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**‘FUZZY’ PREDICTIONS FOR STRATEGIC DECISION
MAKING: A THIRD-GENERATION PREDICTION MARKET**

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'FUZZY' PREDICTIONS FOR STRATEGIC DECISION MAKING: A THIRD-GENERATION PREDICTION MARKET

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'FUZZY' PREDICTIONS FOR STRATEGIC DECISION MAKING: A THIRD-GENERATION PREDICTION MARKET

ABSTRACT

This article theorizes a new way to predict firm performance based on aggregation of sensing among frontline employees about changes in operational capabilities to update strategic action plans. We frame the approach in the context of first- and second-generation prediction markets and outline its unique features as a third-generation prediction market. It is argued that frontline employees gain deep insights when they execute operational activities on an ongoing basis in the organization. The experiential learning from close interaction with internal and external stakeholders provides unique insights not otherwise available to senior management. We outline a methodology to agglomerate these insights in a performance barometer as an important source for problem finding and innovation.

Keywords: frontline employees, information aggregation, innovation, operational capabilities, prediction markets, sensing, strategic decision-making.

INTRODUCTION

It is a classical assertion in strategic management that the quality of strategic decisions depends on the knowledge available for decision makers (Eisenhardt, 1989; March and Olsen, 1976; Vroom and Yetton, 1973). The frontline employees in the organization should be the first to know what is happening as they front the business and interact on a daily basis with customers, suppliers and other important stakeholders and thereby gain unique experiential insights about the firm's ability to perform its' operational tasks. However, these frontline employees are rarely asked for updated information on about critical issues. They are not consulted on how service delivery will fare, how

business opportunities will develop and how operational conditions will change. One reason can be that frontline employees are believed to lack the 'big-picture' and, therefore are unable to provide strategic information to top-level executives. Another reason may relate to the difficulty of collecting dispersed information effectively where cumbersome consultation processes consume time and resources. As a consequence executive decision-makers are likely to deprive themselves from gaining important updated information that could improve the accuracy of their strategic analysis and reduce the risk of biased decisions.

The ability of humans to infer subtle information from systemic properties is commonplace in the public sphere (Berg, Forsythe and Rietz, 1996; Berg, Forsythe and Rietz, 1997) and this suggests that such inferences also concern knowledgeable employees within the firm (Thompson, 2012). The assumption that employees obtain unique insights about the state of operational capabilities through sensing and personal experience (Cepeda and Vera, 2007; Teece, 2007) makes the idea of aggregating their knowledge highly relevant in a strategic management context. Corporate prediction markets provide organizations with a means to aggregate the knowledge of the companies' own employees. Strategic decision makers may consult frontline employees and tap into their insights using different polling or prediction markets (Abramowicz, 2007; Berg *et al.*, 1996; Berg *et al.*, 1997; Forsythe *et al.*, 1992). These approaches make it possible to aggregate knowledge across a potentially large number of employees. The use of prediction markets has demonstrated how even relatively small groups of people can make accurate predictions even in areas where they are not considered experts (Van Bruggen *et al.*, 2010).

Several companies have responded to this opportunity by incorporating prediction markets as a way to gather intelligence about issues that are important for their business. The increasing interest in prediction markets reflects their accuracy in forecasting the probability of certain events taking place (Servan-Schreiber *et al.*, 2004; Spann and Skiera, 2003). In first-generation

prediction markets, participating employees invest in the outcome of important performance indicators such as next quarter's sales volume, or in second-generation prediction markets where employees are asked to predict the probability of success for various product concepts and ideas (Slamka, Jank and Skiera, 2012). Participants in first- and second generation prediction markets typically invest in the outcome of predefined and time constrained issues.

Here we propose an extension of prediction markets into the domain of *fuzzy events* that characterize the operational conduct of organizations assessed by engaged employees. This involves letting them judge, assess and invest in issues that are not clearly defined or easily measured like, *managers' ability to deal with problems*, or *the ability of departments to cooperate*. The aggregated sensing of these operational capabilities can serve as a barometer for early (warning) signals about changes in firm performance. This explains the reference to *fuzzy* prediction markets since they identify areas that require managerial attention due to operational issues, emergent strategic risks and opportunities. We refer to this as third-generation prediction markets characterized by (1) investment in fuzzy events, (2) ongoing investments performed as continuous time-series, e.g., on a monthly basis, and (3) aggregating the time-series periodically, e.g., monthly, into an operational performance barometer. The ongoing sensing by frontline employees of the operational conditions can detect early performance effects that otherwise are difficult to uncover. In the following we review the literature on prediction markets and pinpoint the differentiating factors of fuzzy events sensed by frontline employees as a relevant agenda for effective strategic decision-making. Finally, we discuss the implications of this predication technique for strategic control processes as a promising new approach to strategic issue identification urging a need to update strategic action plans.

