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Deciding with the Crowd Wisdom : An Overview of Issues Facing the Corporate Application of Prediction Markets

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ABSTRACT

Prediction markets (PM) have emerged as a major tool for contemporary decision making tools within economic, financial and psychological literature. It is arguably one of the most efficient markets in history. Although applicable within financial markets, the principles of PM can also be applied within political frameworks, corporate environments public enterprise management. That is why since its discovery; other areas of human endeavour have applied prediction markets for organization-wide decision making with different outcomes and recommendations for improvement in prediction markets. This review examines the history of prediction markets, its ontology, epistemology and paradigm. It also examines the early applications of prediction market to institutional decision making and how early challenges have strengthened modern prediction markets. The key issues facing prediction market as a decision making tool is revisited in the last section before summarizing our findings and future research direction.

Keywords : Prediction Markets , Decision Making Tools , Iowa Electronic Markets , Hollywood Stock Exchange , General Electric , Virtual Concept Testing , PAM

I. INTRODUCTION

A relatively new phenomenon within economic, financial and psychological literature, Prediction Markets (PM) has emerged as "arguably one of the most efficient markets in history" (Sporer et al, 2010). PM are defined as markets that are designed and run for the primary purpose of mining and aggregating information scattered among traders and subsequently using this information in the form of market values in order to make predictions about specific future events (Berg and Rietz, 2003; Bagust et al, 2009). Although applicable within financial markets, the principles of PM can also be applied within political frameworks and most notably for this paper, corporate environments (Strumpf, 2009), an aspect that will be later discussed in detail. Indeed, further to Berg and Rietz's definition of PM, Strumpf states that PM utilize the knowledge of a pool of individuals to help forecast questions of importance to companies such as whether a project will be completed in a timely manner or whether a sales target will be reached (Abdel-Aal and angoud, 2013). As both of the above definitions portray, PM have built upon many of the conditions discussed by Surowiecki and his peers, utilising the diversity of wisdom that is available within a given gathered crowd. As will be seen, there has been an "exploding growth of interest" in PM over the past two decades (Tatziopoulos & Tziralis, 2007; Batchelor, et al, 2015) with many major multinational businesses opting to operate their own internal PM.

II. METHODS AND MATERIAL

A. The First Prediction Markets

PM were first introduced in a series of articles written by Robin Hanson (1990a, 1990b, 1991, 1992) yet prior to this in 1988 the earliest known application of PM, the Iowa Electronic Markets (IEM), were initiated. These markets were aimed at studying market dynamics whilst acting as a predictive mechanism for the outcome of elections (Israel & Silber, 2012; Connolly et al, 2010). Within the market various contracts can be traded such as simple binary and winner-takes-all contracts and slightly more complicated contracts that are designed to predict the vote share rather than the simple outcome. Since their introduction in 1988, the IEM have proved to be “highly consistent” returning “remarkable accuracy” outperforming traditional, and often more publicly appraised political polls over three-quarters of the time (Hall, 2010). Additionally, these markets didn’t consist of more than 1,500 individual traders over this period (Israel & Silber, 2012; Cook et al, 2010) and as Surowiecki reports, the vast majority of these were male and despite being an online platform open to all, a disproportionate amount of participants were from Iowa, thus representing a relatively un-diversified sample.

The IEM requires participants to put their “money where their mouth is” (Hanson 1999; Kugler, et al, 2012) and whilst most economists believe markets where traders risk their own money should produce better forecasts than markets where traders run no financial risk (Galebach et al, 2004;p Diaz-Aviles, et al, 2012), as with the wisdom of crowds literature there is no concrete evidence to suggest that there is a disparity in accuracy when using real- or play-money (Galebach et al, 2004). Diemer and Poblete did find in their study however, that play-money incentives generated more accurate results on a portfolio consisting of various events. In direct contract comparison, nevertheless, real money was shown to be the more effective incentive scheme (2010). A further example of a PM is The Hollywood Stock Exchange (HSX). The HSX is an internet based play-money market that allows participants to trade on box-office returns and award show results. In amongst the markets consistent level of high accuracy, in 2000 and 2002 respectively, the HSX correctly predicted six out of six Oscar winners and 35 out of 40 eventual Oscar nominees (Surowiecki, 2004). As can be seen, the efficiency of the IEM and HSX represents the power of such open markets. Given this accuracy it is unsurprising that academics such as Sunstein (2006) have heavily backed PM as the future of predictive methods; indeed the volume of research being conducted by academics into PM has increased 700% in the period since 1990 – 2006 (Tatsiopoulos & Tziralis, 2007), if anything, a sign that research is proving fruitful.

