MADNESS OF THE CROWD – HOW BIG DATA CREATES EMOTIONAL MARKETS AND WHAT CAN BE DONE TO CONTROL BEHAVIOURAL RISK

Research in Progress

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Abstract

In the recent years the term Big Data has been vividly discussed in management, the IS community and in the IT departments. Due to its potential for corporate performance and competitive advantage it has gained large attention up into the C-level-management. Observations on the possible negative consequences of living in a data-driven world have mostly been limited to the perspective of an individual. For instance, concerns about data privacy have been vividly discussed when the growing hunger of governmental or private institutions for ever more and more personalized data was made public. This article starts with a critical reflection on the phenomena of Big Data, focusing on the consequences for organizations and decision making. Next a case from the field of risk management is investigated in more detail using behavioural economics. Upon a series of experiments this paper sheds light on the possibility to create emotional markets using Big Data analytics in an un-reflected way. As a key takeaway this article should raise the awareness of behavioural risk. The presented work suggests extending the organizational risk framework by addressing behavioural risk.

Keywords: Big Data, Actuary, behavioural economics, risk management.

1 Introduction

“Chance favours the prepared mind.” – Louis Pasteur (1822 – 1895)

Lately the term Big Data has been vividly discussed. In order to gain competitive advantage in a volatile business environment, large organizations increasingly face the need to maintain and analyze large amounts of structured and unstructured data (Davenport and Harris, 2007; Laney, 2001). The sources of these data can lie inside or outside the organizational borders and they need to access the data be of an ad-hoc or a dispositive characteristic. Due to its potential for corporate performance and competitive advantage it has gained large attention up into the C-level-management. Observations on the possible negative consequences of living in a data-driven world have mostly been limited to the perspective of an individual. For instance, concerns about data privacy have been vividly discussed when the growing hunger of governmental (e.g. the NSA) or private (e.g. Google or Apple) institutions for ever more and more personalized data was made public. The overall impact on organizations and the risk they impose themselves to if they rely of data only, has not been reflected in detail.

Enterprise risk management (ERM) is a prominent topic in the insurance industry where it has concentrated on such tangible risks as mortality, reserving, financial, catastrophe and operational risk.
There exists a long history of Information Systems (IS) to support managing such tangible risks – e.g. models, algorithms and specialized software. In addition, banks and insurers, particularly life insurers, have increasingly considered the behavioural traits of their policyholders (Murray-Webster, 2007). In order to support that task, supporting IS had to move from isolated operations research models to sophisticated integrative capabilities such as for instance network analysis, sentiment analysis. That development was basically backed up by the technical development that is commonly summarized under the term ‘Big Data Analytics’ and the increasing availability of data on policyholders. This data of enterprises and individuals can be accessed relatively easy e.g. by retaining data from social media or buying stocks of data from loyalty programs.

After a short introduction of the phenomena summarized by the term Big Data, this article will focus on the consequences for organizations. Build upon a series of experiments grounded in behavioural economics; we intend to shed light on the possibility to create emotional markets using Big Data analytics. As a key takeaway this article should raise the awareness of behavioural risk. We suggest extending the organizational risk framework by addressing such scenarios. While the promise of a broader data base sounds very valuable for risk managers, this article will argue that a) rely on Big Data Analytics has pitfalls that make the risk analysis even less reliable, b) insurers should pay particular attention to the actions of their own risk stakeholders and c) discuss the potential future role of actuaries in that matter.

2 Background

2.1 Big data, Big impact, big confusion

Neither the trend towards ever more data integration nor the promise of finding value in the amounts of accessible data is exactly new. Yet, recent developments in social behaviour (i.e. people become reluctant to provide and share personal behaviour on social media sites), technological pervasion (e.g. increasing amounts of sensor data becoming available) and the capability to store and analyze these data (enabled mostly by innovation in database technologies e.g. in parallel data storage and processing) lead to the emergence of a new phenomenon that goes beyond the capability of standard analytical software and is commonly summarized by the term ‘Big Data’.