Financial economists have established the notion that stock markets have the capability to ‘see through form or cosmetics . . . to the underlying economic substance’ (Lee and Verbrugge, 1996: 39). This notion is commonly referred to as the ‘wisdom of crowds’ (Surowiecki, 2004), which suggests that investor reactions are ‘a reliable sign of [a given event’s] outcome’ (Zajac and Westphal, 2004: 434). For instance researchers in behavioral finance have demonstrated that investment decisions are not made in a vacuum (Barberis and Thaler, 2003; Shleifer, 2000). More precisely they provide support for the fact that investors, being boundedly rational, take one another’s anticipations into account when making judgments. Consequently, these scholars have been able to explain stock market bubbles and other phenomena that influence capital market efficiency (e.g. Shiller, 2003; Shleifer, 2000).

Extending this reasoning to the domain of strategic management, we develop the argument that anticipations of changes in operational conditions among frontline employees are shaped, to an significant extent, by the crowd perceptions of frontline employees, which is important information of relevance for strategic decision making (Thompson, 2012). Leaders must constantly use heuristics to determine the relevant information and try to make sense of it (Starbuck and Milliken, 1988). The limited capacity of individuals to process vast amounts of information means that leaders end up using only a simplified subset of available information for decision making (Mintzberg, Raisinghani and Théorêt, 1976). The asymmetry between the amount of information available and the capacity to process it could thus result in bad decision outcomes.

The newer aggregation mechanisms, such as crowdsourcing and predictions markets, serve to source relevant information from traditional public crowds but these techniques may also be applied towards internal agents. Crowdsourcing and prediction markets are mechanisms closely linked to the ‘wisdom of crowds’. This notion assumes that large groups of people are smarter than

an elite of one or a few people, no matter how brilliant. The crowd is better at solving problems, fostering innovation, devising good decisions and even predicting the future (Surowiecki, 2004).

Propositions about what constitutes ‘wisdom’ are at the core of economic theory. For example, Hayek (1945) noted that dispersed and heterogeneous knowledge amongst a group of people is central to the design of an efficient economic system. As he argued: ‘[we] need decentralization because only thus can we insure that the knowledge of the particular circumstances of time and place will be promptly used’ (Hayek, 1945: 84). The capacity to aggregate heterogeneous and dispersed information from the environment is also seen as a critical input for strategic decision making (Arrow, 1974; Stinchcombe, 1990). Prediction markets draw heavily on the belief that markets are efficient in aggregating and disclosing dispersed information among a group of diverse and involved agents.

Page and Hong (2012) provide some empirical foundations for the ‘wisdom of crowds’. With their diversity and complexity models arguing that some level of experience and diversity among participants is required for the ‘wisdom’ to occur. This is in accordance with the underlying ideas of “wisdom of crowds”; ‘diversity and independence’ are important because the best collective decisions are the product of disagreements and contest, not consensus or compromise’ (Surowiecki, 2004; xix). That is, an intelligent group would not expect its members to modify their positions when confronted with cognitive problems to reach consensus. In contrast, the group figures out how to aggregate information for example expressed in market prices, or use intelligent voting systems that represent not what every person of the group thinks but rather what they all individually think.

The prediction markets technique creates actual markets for problem-solving through open calls typically solicited among the company’s external stakeholders including customers and suppliers (Howe, 2006; Zenger, Felin and Bigelow, 2011). The prediction

markets can collect decentralized information from dispersed agents and use it to obtain the most accurate and reliable predictions. Such techniques can be useful for problem solving by inviting contributions from a much broader and diverse set of knowledgeable constituents. However, academic research on information aggregation from frontline employees is lacking and constitutes one of the least understood ideas in management research. While studies have discussed crowdsourcing in terms of outsourcing open calls to individuals outside the firm, crowdsourcing among employees within the firm to solve distributed problems has barely been touched in management research (Stieger and Ladstaetter-fussenegger, 2012). There are some notable exceptions that look at the collective intelligence of employees (Berg, Neumann and Rietz, 2009; Cowgill, Wolfers and Zitzewitz, 2009; Thompson, 2012), but only described through anecdotal case examples where firms aggregate information from individuals inside the firm. First-generation (G1) and second-generation (G2) prediction markets are applied by some businesses today, but the theoretical and empirical implications of such markets are presently understudied.