B. Corporate Applications of PM

Within corporate firms, PM have been utilised to produce outcomes to numerous issues; Numerical forecasting, decision making and risk management to name a few. Whether used to predict demand for a good or service; assist management to decide which product to produce; or to develop ideas as to the level of exposure within a marketplace, PM can, when used in a functional environment asking the correct questions, be an extremely effective tool for decision makers. This section will review some of the different types and successes of markets conducted to date and discuss some of the debated issues that threaten on occasion to detract from the accuracy of these markets when carried out in a corporate setting.

For many firms conducting business within a competitive marketplace, product innovation and being the first to bring a specific new product types to the market is a crucial component of maintaining a strong market presence. Technology firms such as Hewlett Packard (HP) are one such firm, experiencing difficulties in forecasting demand when lifecycles are short and demand variability is high for technical products (Chen and Ho, 2007). In 1996 HP conducted its first field application of PM requesting that 26 “involved executives” forecast the future demand for a family of products (Chen and Ho, 2007). Despite the crowd not being as large or has perhaps diverse as Surowiecki may have wished, the Prediction Market error was more accurate than the official forecast error for six of the eight comparable events (Chen & Ho, 2007). In the example above, HP’s incentive to use the aggregating power of PM was to test the accuracy of their usual forecasts developed by one ‘expert’ manager. In a similar market to that of HP, academics Ilan Silber and Aviad Israeli attempted to find a mechanism in which “a relatively small group of novice participants could achieve the same results as experts that generate pricing decisions (within the airline industry) by engaging in a costly and intelligent process of analyzing quantitative and qualitative data” (Israeli and Silber, 2012). Conducting their study based on the airline El Al, the academics found that through the use of a simple Prediction Market, consisting of only 51 participants, they could produce a pricing structure that was only 0.4% or $3.50 different from the pricing set by the airline (Israeli and Silber, 2012).

The above examples, represent the use of PM in testing a firm's accuracy of current methods and the results question whether expensive decision techniques are really necessary. In addition to utilising PM to review cost cutting potential, some firms have used PM to assist decisions over what and when products should be brought to market, as well as them being employed to help combat a leading factor in bad decision-making - the isolation of executives from the views and insights of the company's workforce (Strumpf, 2009). Over the past decade, General Electric (GE), one of the world's most powerful organizations, held their own internal "Ideas Markets" (La Comb et al, 2009). This market is a Prediction Market but it does not seek to reaffirm or test a decision mechanism but instead allows the market to actually define the decision that is to be taken. Based on the concept of Virtual Concept Testing (VCT) (Dahan and Srinivasan, 2000), participants 'purchase' their 'securities' by means of which products or ideas they most highly favor. Once a predetermined time period has elapsed, the market operators close down the market and have the opinions of the crowd aggregated within the trading price of each of the 'securities' (Chan et al, 2002). The idea is that the top rated project ideas receive funding and at the same time boost the morale of the idea's creator. GE used such a market in 2006 to elicit and rank-order technology and product ideas from across the sub-businesses. They, like a number of leading academics, feel that such markets offer more promise than more traditional methods such as surveys, suggestion boxes and brainstorming sessions (see: Chan et al 2002; LaComb Barnett and Pan 2007; Strumpf 2009) in addition to the fact that market participants can experience the "fun of competitive play" (La Comb et al, 2009) rather than "dreaded meetings" (Strumpf, 2009), another factor in allowing the "quiet geniuses" to emerge (Lavoie, 2009). As in any PM, the orchestrators of such markets are faced with the same issues as those carried out in financial and research markets; questions such as: Should incentives be provided? Can the market be manipulated and what effect can this have? To whom should the market be open? Should the market use real- or virtual-money? These questions are ones which this paper will attempt to answer in the forthcoming section.

III. RESULTS AND DISCUSSION

Issues Facing the Corporate Application of Prediction Markets

When a Prediction Market is due to be implemented within a business, the market makers are faced with several unique challenges. Whatever the reason for the market to be administered, there are various stages leading up to and during the duration of the market where important decisions must be made.