As catchy is this might sound, these and similar introductions to the field of Big Data make the term so difficult to work with. First, when taken the term literally one is looking at a constantly moving target; since the 1980s the planet’s technological capability to store electronic data per-capita doubles approximately every 40 months (Hilbert and López, 2011). When the Sloan Digital Sky Survey (SDSS) started to store astronomical data in the year 2000, it took a few weeks of operation until it gathered more (raw) data than the data collected in the previous history of astronomy combined. Storing roughly 200 GB per night, SDSS has by now build-up more than 140 terabytes of data. When the Large Synoptic Survey Telescope (LSST), successor to SDSS stationed in Chile, starts to operate in 2016 it is expected to obtain the same sum of data in a few days (Casey and Perez, 2012). Computer scientist Jim Gray, who was involved in the SDSS working on the “SkyServer” proclaimed the beginning of the age of “data science” in the late 1990s (Hey, Tansley and Tolle, 2009) well beyond the natural sciences. Soon after, the Business Intelligence field moved from analysis of historical data collected in data warehouses to quasi real-time analysis of high-frequency trading in finance added the data stream aspect to data mining. Today, search engines, web commerce, and social media have added text mining, social network analysis, and heterogeneous data analysis to the spectrum that is called Big Data. Particular due to the recent improvements in database technology and the ability to process and visualize large amounts of streaming data, potentially enables organizations to realize business cases that would not have been possible or feasibility in the past. E.g. decoding the 3 billion base pairs of the human genome originally took around 10 years (Collins, Lander, Rogers and
Waterston, 2004). Given the today’s technology it can be achieved in less than a week (Sboner, Mu, Greenbaum, Auerbach and Gerstein, 2011). Since the previously stated ‘commonly used software tools’ also catch up quickly in processing ever more data. There also might be something like ‘perceived’ or ‘relative’ Big Data since the view of a data set as being big might vary in different user groups – let’s say from the amount of data processed within the Worldwide LHC Computing Grid (WLCG) at the Conseil Européen pour la Recherche Nucléaire (CERN, 2013) to the data needed to the data needed in a factory to demand the optimum of supply to stock in the next quarter.

Second, and even though Big Data is about to peak the Gartner hype-cycle (Lapkin, 2012), Big Data is likely to be not of immediate appearance or current fashion. It can be considered as a logical development building on technological advances (mostly in database technology and visualization) and a large base of knowledge grounded in various fields such as Operations Research (Churchman, Ackoff and Arnoff, 1957; Gass and Assad, 2005; Kirby, 2003), Management Science – particular the decision-making process (Simon, 1976) and (Management-) Information Systems (Inmon, 1996; March and Hevner, 2007; Shim, Warkentin, Courtney, Power, Sharda and Carlsson, 2002; Turban and Walls, 1995). Particular the field of Business Intelligence (Dresner, Buytendijk, Linden, Friedman, Strange, Knox and Camm, 2002; Luhn, 1958) made it possible to structure the underlying strategies and concepts regarding the integration of large data sets in order to prepare them for analysis and visualization (Moss and Atre, 2003; Turban, Sharda, Delen and Aronson, 2011; Watson, 2010; Wixom and Watson, 2001). Google’s director of research, Peter Norvig, puts it this way: “We don’t have better algorithms. We just have more data” (McAfee and Brynjolfsson, 2012). Epistemologically speaking, this might be relevant for IS theory. Since data and information are currently distinguished by context in the standard textbooks (e.g. Krcmar, 2010). Combining enough raw data, suitable models, advances algorithms (partly self-learning) and powerful computers Big Data Analysis can reveal new insights that would in the past have remained unseen. As a consequence, data and information are increasingly tricky to tell apart.

Last, the term would probably not have reached so much attention among non-specialists, or given as ‘natural’ consequence of continuous technological integration, if it was not for a certain media attention; particular concerning the issue of data privacy. Providing spatial and statistical data the perception was initially received positive. Particular as a consequence of the financial crisis, authorities enforced a set of regulations demanding ever more data to be provided to the authorities. Recent court cases in the USA have also lead organizations to keep large masses of documents, E-Mails and other forms of electronic communication that may be required in case they face litigation. Recently the issue has become increasingly controversial as governmental efforts to collect an increasing amount of (private) data (e.g. Bamford, 2012; NSA, 2011) was made public. Hence, researchers and media have been increasingly busy pointing out the negative consequences Big Data has on the individual – e.g. the impact on data privacy (Wigan and Clarke, 2013).