FIRST-GENERATION (G1) PREDICTION MARKETS

A first-generation (G1) of prediction markets were construed as markets for contracts – traded as stocks – with payoffs linked to the final outcome of specified future events. They were initially developed to predict presidential elections and other political elections (for a complete review see Forsythe, Rietz and Ross, 1999). These political market models adopt a design proposed by (Forsythe *et al.*, 1992) to elicit information about the outcome of a random variable. One of the most cited and most successful prediction markets is the Iowa Electronic Market (IEM). Since 1988, IEM has run political elections using real-money prediction markets. 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).

Participants in a prediction market react to new information rapidly and mostly before the information has been widely disseminated. The markets are accurate despite documented evidence that individual traders often are biased, irrational, and make mistakes (Abramowich, 2007; Pennock and Sami, 2007).

G1 markets are set up to elicit and aggregate information prior to an outcome of a random variable or set of variables. For example, the presidential election contract can be structured as a binary variable ('will a Republican win the next US Presidential election?') or a discrete variable ('who will win the next US Presidential election?'). Such contracts offer a certain payoff to the holder of the contract with the correct prediction on Election Day. 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). For example, in the presidential election contract structured as a binary variable ('will a Republican win the next US Presidential election?') each share of virtual stock will receive a certain 'cash dividend' (payoff), e.g., \$1 per unit bought, according to a specific predetermined (market) outcome payable once the actual outcome is known, (Spann and Skiera, 2003).

The idea with G1 markets is to create an efficient market for specific situations with predictable outcomes by trading virtual stocks. The trading price of shares of virtual stocks will reflect the aggregate expectations of the market outcomes specified in the contracts. The fundamental idea is to make an efficient futures market for given situations with predictable outcomes by trading virtual stocks. The trading price of such 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:

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

Where:

- $d_{i,T}$ 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 usually predetermined 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). In accordance with the literature dealing with political events (Forsythe *et al.*, 1992; Forsythe, Rietz and Ross, 1999) the denomination ‘stocks’ is used to make the concept easier to understand for the market participants.

Some corporations adopted prediction type markets in the late 1990s to collect intelligence from employees to forecast total sales (Chen and Plott, 2002) and probabilities that certain competitors would enter the market, etc. (Cowgill *et al.*, 2009). Hence, General Electric, Google, Motorola, Microsoft, Hewlett-Packard and Eli Lilly have all implemented such markets to advance strategic decision-making (Thompson, 2012). Table 1 provides an overview of existing corporate G1 markets.

[Insert Table 1]

Corporate first-generation prediction markets draw primarily on the company's own employees as market participants. This has engaged people within the firm to estimate the probability of future events including sales forecast and new product success. These approaches are set up as internal markets in contracts where the payoff is directly linked to the accuracy of the predictions. Yet, the first-generation (G1) prediction markets only address a limited set of predetermined questions within a finite timeframe where specific outcomes are revealed shortly after the market is closed. This imposes limitations 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.

SECOND-GENERATION (G2) PREDICTION MARKETS

In corporate environments with accelerating technologies and shortened product life cycles, firms and communities engage in fast product development and must filter the most promising product opportunities very rapidly. This applies to both tangible and intangible products, e.g., smart phones, video gaming systems, home entertainment, information appliances, and other goods and services that require development teams to prioritize multiple design decisions (Thompson, Hamilton and Rust, 2013). As such, there is a growing need to bridge the front end- and design phases by narrowing many features and concepts down to a few 'make-or-break' success factors, which requires a fast prioritization methodology.

