Market-Based Collective Intelligence in Enterprise 2.0 Decision Making

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1. INTRODUCTION

Organizations increasingly use social computing to harness the collective intelligence of their employees, partners, and customers in collective problem-solving and decision making. This trend towards Enterprise 2.0 can be defined as “the use of emergent social software platforms by organizations in pursuit of their goals” [McAfee 2009, p. 73]. One Enterprise 2.0 benefit is collective intelligence [McAfee 2009, p. 130], e.g. the use of prediction markets to elicit and aggregate information from a crowd and form a group prediction [Surowiecki 2005; Malone et al. 2010]. Prediction markets incentivize information revelation and frequently produce more accurate predictions than other information aggregation mechanisms [Berg et al. 2008; Ledyard et al. 2009; Teschner et al. 2011; Bennouri et al. 2011]. Given these properties, it is not surprising that many organizations adopt prediction markets as emergent social software platforms in crowdsourcing information. Enterprise prediction markets are, for example, used to forecast product development outcomes, demand, company and industry news [Cowgill et al. 2009], to forecast sales [Gillen et al. 2012], and to support project management [Ortner 1998]. In a recent survey among 2,609 entrepreneurs and employees, 9% reported that their company’s set of social computing tools includes prediction markets [Bughin et al. 2013].

Today, “practice is still far ahead of theory in the field of collective intelligence [... with the notable exception of prediction markets (for which a large body of work helps us understand what works and why)” [Bonabeau 2009, p. 50]. Using this large body of work might seem promising – it is, however, intricate as this work typically relies on the assumption that either prediction is an end by itself (there is no subsequent decision) or that market participants are decision-agnostic. On the contrary, contemporary use of prediction markets as Enterprise 2.0 decision support tools typically involves market participants with a vested interest in the decision. As market participants (employees) are directly affected by the decision taken, they have incentives to manipulate market prices and the subsequent decision. In literature these markets are sometimes referred to as decision markets [Hanson 1999]. Hence, simply carrying over knowledge on prediction markets to the design of such decision markets might be premature. To back this hypothesis, we build on theory and evidence on prediction markets, decision markets, and market manipulation, and test the key theoretical predictions in a lab experiment. Our data suggest that indeed, people who have a stake in the decision manipulate the market and partially corrupt information aggregation. More precisely, we show how different designs of the principal’s decision rule affect manipulation, information aggregation, and decision quality. In a nutshell, we find that the common practice is better than random but worse than an alternative design.¹

2. EXEMPLARY SCENARIO

Consider a manager or management board pondering two alternative product development projects, e.g. two new active pharmaceutical ingredients on the verge of entering clinical development. The two

¹More extensive versions of this extended abstract are available [Gimpel and Teschner 2013a; 2013b].
alternatives appear as close substitutes and the company can only afford to develop one of the products. The manager assumes that the R&D personnel, having worked on the projects, has private information regarding the likelihood of either product getting regulatory approval. Thus, the manager sets up two markets, one for each alternative, to predict the likelihood of regulatory approval, conditional on the decision to invest in product development. Now consider an R&D expert having worked on product A who has private information that makes it highly unlikely for product A to be approved, e.g. due to severe side effects. This expert faces a conflict of interest: Trading based on this information will improve the manager's decision and might yield profits from trading – maybe a bonus payment or an award. On the other hand, development of product A might be stopped and the expert might, in the worst case, be laid off. Thus, he might rather aim for manipulating the market, predict a high probability of success for product A, and wait for the truth to become apparent years later. Clearly, the potential gain from influencing the decision is often much higher than the minor gains from trade. This example relates to the typical applications described by Montgomery et al. [2013] and Cowgill et al. [2009]. The tendency to manipulation might even be intensified by the fact that in corporate decision markets, traders are typically anonymous and performance-based payments are commonly low.

The key issue with these corporate prediction markets is that prediction is not an end by itself but merely an input for a management decision. Decision markets bear two issues compared to prediction markets: First, markets need to predict outcomes conditional on a decision. As some decisions are not taken, the respective outcome cannot be observed. Hence, after the decision, the markets predicting conditional on counterfactuals are void [Othman and Sandholm 2010; Chen et al. 2011]. This allows ex-post costless manipulation of such markets. Second, experts having a vested interest in the decision – in most realistic scenarios for corporate decision markets this will be any expert – might aim at manipulating the markets to manipulate the decision. Such a manipulation may be costly within the scope of trading, but might maximize the sum of gains from trade and the decision's consequences.