Yet, the practical challenges of Big Data do not stop at the individual level. The most obvious threat is that Big Data projects fail because of the same reasons as previous attempts to establish analytics in an organization did (Baars, Felden, Gluchowski, Hilbert, Kemper and Olbrich, 2014). Particular the Business Intelligence (BI) literature offers a huge amount of knowledge on reasons for failure and critical success factors and should be respected (Chenoweth, Corral and Demirkan, 2006; Hwang and Hongjiang, 2005; Joshi and Curtis, 1999; Olbrich, Niehaves and Pöppelbuß, 2011; Yeoh and Koronios, 2010). In principle the established success models seem be adaptable to Big Data as well (DeLone and McLean, 2003; Wixom and Watson, 2001). However their might be particularities to Big Data that are unique, as some known success factors might be bound to new moderators or must be re-investigated. Take the success factor of adequately skilled labour for example. One might argue that the quality of that influence factor changes drastically since truly data-driven organizations will need a lot more analytical staff, the service approach reaches its limit with Big Data and analysts must now truly engage business and the harm of feeding analytical models with incorrect assumptions is far higher and for instance running standard reports (Davenport and Patil, 2012). It will be interesting to
see if a new class of analysts emerge or exiting field of skilled analysts like actuaries will take the lead (Jobanputra, 2013).

The mainstream critique on such a data-driven approach usually questions to what degree the statistical results can be trusted or not - "A crucial problem is that we do not know much about the underlying empirical micro-processes that lead to the emergence of the typical network characteristics of Big Data" (Snijders, Matzat and Reips, 2012). In other disciplines like medicine and bioscience, the standard scientific approaches are grounded on experiments. Hence, the limiting factor for a successful experiment is the significant data that can confirm or disprove the preliminary hypothesis. The information collected from ‘big’ data without prior premise is complementary to the experimentation approach and occasionally essential to support conventional approaches (Jones, Schildhauer, Reichman and Bowers, 2006). Consequently, the challenge in such a data-driven process is the ex-post articulation of a sound hypothesis to explain the data (Hey et al., 2009). If the search logic is reversed – as it is by Big Data Analytics - the limits of induction have to to be considered (see "Glory of Science and Philosophy scandal" (Broad, 1914)).

While some consider the lack of ex-ante hypothesis as being the “end of Science” or at least “end of theory” (Anderson, 2008), others point out the social-technical dimension of the Big Data phenomenon and the opportunities for researchers since it has to be framed constantly in its social and organizational context. Since organizations spend substantial sums to derive insight from Big Data on their supplier networks or customers behaviour, little of the current workforce has sufficiently mature skills to do so and little to no organizations support processes to absorb these information (Redman, 2008). Yet, independent of how comprehensive or widespread the statistics, Big Data Analytics needs to be flanked by a ‘big level of judgment’ (Shah, Horne and Capellá, 2012).

Highlighting that the actions that are supported by or derived from Big Data are inevitably "informed by the world as it was in the past, or, at best, as it currently is", Hilbert (2013) questions the ability of prediction at all. Certainly, sophisticated algorithms can predict future development but only on the pre-conditions that they can work on the basis of a large volume of historic data on comparable experiences and that the future developments are similar to the ones in the past. Past occurrences will have little effect on predictions about the future however, if the systems dynamics change. Understanding of the systems dynamic requires sound theory respecting boundary conditions. The most promising combining approach currently is agent-based models that are used in natural (mostly Biology), technological (e.g. Sensor Networks) and Social Science (e.g. in Agent-Base Simulations). In practice the question remains on who will feed these models. Particular when models are generated without underlying theory or strong assumptions are made (e.g. concerning risk avoiding strategies or disaster planning) the modelling task itself becomes a behavioural risk.