This new form of 'collaborative creativity' of the Web 2.0 paradigm is performed by using preference markets (Dahan, Soukhoroukova, and Spann, 2010). These are second-generation (G2) prediction markets operating with different prioritization mechanisms (Spann and Skiera, 2003). They provide fast and responsive market feedback to decision makers about the expected

viability of new product development ideas. Preference markets measure the potential of new products and ideas suggested by users by predicting the concepts expected future market share or value in the market expressed as a price. Preference markets are also referred to as ‘securities trading of concepts’ (Chan *et al.*, 2002; Dahan and Hauser, 2002). This labeling is used because it is the intention to reflect consumer or employee preferences for different product concepts. 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). As competitive conditions require ongoing product development, companies have increasingly adapted G2 prediction markets to advance and evaluate ideas. Examples are XPree, which offers ‘open innovation markets’ and Nosco, which offers an ‘idea exchange’. NewsFutures, a leading prediction market software provider, incorporates idea and preference markets in their standard product portfolio. Table 2 presents overview of other type of G2 prediction markets.

[Insert Table 2]

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. In G2 markets there are no actual or realized market shares to be predicted, but rather a ranking among proposed product concepts and ideas. The products that receive the highest bets are high on the list of chosen products. Therefore the classical incentive structure of the virtual stock market in G1 where participants can make money either by being correct about the final outcome, or by accurately speculating on the behavior of other market participants, falls apart in preference markets (Slamka, Jank and Skiera, 2012; Spann and Skiera, 2003). Participants in preference markets cannot be rewarded based on the precision and correctness of their predictions of actual outcomes. Instead G2 prediction market participants must determine

the volume-weighted average (vwap) of the last traded price. In other words; participants are rewarded primarily on their ability to accurately foresee the future market preferences by other participants in combination with their own expectations about the winner products or concepts. Therefore, participants have no incentive to disclose their own private information as they cannot gain any rewards from this. As a consequence a form of information drop might occur (Bikhchandani *et al.*, 1992) whereby the private information gets underweighted and transactions instead depend on transactions by other participants. Therefore, G2 prediction markets are not based on external information about market changes as is the case in G1 markets. Instead the valuation mechanisms are based on the volume-weighted average (vwap) of trading prices (LaComb *et al.*, 2007; Slamka *et al.*, 2012) expressed as;

$$\text{payoff}_i^{\text{vwap}} = \frac{\sum P_{i,t} - q}{\sum q_{i,t}}, \text{ with time } (t) \geq \text{vwap_start} \quad (2)$$

where,

$P_{i,t}$ denotes the price of a share of the i th stock at the t th trade,

$q_{i,t}$ denotes the corresponding number of shares per trade

vwap_start is the point in time at which the vwap calculation starts

time (t) is the point in time at which the i th trade is executed.

Since the vwap includes trades over a certain period of time to determine payoff values there is an attempt to reduce reliance on single trades.

An alternative G2 payoff mechanism relies on the last price at which a stock traded at a fixed publicly known point in time, T^{fixed} payoff last price (Chan *et al.*, 2002; Soukhoroukova and Spann, 2005):

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

The rationale behind this payoff derives from the efficient market hypothesis, which states that all available information at the end of the market should be reflected in the last price. Such market contracts are easily understood by all market participants (Slamka *et al.*, 2012). While G1 typically runs for weeks or longer, preference markets (G2) require only minutes to work, because they are not affected by external market influences (Dahan *et al.*, 2010). For example, Dahan *et al.* (2011) demonstrate how product concepts can be evaluated in stock trading that run for less than an hour.

The shortcomings of G2 markets are that market participants may never know if the winning product will be constructed and sold. The actual preference of the target consumer market will never be revealed. As such, there are no certainties that market participants are representative of the targeted consumer market. Hence, the G2 markets are limited in terms of prediction accuracy. Accordingly experimental studies comparing the accuracy of G1 with G2 prediction markets have demonstrated that G1 mechanisms perform the best (see Slamka *et al.*, 2012 for an overview).

THIRD-GENERATION (G3) PREDICTION MARKET MODEL

Base assumptions

The strategic management literature describes how local operational knowledge held by individuals deep within an organization inspire autonomous initiatives that can have significant strategic consequences for the firm (e.g. Burgelman 1983, 1994; Burgelman and Grove, 1996, 2007; Mintzberg and Waters 1985; Noda and Bower, 1996). Essential information about specific operational conditions is typically decentralized and held among lower-level employees associated

with daily operations (Mintzberg, 1990). This is consistent with an information processing perspective suggesting that turbulent conditions require flexible organic forms where updated information is readily available for adaptive responses to emerging changes (Galbraith, 1977; Thompson, 1967).

