The Evolution of Corporate Prediction Aggregation Mechanisms: Towards Leveraging the Frontline for Strategic Issue Identification under Uncertainty

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1. INTRODUCTION

This paper presents different corporate prediction aggregation techniques and introduces a new type of prediction mechanism linking the sensing of operational capabilities by frontline employees to the identification of fuzzy events and emerging strategic issues as 'early warning signals'. Based on the literatures on prediction markets and fuzzy logic the methodology collects information from many diverse frontline employees to develop valid signaling predictors. Individuals in the frontline gain deep insights as they perform operational activities in direct interactions with many internal and external stakeholders and we tap into this unique knowledge source to identify new issues and opportunities for ongoing strategic decision-making.

Aggregating dispersed information from crowds is not a new phenomenon. The capacity to aggregate heterogeneous and dispersed information from the environment is seen as a critical input for strategic decision making [Arrow, 1974; Hayek, 1945; Stinchcombe, 1990]. Hayek's notion of information aggregation and dispersed knowledge, has established the foundations for prediction markets where the main objective of prediction markets is to create accurate predictions of given issues of interest, and such markets have demonstrated that crowds have the ability to predict outcomes [Berg, Forsythe and Rietz, 1996; 1997; Thompson, 2012: Wolfers and Zitzewitz, 2004].

Corporate prediction markets take various forms. Borrowing from the concepts used by Spann and Skiera (2003), they refer to the evolution in prediction aggregation as first-generation (G1) and second-generation (G2) prediction markets. In G1 markets participating employees invest in the outcome of already defined problems, such as, forecasts on next quarter's sales volume, market entries by new competitors or performance of certain markets. In recent years, G2 markets, *preference markets*, aggregate predictions from the firm's stakeholders about the probable success rates of various product concepts and ideas [Slamka, Jank and Skiera, 2012]. Hence, the participants in G1 and G2 prediction markets typically invest in the outcome of predefined time constrained issues.

Here we propose a spring-off mechanism to G1 and G2 markets based on predictions *without markets* of *fuzzy events* or *emerging issues* not yet clearly defined, but nonetheless evolving phenomena to consider for responsive strategies. The notion of an event and its related probability constitute the most basic concepts of probability theory. An event is an accurately specified collection of points in a sample range. In contrast, in everyday life individuals often encounter situations in which an "event" is fuzzy and rather ill-defined than being a sharply defined collection of points [Zadeh, 1965]. We draw on fuzzy sets theory that offers mathematical models to deal with information that is uncertain and vague. That is, our contribution proposes formalized tools to deal with the intrinsic fuzziness in decision making problems [Fisher, 2003].

2. FIRST-GENERATION PREDICTION MARKETS

The G1 prediction markets were construed as markets for contracts with payoffs linked to the final outcome of specified future events. They were developed to predict presidential elections and other political votes [for a complete review see Forsythe, Rietz and Ross, 1999]. These political market models adopt a design proposed by Forsythe, Nelson, Neumann and Wright [1992] to elicit information about the outcome of a given random variable. Scholars have demonstrated that on average the market's predictions are more accurate and less volatile than political opinion polls, particularly with respect to predicting the outcome of large US elections [Forsythe *et al.*, 1992].. The predictions elicit information prior to an outcome of a specified random variable or set of variables. Once the outcome of a specific market situation is known, each share of virtual stock receives a 'cash dividend' (payoff) according to a predetermined (market) outcome [Pennock and Sami, 2007]. The trading price of shares of virtual stocks will reflect the aggregate expectations of the market outcomes specified in the contracts. Borrowing from the notation used by Spann and Skiera [2003: 1312], the payoff of a specified event at time T can be expressed as follows:

$$d_{i,T} = \phi(Z_{iT}) \ (i \in I) \qquad (1)$$

Where, d_{iT} =cash dividend of the stock modeling the outcome of the *i*th event at time *T*, $\phi(\bullet)$ = transformation function, (Z_{iT}) = outcome of the i^{th} event at time T, I = index set of events, T = point of period in time that is relevant for the determination of the outcome of the event.

T is known in advance indicating, for example, the end of the election period in a political stock market. The transformation function $\phi(\bullet)$ can have different forms where one form frequently used in political stock markets is to pay a cash dividend of $1 multiplied by the fraction of votes received by the particular candidate (Forsythe *et al.*, 1999). The limitations of G1 prediction markets are that they only address a limited set of questions within a set timeframe. This imposes constraints on their application for internal corporate purposes, because many managerial decisions relate to events that may, or may not occur, or do not have clear predetermined outcomes or they may have a very long time horizon.