2.2 Behavioural Economics and Enterprise Risk Management

Early foundations of Behavioural Economics reach back until Adam Smith’s “The Theory of Moral Sentiments” (1759) and Jeremy Bentham’s thoughts on usefulness (Bentham, 1952; Bentham, 1995). If was however only later picked up, when more and more scientists gave up strict neoclassical economic positions. Since then, Behavioural Economics are commonly used when the model assumptions of a rational acting ‘Homo Oeconomicus’ fail. It therefore can be described as the study on the role of cognitive or social effects, and emotional factors when individuals or organizations face economic decisions (Mullainathan and Thaler, 2001). Obviously the findings of psychology have had a big impact in this a sub-discipline of economic theory (Kahneman and Tversky, 1979; Rabin, 1998). There exist a few subfields that investigate particular aspects such as behavioural finance that highlight inefficiencies in the financial markets. Interestingly enough from an IS-perspective, the purpose is to frame causes of market trends to irrational reactions to information; in severe cases of market-bubbles such as the dotcom one in 2001 and crashes like the recent financial crises.
Theories of Behavioural Economics are mostly proven by small scenario experiments or answers to specifically designed lab questions. This approach should enable the researchers to limit the possible numbers of explanations; which is particular important since the subject of the investigation is already an anomaly that cannot be explained by mainstream economics (Tversky and Kahneman, 1974; Tversky and Kahneman, 1981). That being said, it should be mentioned that the field of behavioural finance mostly uses market data – not seldom real market transactions – to perform experiments (Shleifer, 1999).

Theories that are developed in Behavioural Economics usually belong to one of the following streams:

I. **Heuristics** to not base ones decisions upon a sophisticated model or evaluating all possible outcomes but rather follow a quick and simple ‘rule of thumb’ approach that can be based in previous experiences or simple a gut feeling (Kahneman, Knetsch and Thaler, 1991).

II. **Framing** refers to the context in which a particular decision or choice is made. It is investigated to what degree the circumstances leaves the organization or the individual biased during the decision process (Kahneman and Tversky, 2000).

III. **Market inefficiencies** also include actors that’s behaviour seems irrational or at least contradicts common expectations, like obvious mistakes in pricing, non-rational decisions, etc. (Thaler, 1994). This is usually explained using Prospect Theory, which is a generalization of the classical utility approach, that allows for the biases that people exhibit when faced with uncertainty (Kahneman and Tversky, 1979).

It has been more than 30 years now that the leading researchers in this field – like the psychologists Amos Tversky and Daniel Kahneman who published their leading articles on heuristics, biases and prospect theory (Only the latter received the Noble Prize for their joint work in Economic Science in 2002, since it is not awarded posthumously). Since then Behavioural Economics have become common currency in research and practice. For instance, the Financial Conduct Authority’s (FCA) first occasional paper was entirely devoted to the subject (Erta, Hunt, Iscenko and Brambley, 2013). The FCA defines behavioural economics as an area that “uses insights from psychology to explain why people behave the way they do. People do not always make choices in a rational and calculated way. In fact, most human decision-making uses thought processes that are intuitive and automatic rather than deliberative and controlled.” In our view, chief risk officers (CROs) and others involved in ERM have much to gain from an understanding of behavioural economics. One of the important roles of ERM is to help firms to make appropriate decisions when facing risk and uncertainty. It is essential for a CRO to understand the common flaws in decision-making, to help individuals to overcome them, and to understand the implications for the firm’s risk management framework. Or as the author and capital manager Luca Celati (2004) puts it „Human emotions, biases and frames surrounding problems and information play a critical and poorly understood role in risk and top management decisions“. Yet, state-of the-art risk management IS do currently not support that task in the modelling process.