The decentralized knowledge may represent unique insights about what is happening in the organization and the market of strategic significance to the firm. In accordance with this view, Grove (1996: 22-23) argues that ‘We need to expose ourselves to lower-level employees, who, when encouraged, will tell us a lot that we need to know ... the leader is often the last of all to know.’ The local knowledge held by lower-level employees should be qualitatively different from that of executives. Strategy scholars suggest that operational capabilities are everyday routines performed by employees deep within the organization as reactions to internal and external stimuli (Zollo and Winter, 2002; Winter, 2003). Lower-level employees perform basic functional activities in the organization and learn about operational capabilities through the enactment of everyday routines. In contrast, executives transform and reconfigure the operational capabilities through strategic decision making supported by the firm’s information systems and management discussions (Helfat *et al.*, 2007; Protogerou, Caloghirou and Lioukas, 2011). That is, lower-level employees and executives obtain information from different sources.

In recent years, the importance of employees sensing changes in the firm’s environment as a strategic capability for decision making has gained general acceptance (Helfat *et al.*, 2007; Teece, 2007). Teece (2007) categorizes sensing as a firm capability that is difficult for other firms to replicate and thus can provide the firm with a competitive advantage. It constitutes a tool for environmental scanning that allows the firm to ascertain important opportunities and risks that need firm responses and as such, it constitutes a dynamic capability (Peteraf and Bergen, 2003; Teece, 2009). Employee sensing is presumed to originate from an exposure to the environment with

which the employees interacts. When individuals reach a plausible interpretation of operational capabilities, they develop anticipations about the future as an automatic, affective reaction (Dane and Pratt, 2007) such as the firm's 'good' or 'bad' abilities to deal with ongoing challenges (Zajonc, 1980).

The sensing construct is variously used in management research. In the organizational behavior literature, Daft and Weick (1984) speak about organizations that functionally look like information processing systems where environmental observations are captured by individuals. The individual sensors observe actions and reactions and process these impressions in symbolic form that allows information to be stored and retrieved from memory. Hence, the individual cognitive schemas act as information structures that sort and accept new impressions that can guide subsequent actions (Neisser, 1976). So, the sensing as organizational systems is interpretative and depends on individual beliefs about the environment (Burrell and Morgan, 1979; Daft and Weick, 1984). As interpretations about the environment can vary due to diversity, uncertainty and complexity, organizations construct processing mechanisms to scan, interpret and diagnose environmental events (Galbraith, 1977; Lawrence and Lorsch, 1967; Thompson, 1967). These interpretive systems derive from social actions where shared meaning is formed through everyday interactions among people in their immediate surroundings (Daft and Weick, 1984; Walsh and Ungson, 1991). Hodgkinson and Healey (2011) use Teece's (2007) framework to organize and demonstrate the fundamental capabilities of sensing: 'Opportunity discovery and creation originate from the cognitive and creative ('right brain') capacities of individuals, requiring access to information and the ability to recognize, sense, and shape developments and groups to blend effortful forms of analysis with the skilled utilization of less deliberative, intuitive processes' (Hodgkinson and Healey, 2011: 1502). That is, 'Recognizing, scanning, and shaping depend on individuals' cognitive capabilities and extant knowledge' (Hodgkinson and Healey, 2011: 1502).

As frontline employees engage in business execution, they gain detailed insights about changing conditions, stakeholder sentiments and the quality of internal competencies in dealing with those changes. This provides an intuitive understanding of internal strengths and weaknesses and the ability to deal with emergent risks and opportunities that cannot be accessed elsewhere in the organization. From daily operations, frontline employees sense actual operational problems that over time can amount to potential threats of firm survival. The aggregated sensing information from frontline employees about changes in operations concerns ongoing and precise *operational problem identification*. So, strategic issue identification predictions and suggested solutions to such issues by operational employees can constitute the foundations a new type of online trading market; a third-generation (G3) prediction market. Therefore, sensing the evolution of operational capabilities (routines) against changing external conditions and new environmental requirements can provide information about an organization's capacity for strategic adaptation. But what are the emergent operational problems frontline can sense, foresee and solve?

