives 1€ as “group-bonus”.

Example: The current price is 100; 5 participants predict a price of 120 (+/-5%). The actual price, 5 periods later, is 150. The prediction was thus inaccurate. However, each of the 5 participants receives a *1€ group bonus and has prediction costs of -0,20€*.

Overview:

There are four situations in every period that lead to different payoffs.

1. Your prediction is inaccurate and you and at least 4 other participants have not predicted a common price.

Your Payoff: You earn 0€ minus your prediction-costs.

(Payoff = 0€ accuracy bonus + 0€ group-bonus – prediction costs)

2. Your prediction is inaccurate, but you and at least 4 other participants have predicted a common price (+/- 5%).

Your Payoff: You earn 1€ minus your prediction costs.

(Payoff = 0€ accuracy bonus + 1€ group-bonus – prediction costs)

3. Your prediction is accurate and you and at least 4 other participants have not predicted a common price.

Your Payoff: You earn 2,50€ minus your prediction costs.

(Payoff = 2,50€ accuracy bonus + 0€ group-bonus – prediction costs)

4. Your prediction is accurate and you and at least 4 other participants have predicted a common price (+/- 5%).

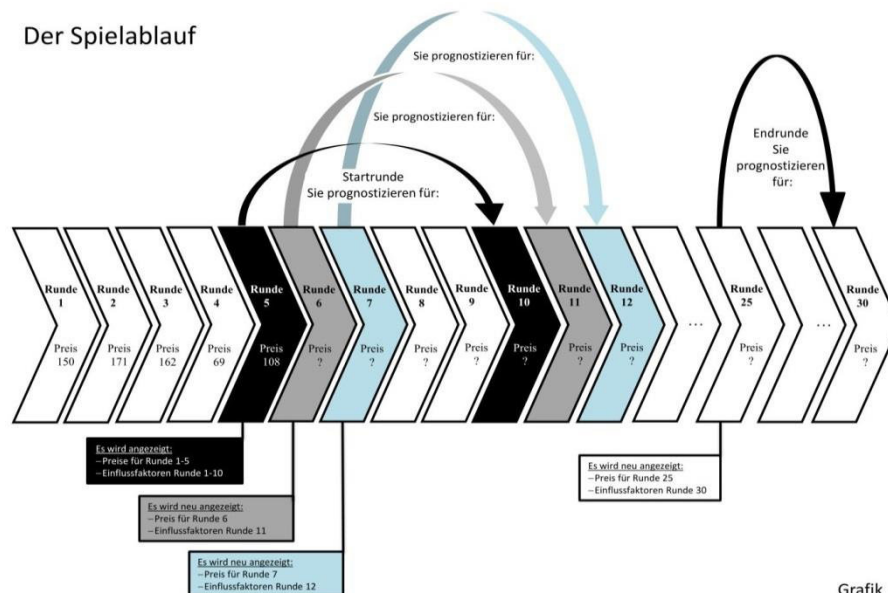
Your Payoff: You earn 3,50€ minus your prediction costs.

(Payoff = 2,50€ accuracy bonus + 1€ group-bonus – prediction costs)

We now ask you to answer some control questions on your computers. The game will start as soon as all participants have answered these questions correctly.

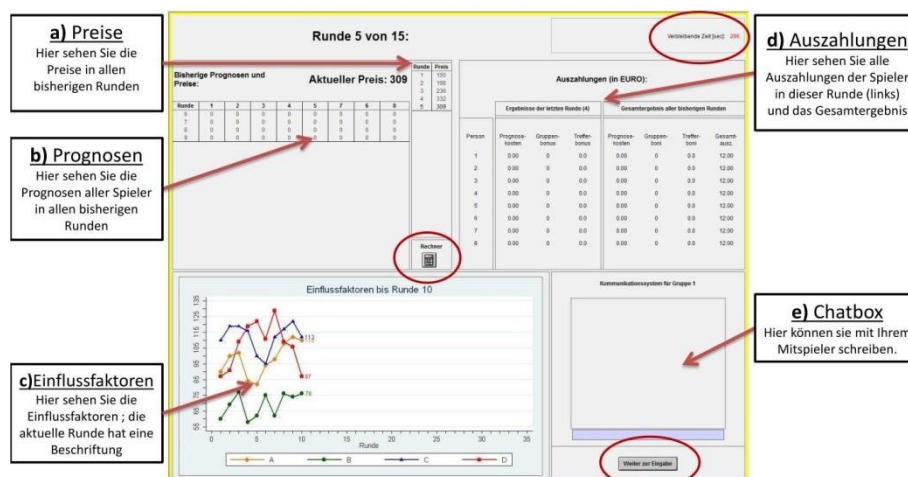
APPENDIX B

Additional explanatory graphics that were given to participants, along with the instructions that describe the structure of the game and the main screen.



Grafik 1

Der Informations- und Eingabebildschirm



Grafik 2