### 3 Research Approach

In his recent book Daniel Kahneman has summarized the joint work in this field over the last decades: Kahneman (2011) introduces two mental systems, that we use judging the world around us. The fast system is mainly unconscious and makes immediate decisions based on heuristics – e.g. past experiences of similar events, stories and emotions. According to Kahneman we are as likely to be wrong as right using the fast system since we are easily swayed by our emotions (see I). The process by which we consciously check the facts and think carefully and rationally about a given choice makes the second system painfully slow. Because of the careful framing (see II), the slow system is easily distracted and hard to engage. We consider this to be a connection to Business Intelligence literature.
which identified similar obstacles when introducing Information Systems with dispositive character (Hwang and Hongjiang, 2005; Sandler, 2010; Zimmer, Baars and Kemper, 2012) and the claim for more agile decision support (Conboy, 2009; Knabke and Olbrich, 2013; Rouse, 2007). The two systems work together, shaping our impressions of the world and help us to make choices. It also developed a terminology that individuals and organizations can use to acknowledge and reflect these biases and also prepare for individuals or organizations seem to make irrational choices (see III). We base our experiments with actuarial software on that, conducting experiments in all of the streams and using the concept of the two mental systems.

Kahnemann (2011) further provided a selection of previous experiments and observations on the various biases to which we are subject when facing uncertainty and risk. For instance he refers to the fact that professional golfers are putting – independent from the distance to the hole - more precise when aiming for par than when they are for birdie. Another example is that individuals buy way more cans of soup when there's a sign indicating a limitation like 'Limit 12 per customer’. Yet, the anecdotes and theses seem rather simple; particular given certain maturity in the mature field of risk management and today’s media competency. Given the reliance on professional risk managers and the increased grounding of decisions in (big) data, we want to find out if the theses still hold true and the stream of Behavioural Economics also apply to experts in statistics, decision making and risk assessment. Therefore we conduct experiments on practising actuaries and actuary consultants in order to answer the following questions:

- Do trained experts (like actuaries) use better heuristics?
- Does framing and bias has the same effect on (professional) decision makers?
- To what degree is market inefficiency considered by analytical experts?

The actuaries we conducted the experiments on are employed at a private company that is among the most successful firms that offer actuarial consulting services and software solutions for actuaries. The company has earned this brand name by offering a holistic serve portfolio reaching from pension benefit plan valuations to financial services related to insurance and risk assessment and mitigation. Considering the importance of computer-aided statistical skills and knowledge about (software) modelling in today’s actuarial science, this firm can be appreciated significantly for being one of the major suppliers on the market. We asked 115 employed actuaries in the London office to join the experiments. The selection was made based on the work experience (more than three years) and experience in risk assessment (more than one year). Depending on the individual experiment between 33% and 47% participated. Later we introduce a risk management framework that was established at one of Europe’s major (re-) insurance companies. Still, under the impression of recent turbulences that financial markets and newly introduced regulations by national legislature and the European authorities, the reinsurer contracted a team of actuaries respectively revise their current risk management framework.

4 Preview to expected results

To address the streams I-III of behavioural economics (see section 2.2) we conducted a set of experiments that deal with rational decision making, biases and framing. In this research in progress paper we take the example of anchor bias as it is one of the best-known findings of experimental psychology. Anchor bias occurs for instance when individuals are asked to guess an unknown quantity. If before estimation the individuals are presented with a particular value for that quantity then their estimates inevitably stay closer to that prior value than would otherwise have been the case.

In a merely ERM context, anchor bias is frequently exhibited by insurers in their choice of parameters when building models. This bias is often even encouraged by regulators and auditors expecting firms to lie close to some market benchmark or standard regulatory formula. Anchoring can also apply in a
qualitative sense as insurers can be anchored in their model design to market-standard approaches or to models developed for altered purpose. Anchor bias can also be important for finance and actuarial teams in insurers when setting reserves for new lines of business; particularly where they are long-tailed. In this case it is often the business plan of the new underwriting team which can unwittingly act as an anchor; for instance the business plan that may have formed part of an acquisition or interview process in some cases. Commonly, the standard implemented actuary software uses the standard Bornhuetter-Ferguson (1972) reserving technique that mathematically incorporates such results as an anchor on the real results for many years if the business plan is used to set prior loss ratios.