3. SECOND-GENERATION PREDICTION MARKETS

In corporate environments with accelerating technologies and shortened product life cycles, firms and communities engage in faster product development and must filter the most promising product opportunities very rapidly. The new forms of 'collaborative creativity' of the Web 2.0 paradigm where users can engage and interact to create new content is performed by using preference markets [Dahan, Soukhoroukova, and Spann, 2010]. These are G2 prediction markets operating with different prioritization mechanisms [Spann and Skiera, 2003]. Preference markets are also referred to as 'securities trading of [product] concepts' [Chan, Dahan, Kim, Lo and Poggio, 2002; Dahan and Hauser, 2002]. This label reflects consumer or employee preferences for different product concepts that have yet to be launched in the marketplace. In contrast to preference markets, idea markets allow participants to introduce their own ideas and evaluate them in a combined single trading instrument [LaComb, Barnett and Pan, 2007]. G2 prediction markets are fundamentally different from G1 prediction markets because there is no measurable outcome against which to compare market performance, or at least none that can be determined in the near term. As a result, there are no actual or realized market shares to be predicted in G2 markets, but rather the output is a preference ranking among proposed product concepts and ideas. Hence, participants in preference markets cannot be rewarded based on the precision and correctness of their predictions of actual outcomes. Instead they are rewarded primarily on their ability to accurately foresee the future market preferences by other participants. In practice, this means that participants must determine the volume-weighted average of the last traded price (vwap), which reflects those preferences. G2 prediction markets are not based on external information about market changes as is the case in G1 markets [LaComb *et al.*, 2007; Slamka *et al.*, 2012]. The valuation mechanisms are based on the volume-weighted average of trading prices (vwap) expressed as;

$$\text{payoff}_i^{\text{vwap}} = \frac{\sum_t \text{Pi,t} \bullet \text{qi,t}}{\sum \text{qi,t}}, \text{with time } (t) \geq \text{vwap\_start} \qquad (2)$$

where, *Pi, t* denotes the price of a share of the *i*th stock at the *t*th trade, *qi,t* denotes the corresponding number of shares per trade, vwap_start is the point in time at which the vwap calculation starts, and time (*t*) is the point in time at which the *t*th trade is executed. Another G2 payoff mechanism is based on the last price at which a stock traded at a fixed and publicly known point in time, T^{fixed} payoff last price [Chan *et al.,* 2002; Soukhoroukova and Spann, 2005]:

$$\text{payoff}_i^{\text{lastprice}} = Pi, \max(t), \text{with time } (t) \leq T^{\text{fixed}} \qquad (3)$$

The shortcomings of G2 markets are that market participants may never know if the winning product actually will be developed, produced and sold.

4. PREDICTION OF FUZZY EVENTS

Considerable effort has been devoted in strategic management for explaining the importance of uncertainty assessments [e.g., Aguilar, 1967; Ansoff, 1980; Bettis & Hitt, 1995; Teece, 2007], where local sensing of both external and operational environmental uncertainties are considered important for innovative opportunism [Teece, 2007]. Knight [1921] links risk to situations in which the probability distributions of outcomes are known, while in the case of uncertainties, probabilities and effects are unknown. In other words, uncertainty is associated with events that cannot be quantified and are ill-defined problems that are hard to specify. Thus, it is expected that better estimates of emergent uncertainties, namely fuzzy events in the firm's surroundings, should allow for building competitive advantage [Ansoff, 1980; Bettis and Hitt, 1995].

Theory of fuzzy logic and fuzzy set theory offers a mathematical strength to capture such uncertainties associated with human cognitive processes by intuitive judgments, thinking and reasoning [Zadeh, 1965]. Fuzzy set can represent concentration within the quality of a 'poor', 'medium' and 'good' development of an uncertain event/strategic problem. That is, formally a fuzzy set is defined in terms of a membership function which captures the domain of interest, e.g. concentrations, onto the interval [0,1]. The membership function of the set A is defined over a domain X takes the form

$$\mu_A : X \rightarrow 1, [0; 1]. \tag{4}$$

The set A is defined in terms of its membership function by

$$A= \{ \mu_A (\chi), \chi , \in X \} \tag{5}$$

The strategy literature describes how local knowledge held by individuals inside the organization can inspire autonomous initiatives with significant strategic consequences [e.g. Burgelman and Grove, 1996, 2007]. Hence, essential information about fuzzy operational events is typically decentralized held among operational employees. Hence, the frontline employees constitute the foundation for a new type of forecast – *prediction of fuzzy events*. For this purpose we construe an Employee-Sensed Operational Capabilities (ESOC) index and test its accuracy through its ability to predict firm performance. A way to construe this index is by first calculating diffusion measures for each of the identified prediction items. The diffusion measures are then calculated as the difference between the number of positive and negative responses for each fuzzy set of capabilities in each time period divided by the total number of responses in that period. If the positive responses outnumber the negative ones on a specific prediction item, the diffusion measure is above 100. In the opposite case, the measure is below 100. The overall ESOC index is then calculated by aggregating the diffusion measures for each of the identified indicators for each period divided by the sum of the base period:

$$\mathrm{ESOC}_t = \frac{\sum_{i=1}^{13} \mathrm{ESOC}_{it}}{\sum_{i=1}^{13} \mathrm{ESOC}_{i0}} \times 100 \tag{6}$$

Following the above convention, the result is multiplied by 100 to get an index with a base period equal to 100. In this computation, an ESOC value greater than 100 indicates that frontline employees are positive about the future state of the operational performance (a potential opportunity), and a value less than 100 indicates that employees have a negative view of the future state of capabilities (a potential threat). This way, we have effectively construed a 'performance barometer', where a current index value below 100 indicates potential downside problems that need attention and a value above 100 calls for attention to drive opportunities. The index is then tested against super normal firm performance to assess its predictive power on financial measures. Hence, this study develops a new mechanism to identify fuzzy events that signal significant emerging issues of strategic importance from prediction aggregation without markets based on regular-series surveys. The study links predictions on operational conditions to actual firm performance and thereby provides early warning signals about impending needs for strategic responses. We believe this is an important first step towards harvesting collective predictions from the wisdom of frontline stakeholders for dynamic responsive decisions.

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