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Analyzing the determinants of the voting behavior using a genetic algorithm

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ABSTRACT

Using data about votes emitted by funds in meetings held by United States banks from 2003 to 2013, we apply a genetic algorithm to a set of financial variables in order to detect the determinants of the vote direction. Our findings indicate that there are three main explanatory factors: the market value of the firm, the shareholder activism measured as the total number of funds voting, and the temporal context, which reflects the influence of recent critical events affecting the banking industry, including bankruptcies, reputational failures, and mergers and acquisitions. As a result, considering that voting behavior has been empirically linked to reputational harms, these findings can be considered as a useful insight about the keys that should be taken into account in order to achieve an effective reputational risk management strategy.

1. Introduction

The voting behavior disclosed by shareholders in corporate meetings is a key concern for researchers into the corporate governance field. Actually, many investigations have been carried out regarding the motivations of the vote direction (Choi, Fisch, & Kahan, 2008), as well as its effects (Becker, Bergstresser, & Subramanian, 2013; Fischer, Gramlich, Miller, & White, 2009), including its connection with shareholder wealth (DeAngelo & DeAngelo, 1989; Dodd & Warner, 1983; Mulherin & Poulsen, 1998) and corporate reputation (Bernile & Jarrell, 2009; Ertimur, Ferri, & Maber, 2012; Ferri & Maber, 2013).

Genetic algorithms are methods of inductive learning based on adaptive search techniques, which have the strength of using accumulative information regarding an unknown search space with the aim of redirecting successive searches into the most suitable subspaces, as an imitation of the biological evolution (Vafaie & De Jong, 1992). A candidate solution is characterized by means of a linear string similarly to a chromosome. A population advances toward better solutions, and a fitness function quantifies the suitability of each solution. As a consequence, this methodology has been successfully applied to the analysis of different scenarios, with the aim of discovering the most relevant features for the explanation of a certain phenomenon (Huang, Cai, & Xu, 2007; Rozsypal & Kubat, 2003; Yang & Honavar, 1998).

The recent developments into the quantitative finance field have resulted in the appearance of complex mathematical models for the explanation of different financial phenomena, which are frequently characterized by a lack of analytic representation. In this sense, several metaheuristic algorithms have demonstrated to be a suitable methodology for addressing these financial problems. In particular, genetic algorithms have been successfully applied to the analysis of different financial scenarios with promising results. Thus, genetic algorithms have been recently used in value-at-risk computing (Sharma, Thulasiram, & Thulasiraman, 2015), bankruptcy research (Davalos, Leng, Feroz, & Cao, 2014; Shin & Lee, 2002; Wu, Tzeng, Goo, & Fang, 2007), optimal insurance risk allocation (Ha, 2013), exchange rates prediction (Vasilakis, Theofilatos, Georgopoulos, Karathanasopoulos, & Likothanassis, 2013), financial failures forecasting (Chen, 2014), financial fraud detection (Hoogs, Kiehl, Lacomb, & Senturk, 2007), portfolio optimization (Chang, Yang, & Chang, 2009; Oh, Kim, & Min, 2005) and stock markets prediction (Ghoshal, Mukherjee, & Dhar, 2011; Karimi, Dastgir, & Shariati, 2014; Leigh, Purvis, & Ragusa, 2002).

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The aim of this research is to address an empirical examination of the global vote direction observed in corporate meetings held by United States banks, applying a genetic algorithm over a large set of financial variables in order to identify the key determinants of the voting decisions.

2. Literature review

The voting behavior disclosed by shareholders in corporate meeting has attracted increased attention from academics and practitioners in recent times. Thus, a direct relation between shareholder wealth and proxy contests has been demonstrated (DeAngelo & DeAngelo, 1989; Dodd & Warner, 1983; Mulherin & Poulsen, 1998), with palpable consequences observable throughout financial markets (Becker et al., 2013; Fischer et al., 2009). In addition, although there is a lack of consensus regarding the criteria that proxy advisors take into account in order to disclose their voting advise (Choi et al., 2008), they tend to acclaim a non-pro vote when a company with low results discloses high executive compensation (Ertimur, Ferri, & Oesch, 2013), with a demonstrated direct relation between the application of the Say on Pay policy and corporate performance (Cuñat, Gine, & Guadalupe, 2013), and some empirical findings on how corporate governance is linked to vote direction (Cai, Garner, & Walkling, 2009). Moreover, the damages derived from reputational risk have been explored through voting behavior, with voting pattern suggested as an adequate indicator for reputational harm (Bernile & Jarrell, 2009; Ertimur et al., 2012; Ferri & Maber, 2013).