Nelson and Winter (1982) introduce the notion of operational capabilities, as they view the organization as a set of operating and administrative routines that evolve on the basis of ongoing performance feedback. Zollo and Winter (2002) refer to operating routines, as opposed to the more generic 'competencies,' and argue that routines are stable patterns of behavior that characterize organizational reactions to internal and external stimuli. Operational routines depend on the type of industry the firm operates in and the firm-specific capabilities it possesses. Empirical research on operational capabilities is sparse, although the operational management literature offers a broad spectrum of operating capabilities to consider (Li *et al.*, 2005; Shah and Ward, 2007; Wu, Melnyk and Flynn, 2010). For example the classical operational capability framework by Swink and Hegarty (1998: 383–385) proposes seven core operational capabilities. They argue that operational

effectiveness is influenced by three change capabilities of improvement, innovation and coordination, and four response capabilities of acuity, control, agility and responsiveness.

Prediction and pay-off mechanisms

The prediction tasks in G3 differ from both G1 and G2 markets because they focus on operational issues that are fuzzy. An example would be prediction of employees' expectations about their 'department managers' ability to deal with problems effectively in the department'. To generate relevant operational capability items for survey predictions in a G3 market, therefore, requires some preparation studies for the market to succeed (Hallin, Andersen and Tveterås, 2012). The critical operational capabilities for firm performance can be assessed through; 1) interviews with the operational employee population about critical operational capabilities for firm performance, and 2) administration of surveys asking operational employees to rank the importance of unique operational capabilities for firm performance. The G3 prediction market is built on the highest ranked items and can run on a monthly basis using the same prediction items. The prediction items can be revised over time when variables become outdated as a source for firm performance predictions.

G3 markets invest in strategic issue identification that may need solutions. The operational capability(ies) that constitute the highest risk(s) or opportunity(ies) according to the participants assessments can provide both problem identification and suggestions for how the problems can be solved. Typically, predictions will be based on a continuous scale (e.g. 1-3) where 1 denotes anticipations of a negative development – that is value 1 of each item represents 'problem identification' values, 2 corresponds to expectations of no change, and 3 on the scale indicates expectations of a positive development, that is 'opportunity identification'. In a G3 market with a set of continuous fuzzy events (e.g., adopting 13 operational capability items) in monthly surveys,

participants can be given a sum of ‘fictive’ money (e.g., US\$1.000.000) for each survey month where they are asked to invest in different operational capabilities they expect constitute the highest concern (risk or opportunity) for the firm within the prediction horizon (say the next 3 months). When prioritizing the capabilities, the market participants will ‘trade’ or allocate resources based on their personal preferences around these fuzzy events while combining their own expectations with those of others peoples’ anticipations of the critical problems. Only the identified problems with the highest accumulated bets, or resource allocation, will be ‘chosen’ as winner of the month. This G3 betting system can also adopt a G2 payoff mechanism relying on the last stock trading price at a publicly known point in time, T^{fixed} payoff last price (Chan *et al.*, 2002; Soukhoroukova and Spann, 2005). This payoff mechanism relies on the last price *it will cost the firm* within the prediction horizon (e.g. 3 months) if management does not deal effectively with the identified problem. The G3 prediction markets can use the same payoff mechanisms as G2 markets, because market participants need to invest in fuzzy operational capabilities that are hard to verify after the predictions are made. Unlike G1 prediction markets the payoff mechanism cannot be linked to actual outcomes of specified events. Instead payoffs can be determined by using one of the three mechanisms described for G2 markets. This means that payoff in some way is linked to a market ‘consensus’ where payoff depends on how close the predictions are.

Analogously to G2 markets, G3 markets can contain idea markets for problem solutions to the fuzzy events. G3 markets can comprise both quantitative and qualitative prediction information. The latter type of predictions entails follow-up questions to quantitative predictions about, e.g., ‘Why do you expect the development you ranked in the previous question?’. The qualitative prediction information then works as an idea market collecting information about how management can deal effectively with the fuzzy issues and devising innovative solutions to identified problems.