A. Pre-market Decisions

1. Contracts & Questions

In the phase leading up to the market opening, appropriate questions must be formulated ensuring, that any questions that may require the crowd to have knowledge of quarantined information, are not present within the market (Strumpf, 2009). Contracts must also be carefully selected. Although heavily dependent upon the type of information sought from the market, the exclusivity of information surrounding that particular topic also plays a huge role. Caitlin Hall states that the more specific the topic, the smaller the number of traders who will hold relevant information thus creating a less liquid market which, in turn, is likely to decrease accuracy (Hall, 2010;43). This, therefore, leaves market-makers the challenge of balancing causal specificity and trade volumes (Hall, 2010).

2. Participants, Law and the Question of Real or Virtual Money

In order for the wisdom of a crowd to be gathered, market participants must first be selected ensuring, where possible, they are independent and diverse. Take the example mentioned earlier in this paper of Galton's Ox. The nature of Galton's experiment required very little or no pre-requisite knowledge in order to reasonably attempt to answer the question posed. Galton's crowd was therefore simply anybody present that day who was willing to wager sixpence. Craven, on the other hand, when looking to tap group wisdom in order to try and relocate a sunken and lost submarine, did not let just anybody participate within his market (see Drew and Sontag, 1998;146-150; Surowiecki, 2004; XX) . Instead he chose a wide range of knowledgeable individuals with expertise in mathematics, submarines and vessel salvaging. This more specific pool of individuals maintained the criteria of being diverse and independent, yet the knowledge possessed was related to a specific skill unlike that of the participants in Galton's study. Despite both using the same principal, and obtaining a high level of accuracy, had the selection of participants not been of the correct nature, accuracy would have been compromised. In addition to selecting the participants within the market, a market maker must decide on how these participants will become involved in the market. In some circumstances, real-money trading may not be permitted by law due to insider trading rules. On the occasions where this is not the case the decision must be taken whether real-money is to be used or alternatively how much play-currency will be issued to participants.

3. Incentive

As has been previously alluded to, the role of incentive must be reviewed. If conducting an open study, participation can be increased through better prizes, monetary incentives and no entry fee, yet quality of estimate may then decrease (Ottaviani, 2009). Hanson and Oprea believe however that there is no reason to be concerned with limiting noise traders; "by inducing more traders to become better informed, an increase in noise trading indirectly improves the accuracy of market prices" (Hanson and Oprea, 2004). Hall (2010) meanwhile suggests linking monetary rewards with trading profits or doubly rewarding the provision of good information.

B. During the Market

Manipulation and Bias

A potential limitation of conducting internal corporate PM is the possibility of the market being manipulated. Participants who trade on their own idea in an ideas market or on an outcome that they feel would be indirectly beneficial to them would be expected to distort the accuracy of the market in reflecting the real view of the crowd (Ottaviani, 2009). Although manipulation may be more attractive where rewards for doing so are greater, such as in a financial market, it is not only money that may entice market participants to become manipulators; kudos and status could also be driving factors (Hall, 2010).

PM may also be more susceptible to manipulators for two reasons. Firstly, due to the fact that PM are relatively 'thin', prices are more easily moved by the nature of high-volume transactions (Hall, 2010) and due to the fact that the ability to move the market price of an asset is a key condition of profitable manipulation, PM are ideal targets (Camerer, 1998). Secondly, it may be conceived by other traders in a market that so called 'opinion traders', traders who trade on private information, are greater in number than reality. Should this prevail, traders may follow the trade direction of the conceived opinion traders and indeed assist a manipulator in manipulating the market to his advantage (Hall, 2010).

Despite the concern regarding the negative effect on accuracy, manipulation within a market could have the reverse effect. Hanson and Oprea in their aptly named paper, 'Manipulators Increase Information market Accuracy' (2004), state in their research that manipulators may not decrease accuracy within markets after all. Making examples of manipulative situations such as DARPA's PAM they explain that a manipulator within a "standard market microstructure model of thin information markets, with rational or irrational traders who can obtain information with effort, a manipulator bias that is within the range of biases that traders suspect might exist, will on average improve price accuracy" (Hanson and Oprea, 2004). Although PM provide a powerful incentive for truthful disclosure of information, biases, as revealed in section 3:2, may exist within markets and collected data sets. Biases such as Optimism Bias and Favourite Longshot Bias (see Manski 2004; Vaughn Williams 2005) are often present, not through conscious thought of individuals, but idiosyncrasies of the human mind affecting judgment and rationale (Wolfers, 2009).