Despite being a general concern, lately the focus has turned toward the banking industry and the investigation of the voting pattern in this specific sector has been addressed, with special attention to the effects of the Say on Pay policy (Yahr, 2013). That is a consequence of the relevant role in the germen of the financial crisis attributed to financial institutions, and also frequent reputational scandals affecting the banking industry contribute to explain this raising degree of interest (Fiordelisi, Soana, & Schwizer, 2013). Indeed, it has been pointed out that the banking activity is particularly sensitive to reputational issues (Allen & Santomero, 1997; Allen & Santomero, 2001; Bhattacharya & Thakor, 1993). As a matter of fact, corporate reputation has been referred as a strong competitive advantage for financial institutions (Xifra & Ordeix, 2009) and reputational risk has been identified as a severe threat for the banking business (Limentani & Tresoldi, 1998).

Actually, the banking industry has been traditionally considered a suitable scope for research purposes, due to the special characteristics of the banking products, as well as the role that banks play as financial intermediaries in an asymmetric information scenario (Allen & Santomero, 1997, 2001; Bhattacharya & Thakor, 1993). In fact, the United States banking industry is a particularly motivating focus for investigation, considering that the deregulation process that has been affecting this sector in recent times makes it an adequate choice for addressing the corporate consequences of environmental changes (Berger, Kashyap, Scalise, Gertler, & Friedman, 1995; Calomiris, 2000; Lounsbury, Hirsch, & Klinkerman, 1998; Marquis & Lounsbury, 2007).

3. Method and data

For the purpose of this research, we use the software WEKA, which is the short form for Waikato Environment for Knowledge Analysis, a famous solution deployed with Java technology by the University of Waikato and distributed as free software under the GNU General Public License, with remarkable applications for machine learning. The WEKA software includes a specific algorithm for genetic search, which is the simple genetic algorithm described in Goldberg (1989). This method estimates chromosomes considering certain parameters previously stablished, including learning rate and momentum. For each chromosome, a merit indicator is provided, as a measure of the classification error rate. In addition, a scaled fitness measure for each chromosome is also supplied (Larose, 2006). As a next step, the algorithm crosses over taking pairs of the best estimated chromosomes, and it also considers the presence of mutations affecting descendants (Ahmed & Zeeshan, 2014). Consequently, this technique results useful when it comes to build a subset of key attributes from a large dataset (Larose, 2014).

The data used in this study comprise votes emitted by the largest large cap funds and by socially responsible investing funds regarding managerial proposals about directors' election and executive compensation presented in corporate meetings organized by companies in the United States banking sector from 2003 to 2013. These voting data are collected from official SEC N-PX fillings by the non-profit and non-partisan organization ProxyDemocracy, which has been recently referred as a suitable data provider for research purposes (Burns & Minnick, 2013). The final dataset is formed by 95,234 votes corresponding to 309 United States banks. In addition, we pick different accounting and financial indicators concerning the companies in our research from the Bankscope database, with the aim of discovering how these indicators affect the vote direction disclosed in corporate meetings. As a result, this is the list of the variables considered in this investigation (Table 1).

Beyond the reported calculations, no additional data transformation is accomplished.

4. Results and discussion

As a first step, we provide summary statistics for the numeric attributes of this research (Table 2).

In order to apply the genetic search algorithm available in WEKA to our set of data, we begin by selecting the full training test mode with the following parameters: population size, 20; number of generations, 20; probability of crossover, 0.6; probability of mutation, 0.033. The results of this first experiment are reported in the following table (Table 3).

This table shows the attributes subset in the third column. Each individual in the population represents one possible solution (one attributes subset). Those with a highest fitness (0.12746) correspond to a better solution (attributes: 1, 3, 13). Thus, the algorithm ends selecting the attributes "Year (1)", "Total number of funds (3)" and "Market capitalization (13)". To test the stability of the results, we carry out different experiments changing the initial parameters (Table 4).

As we can see, the results are consistent throughout all the experiments, and the selected subset of attributes is always the same. Finally, using the initial parameters, we accomplish a final experiment using a 10-fold cross validation mode (Table 5).

The results reinforce the previous conclusions and they show that the three main attributes still are "Year (1)", "Total number of funds (3)" and "Market capitalization (13)", since they appear in 100% of the cases. However, a fourth attribute shyly arises, and "Tobin's q (11)" is included in 20% of the folds.

Ultimately, all the consummated experiments point out the predominance of three attributes in explaining the direction of the aggregated voting behavior observed in corporate meetings. Thus, the market capitalization appears as one of these main explanatory factors, indicating that the market value of the firm influences the global vote direction. In addition, the total number of funds voting is also relevant, showing that the degree of activism disclosed by institutional investors is a key determinant of the whole