Accuracy performance measure

The accuracy of G3 markets is determined differently from G1 and G2 markets. As the accuracy of predicted performance cannot be tested with actual performance in G3 markets, the employee predictions are tested against indicators of firm performance. We can construe an Employee-Sensed Operational Capabilities (ESOC) index to predict firm performance, which consists of a diffusion measure for each of the identified prediction items, say 13 of them. The diffusion measure is then calculated as the difference between the number of positive and negative responses in each time period divided by the total number of responses in that period. If the positive responses outnumber the negative ones, the diffusion measure is above 100. In the opposite case, the measure is below 100. This is expressed as:

$$ESOC_{it} = \left[\frac{(No. of positive responses_{it} - no. of negative responses_{it})}{Total no. of responses_{it}} \times 100 \right] + 100 \quad (3)$$

where $ESOC_{it}$ is the diffusion measure for ESOC indicator i , and t is the time period. The ESOC index is then calculated by aggregating the diffusion measures for each of the 13 indicators for each period and then dividing by the sum of the base period:

$$ESOC_t = \frac{\sum_{i=1}^{13} ESOC_{it}}{\sum_{i=1}^{13} ESOC_{i0}} \times 100 \quad (4)$$

Following this convention, the result is multiplied by 100 to get the representation of an index with 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 capabilities, and a value less than 100 indicates that employees have a negative view of the future state of

capabilities. All items are equally weighted and it is difficult to find ways to measure the weight of the various items beside the descriptive statistical output of the survey ranking. The investment of virtual money into different capabilities might, however, increase the accuracy of predictions and give some indication of how much each capability should be weighted in the aggregated index.

The performance measure should be a standard industry performance indicator. For example in the in the hotel industry, occupancy rate and revenue per available room (REVPAR) (Enz, Canina and Walsh, 2001) are common benchmarks. Because REVPAR, unlike occupancy rate, is a financial measure that allows benchmarking, it is the most used performance measure in the industry. We then transform the measure to obtain a relative performance measure for the firm that runs the G3 prediction market. We can calculate the percentage change in REVPAR from one period to the next for the hotel and compare that with the percentage change in REVPAR across relevant peers in the hotel industry. Formally, the relative performance measure of hotel i at time t ($Pfm_{i,t}$) is calculated as:

$$Pfm_{i,t} = \Delta \ln(R_{firm})_{i,t} - \Delta \ln(R_{industry})_{i,t}, \quad (5)$$

where R_{firm} and $R_{industry}$ are REVPAR for the individual hotel and the total hotel industry, respectively. The transformation using the first difference of the logarithms approximates percentage change. As a result, $\Delta \ln(R_{industry})_{i,t}$ estimates the average return of the hotel industry. In other words, $Pfm_{i,t}$ measures the excess return of the hotel compared to the industry average. The measure of excess return ($Pfm_{i,t}$) filters out effects of common market movements, such as, capacity changes in the industry, economic peak times, seasonality, and other common factors, so that only hotel-specific variations remain. As a result, the ESOC will not only test the accuracy of changes in operational performance linking it within actual firm performance, but the prediction market, employing ESOC mechanism, will also attempt to predict whether the firm is performing better or worse than close

competitors. Hallin *et al.* (2012) provide some indications that ESOC as an aggregation mechanism can perform accurately in relation to changes in financial firm performance.

CONCLUDING REMARKS

Prediction markets take various forms that can support strategic decision making in different ways. Table 3 presents an overview of the characteristics of first-, second- and third-generation prediction markets.

[Insert Table 3]

We have theoretically described a G3 prediction market that can be used to inform strategic decision makers about emergent risk and opportunities that need updated strategic responses. The G3 prediction mechanism can be employed proactively for strategic control purposes as valid indicators of significant changes in operational capabilities indicating their immediate consequences for firm performance. Prediction markets take various forms and can support strategic decision making in different ways. In the G3 market an employee-sensed operational capability (ESOC) index can be construed to predict firm performance on the basis of predefined operational capabilities of strategic significance. This provides a forward-looking prediction capability that identifies emergent issues and, therefore, can be utilized for dynamic strategy-making processes. In contrast, G1 and G2 prediction markets are confined to predicting specified events and assess the success of already identified solutions, which also can add potential benefits to strategic decisions. These mechanisms offer new dynamic ways of managing the strategy-making processes in terms of forecasting strategic issues and identifying problem solutions. The new prediction method hold a promise of informing strategic decision makers with continuous and up-

dated information from the operational periphery of the corporate businesses and, thereby, capture emergent risks and opportunities that may affect firm survival and corporate prosperity.

Table 1 Corporate Use of G1 Prediction Markets.