Some academic research has focused on potential flaws with the prediction market concept. In particular, Dr. Charles F. Manski of Northwestern University published "Interpreting the Predictions of Prediction Markets", which attempts to show mathematically that under a wide range of assumptions the "predictions" of such markets do not closely correspond to the actual probability beliefs of the market participants unless the market probability is near either 0 or 1. Manski suggests that directly asking a group of participants to estimate probabilities may lead to better results. However, Steven Gjerstad (Purdue) in his paper "Risk Aversion, Beliefs, and Prediction Market Equilibrium, has shown that prediction market prices are very close to the mean belief of market participants if the agents are risk averse and the distribution of beliefs is spread out (as with a normal distribution, for example). Justin Wolfers (Wharton) and Eric Zitzewitz (Dartmouth) have obtained similar results, and also include some analysis of prediction market data, in their paper "Interpreting Prediction Market Prices as Probabilities.

In practice, the prices of binary prediction markets have proven to be closely related to actual frequencies of events in the real world. Douglas Hubbard has also conducted a sample of over 400 retired claims which showed that the probability of an event is close to its market price but, more importantly, significantly closer than the average single subjective estimate. However, he also shows that this benefit is partly offset if individuals first undergo calibrated probability assessment training so that they are good at assessing odds subjectively. The key benefit of the market, Hubbard claims, is that it mostly adjusts for uncalibrated estimates and, at the same time, incentivizes market participants to seek further information. A series of laboratory experiments to compare the accuracy of prediction markets, traditional meetings, the Delphi method, and the nominal group technique on a quantitative judgment task, found only small differences between these four methods (Rajakovich & Vladimirov, 2009; Paton, et al, 2009). Delphi was most accurate, followed by NGT and prediction markets. Meetings performed worst. The study also looked at participants' perceptions of the methods. Prediction markets were rated least favourable: prediction market participants were least satisfied with the group process and perceived their method as the most difficult (Grainger, et al, 1994; Cook, et al, 2010)

A common belief among economists and the financial community in general is that prediction markets based on play money cannot possibly generate credible predictions. However, the data collected so far disagrees. Analyzed data from the Hollywood Stock Exchange and the Foresight Exchange concluded that market prices predicted actual outcomes and/or outcome frequencies in the real world. Comparing an entire season's worth of NFL predictions from NewsFutures play-money exchange to those of Tradesports, an equivalent real-money exchange based in Ireland, both exchanges performed equally well. In this case, using real money did not lead to better predictions (Kittur, et al, 2008; Schweigler et al, 2009). Hollywood Stock Exchange creator Max Keiser suggests that not only are these markets no more predictive than their established counterparts such as the New York Stock Exchange and the London Stock Exchange, but that reducing the unpredictability of markets would mean reducing risk and, therefore, reducing the amount of speculative capital needed to keep markets open and liquid (Servan - Schreiber et al, 2004).

IV. CONCLUSIONS AND FUTURE DIRECTION

This review has examined the evolution and corporate application of prediction markets. It is evident that the role of prediction market in decision making hold a greater prospect (Lorenz, et al, 2011). This is because the results from corporate organizations that have used the mechanism are very promising despite occasional challenges associated with defining a creative market. It is also noted that the effectiveness of prediction market in corporate decision making especially is also largely dependent on the prevalence of certain conditions (Shaw, Subramaniam, Tan, & Welge, 2001). Ever since the work of Galton, mathematical models have been used to examine the accuracy of simulations of crowd wisdom with psychologists, econometricians and financiers alike attempting to ascertain the conditions under which crowd wisdom is capable of achieving reliable outcomes (Frederick et al, 2011; Kugler, et al, 2012). From work undertaken by Hogarth (1978) and Makridakis and Winkler (1983) it was inferred that If a crowd's judgment contains 'signal-plusnoise', averaging judgments will cancel out noise thus revealing a signal (Arteche 2004; Caporale & Gil-Alana 2010; Graefe et al, 2011). As Surowiecki (2004) states, the real key to 'tapping' crowd wisdom is not so much perfecting the method used but is satisfying three conditions that groups require in order to be "smart". These conditions, Diversity, Independence, Decentralisation and Incentive are outlined below.