3. EXPERIMENT DESIGN

The aim of the experiment is twofold: first, to test theoretical predictions on experts' behavior and information aggregation in decision markets and, second, to measure the effect of manipulation on decision quality. For this, we consider an information aggregation and decision making problem with a single principal making a decision and a set of two experts whom the principal consults by running conditional prediction markets. There are two binary lotteries represented by two urns, A and B, holding 10 balls each, some of them black, the others white. A principal – who will draw one ball from one of the urns – is interested in drawing a black ball. He decides which urn to draw from, the draw itself is random. The principal has a-priori knowledge on the potential states of nature but does not know the exact number of black balls in either of the urns. Experts receive private information on the state of nature [Oprea et al. 2007; Healy et al. 2010; Jian and Sami 2012; Deck et al. 2013]. To gain further information prior to deciding, the principal runs two parallel prediction markets for experts to share their private information. One market for urn A, one for B. Experts are financially compensated based on their trading performance. The market prices are assumed to reflect the aggregate prediction. Depending on their private information and risk preferences, experts might favor one or the other urn and, hence, might have an incentive for manipulating the decision.

The roles of the experts are taken by human subjects while the principal is automated. The principal's decision rule is the treatment variable. In the A-PRIORI treatment, he relies only on his a-priori knowledge on the likelihood to draw a black ball from either urn. By design, this is 50% for both urns. In the DETERMINISTIC treatment, he chooses the urn where the markets predict the higher likelihood of drawing a black ball, i.e. the urn with the higher final market price. In the PROBABILISTIC treatment, the principal uses a logit decision function: either choice has positive probability but he is more
likely to choose the urn with the higher market price; the likelihood increases with the price difference. Markets are conditional on the principal’s choice [Berg and Rietz 2003]: For the urn chosen by the principal, a ball is drawn and its color determines the experts’ compensation for trading. The other market is void. We use a between-subject design in which each of 162 subjects participated in one of three treatments for 10 rounds. Overall, we observed 1,620 markets.

4. EXPERIMENT RESULTS

The first key question is whether markets aggregate information: Fair-Shiller regressions [Fair and Shiller 1989] indicate that markets aggregate information in all three treatments (data not shown). Information aggregation works better in the A-PRIORI treatment than in the other treatments, the ones with an incentive for manipulation.

From the principal’s perspective, the key question is whether he makes a correct decision, i.e. whether he draws from the urn containing more black balls. Figure 1 displays the hit rate of correct decisions by treatment and alignment of preferences. In A-PRIORI, it is 50% by design independent of preference alignment. From this 50% benchmark: In the PROBABILISTIC treatment, the principal does better than in A-PRIORI, in DETERMINISTIC he does better then in either of the other treatments. The hit rate depends strongly on whether the experts’ preferences which urn to draw from are aligned and if they are aligned with the principal’s preferences.

In terms of managerial implications, our study suggests that decision markets can provide valuable information, even in settings with few and well-funded participants that are prone to manipulation. This holds in aggregate over all combinations of preference alignment and decision rules that take market information into account. Manipulation is, however, an issue to consider carefully when employing collective intelligence approaches in corporate decision making: In some cases, markets might not provide valuable information. Corporate decision makers should be clear about their experts’ incentives for manipulation and potentially actively manage who is allowed to enter the market. In addition, they should carefully consider how they will use the markets’ results: The common practice of taking a prediction market into account while retaining the discretion to decide otherwise (PROBABILISTIC) turns out to be beneficial in only very specific cases. In other cases, stakeholders might simply forgo the effort of designing and running a market, as prices are uninformative. Contrary to theory, deterministically tying the decision to the market outcome turns out to more often produce the desired decision. Credibly implementing this policy will, however, have practical hurdles. From a higher level perspective, our results raises question if other collective decision tools are better suited in the Enterprise 2.0 world.

Fig. 1: Decision quality by treatment and preference alignment: Hit rate of correct decisions and 95% confidence intervals.
REFERENCES