Companies	G1 Prediction Market Applications
Henkel	Sales forecasts of existing and new products.
Tchibo	Sales forecasting in retail.
MVZ Zeppelin	Forecasting utilization, actual sales prices, marketing campaigns, impact of new technology, and strategic topics.
Syngenta	Market forecasts, demand forecasting, business planning.
Ford Motor Company	Sales forecast, potential new car features, electrification and economic KPIs, commodity prices.
Siemens	Forecasting project deadlines. Two months advance warning – works as an truth-telling early-warning system.
Illy Lilly	Chances of pharmaceutical products and substances in pipeline.
Pfizer	Changes of pharmaceutical products and substances in pipeline.
Abbott Laboratories	Changes of pharmaceutical products and substances in pipeline.
Best Buy	Sales, new products, new shop openings, launch dates, strategic topics.
Hewlett Packard	Printer sales.
Google	Service utilization, demand forecasting, industry outlook, project deadlines.
Microsoft	Project deadlines.
ElectronicArts	Project management, launch dates and product quality.
ArcelorMittal	Industry outlook, demand forecasts.
Coming	Market growth for LCD TV, price elasticity, predicting industry cycles

Sources: Berg (2007); Chen and Plott (2002); Cowgill *et al.* (2009).

Table 2 Corporate Use of G2 Prediction Markets.

Companies	Areas of G2 Prediction Market Applications
Deutsche Telecom	New product potential, strategic topics
Touchstone, Simon and Schuster	Selection of titles for publication.
General Electric	Ideation/sourcing and assessment of new ideas. Higher quality of ideas than before.
Thompson Financial	Assessment of investment opportunities
Nokia	Increase CRM performance of 1,000 agents across cultures of 174 countries
Motorola	Product innovation, rate new ideas
Intel	Demand planning, 20% lower error than previous methods
Dentsu	Advertising campaign optimization
FritoLay	Predicting the success of new product platforms

Sources: Berg (2007); Chen and Plott (2002); Cowgill *et al.* (2009).

Table 3. Comparing Prediction Markets Mechanisms.

<i>Criteria</i>	<i>First Generation (G1)</i>	<i>Second Generation (G2)</i>	<i>Third Generation (G3)</i>
Time perspective	Finite (I)	Periodic cut-offs (Ti)	Continuous time-series
Strategic motives	Forecasting problem	Prioritize and ideation problem	Problem identification and ideation solutions
Outcomes	Actual outcomes	No actual outcomes	No actual outcomes
Payoff mechanisms	a) 'winner-takes-all' (wta) market b) Payoff value is linear and proportional with the actual outcome.	Market-internal: trading actions serve as proxies for the payoff values: Payoff on the volume-weighted average over a certain time Relies on the last price at which a stock is traded at a fixed point in time Uses the final trading price but closes the market at a random point in time Market-external: Determined externally by experts through a proxy measure.	Relies on the last price consensus at which a problem is traded at a fixed point each month.
Scales	Binary, discrete or continuous	Binary or discrete	Discrete
Number of trades per trader	Multiple trades	Multiple trades	Single trade
Qualitative items	Not applicable	Ideas possible	Fuzzy events with

qualitative feedback.

<i>Criteria</i>	<i>First Generation (G1)</i>	<i>Second Generation (G2)</i>	<i>Third Generation (G3)</i>
Design of security	Contract bidding	Selection among design options	Assessments of fuzzy events
Stock price	Contract value	Average stock rating on a 1-100 scale Number of units that will be sold in a given period Percentage of people who would choose this option.	Estimated consensus price for the potential risk if management does not solve the problem.
Incentives	Maximizing portfolio value	Final portfolio values and <i>intrinsic</i> reward of competition.	Personal involvement, gift lottery, and <i>intrinsic</i> reward of competition.
Shortcomings	Actual long term outcomes may never be known	Actual success of selected concept may never be known	Outcome is when management deal with the problem and initiate an innovation to solve the problem.
Prediction accuracy	Perform well both with real money and play money (e.g. Berg, Nelson and Rietz, 2003; Servan-Schreiber <i>et al.</i> , 2004).	The last price markets perform best (Dahan <i>et al.</i> , 2010).	Aggregated predictions of changes in operational firm performance predict financial firm performance accurately (Hallin <i>et al.</i> , 2012)

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