In order to illustrate the problem of anchor bias incorporated in the modellers and therefore the software models, we framed the question in two parts: for example we asked the participating actuaries the following two questions:

- Was the ‘The Treaty of Utrecht’ signed before or after the year 1800?
- What is your best educated guess of when the ‘The Treaty of Utrecht’ was signed?

Independent of the correct answer (1713), this typically produces answers to the second question significantly later in average than a group asked the same questions but with the 1800 anchor changed to 1500. In our case almost 300 years later to in average 274 years (n=52). Astonishingly, the same bias is produced even when the individuals ‘know’ (or would if they were acting and thinking rationally) that the anchor in the first question cannot have any influence on the second question (such as when they generate the last three digits of the first number themselves, for example from their own telephone number). In a purely ERM context, anchor bias is often exhibited by insurers in their choice of parameters when building internal models. This bias is often encouraged by some of the main ‘hurdles’ in the insurance sector – regulators and auditors – expecting firms to lie close to some market benchmark or standard regulatory formula. Anchoring can also apply in a qualitative sense: insurers can be anchored in their model design to market-standard approaches or to models developed for a different purpose. First indications point to the fact that trained experts, in our case actuaries, fall for exactly the same biases in the experiments. In a world of big data and an increasing demand for statistical knowledge and application, we suggest expanding the ERM frameworks and address that issue (see Figure 1).

Risk culture is at the heart of an enterprise risk framework and we have seen great value in firms commissioning an external risk culture in the organization. Yet, as we have discussed above, even insurance risk professionals may demonstrate various biases in their daily work. One starting point to counter this problem is to include a behavioural assessment in such a risk culture. Another is to introduce software features that support an expert judgement policy and accompanying documentation process. For instance, when developing a capital model one of the most important and often neglected risks is model risk. Model risk can be considered a meta-risk due to largely qualitative factors, for example: re-using an inappropriate old software model; misinterpreting results; or failing to communicate the results of the model effectively. Insurers that are most advanced in capital modelling do understand and mitigate model risk alongside other risks.
Figure 1. Development of risk management

5 Tentative Conclusion, limitations and outlook

There exist prominent critique of the experimental approach and the behavioural economics altogether (e.g., Farma, 2012). The common argument is that market economies work perfectly fine and behave rational. Hence, behavioural economics investigate nothing more than anomalies in the markets that will sooner or later be equilibrated or are even might be priced already (Myagkov and Plott, 1997). As elaborated in the section on the general critique on Big Data, there is an undeniable trend towards Big Data analysis. Just by the size of the trend we argue that this is more than investigating anomalies but has the potential to create self-fulfilling movements in the market by relying on the analysis on potential anomalies. Concerning the approach in experiments questions about real world data and lack of incentive compatibility are raised. In order to address the first issue, we conducted our experiments among practicing experts in the field of risk assessment and bring in their experience. The latter critique cannot be addressed by our sample. However, there is a brought literature that proofs the value of experiments as they could be soundly repeated in different environments and countries; hence, there is a viable empirical foundation of theoretical models (Rabin, 1998).

Our results offer rich opportunity for future investigation. Obviously, Big Data does not uniquely deserve a critical view. Including behavioural aspects in the analysis process and probably even in the underlying models, valuable information can be retrieved and guide organizations towards competitive advantage. As the attention of the topic proves, decision makers are certainly aware of that potential (Lapkin, 2012). However, except a new use cases (e.g., in fraud detection or individual marketing), the full potential of Big Data Analytics is still today still not leveraged in most organizations and many still hesitate to invest. To date, there is not enough literature or competence out there to make a solid case in the eyes of senior management. It will be interesting to observe whether the profession of Actuaries might fill that gap and take a leading role in the Big Data movement (Jobanputra, 2013). Second, we addressed the need of extending organizations risk assessment framework by behavioural risk. The extension we suggested is still on a high level and was applied in one insurance company and their customized actuarial software. Further investigation should be done that implements the framework in different companies and other branches of industry. We intend to review how the framework works with the reinsurer on a regular basis and we are happy to report on it.
References