V. REFERENCES

[1]. Abdel-Aal R, Mangoud AM (2013): Modeling and forecasting monthly patient volume at a primary health care clinic using univariate time-series analysis. Computer Methods and Programs in Biomedicine. 2013, 56 (3): 235-247. 10.1016/S0169-2607(98)00032-7.

[2]. Bagust A, Place M, Posnett JW (2009) Dynamics of bed use in accommodating emergency admissions: stochastic simulation model. BMJ 2009 Jul 17;319(7203):155-158

[3]. Batchelor, Roy, and Pami Dua ((2015). Forecaster Diversity and the Benefits of Combining Forecasts. Management Science, 41, 68-75.

[4]. Connolly M, Deaton C, Dodd M, Grimshaw J, Hulme T, Everitt S, et al (2010). Discharge preparation: do healthcare professionals differ in their opinions? J Interprof Care 2010 Nov;24(6):633-643.

[5]. Cook, Chad, Brismée, Jean-Michel, Pietrobon, Ricardo, Sizer, Philip, Hegedus, Eric, & Riddle, Daniel L. (2010). Development of a quality checklist using Delphi methods for prescriptive clinical prediction rules: the QUADCPR. Journal of manipulative and physiological therapeutics, 33(1), 29-41

[6]. Diaz-Aviles, Ernesto, Stewart, Avaré, Velasco, Edward, Denecke, Kerstin, & Nejdl, Wolfgang. (2012). Epidemic Intelligence for the Crowd, by the Crowd. Paper presented at the ICWSM.

[7]. Graefe, Andreas, & Armstrong, J Scott. (2011). Comparing face-to-face meetings, nominal groups, Delphi and prediction markets on an estimation task. International Journal of Forecasting, 27(1), 183-195.

[8]. Grainger, C, & Griffiths, R. (1994). Day surgery—How much is possible? A Delphi consensus among surgeons. Public Health, 108(4), 257-266.

[9]. Kittur, Aniket, & Kraut, Robert E. (2008). Harnessing the wisdom of crowds in wikipedia: quality through coordination. Paper presented at the Proceedings of the 2008 ACM conference on Computer supported cooperative work.

[10]. Kugler, Tamar, Kausel, Edgar E, & Kocher, Martin G. (2012). Are groups more rational than individuals? A review of interactive decision making in groups. Wiley Interdisciplinary Reviews: Cognitive Science, 3(4), 471-482.

[11]. Lorenz, Jan, Rauhut, Heiko, Schweitzer, Frank, & Helbing, Dirk. (2011). How social influence can undermine the wisdom of crowd effect. Proceedings of the National Academy of Sciences, 108(22), 9020-9025.

[12]. Mannix, Elizabeth, & Neale, Margaret A. (2005). What differences make a difference? The promise and reality of diverse teams in organizations. Psychological science in the public interest, 6(2), 31-55.

[13]. Marbach, Daniel, Costello, James C, Küffner, Robert, Vega, Nicole M, Prill, Robert J, Camacho, Diogo M, . . . Stolovitzky, Gustavo. (2012). Wisdom of crowds for robust gene network inference. Nature methods, 9(8), 796-804.

[14]. Paton, David, Siegel, Donald S, & Vaughan Williams, Leighton. (2009). The growth of gambling and prediction markets: Economic and financial implications. Economica, 76(302), 219-224.

[15]. Rajakovich, David, & Vladimirov, Vladimir. (2009). Prediction markets as a medical forecasting tool: Demand for hospital services. Journal of Prediction Markets, 3(2), 78-106.

[16]. Schweigler LM, Desmond JS, McCarthy ML, Bukowski KJ, Ionides EL, Younger JG (2009) Forecasting models of emergency department crowding. Acad Emerg Med. 2009, 16 (4): 301-308. 10.1111/j.1553-2712.2009.00356.x.

[17]. Servan-Schreiber, Emile, Wolfers, Justin, Pennock, David M, & Galebach, Brian. (2004). Prediction markets: Does money matter? Electronic markets, 14(3), 243-251.

[18]. Sporer, Karl A, Craig, Alan M, Johnson, Nicholas J, & Yeh, Clement C. (2010). Does emergency medical dispatch priority predict delphi process-derived levels of prehospital intervention? Prehospital and disaster medicine, 25(04), 309-317.