USING ADABOOST FOR EQUITY INVESTMENT SCORECARDS*

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ABSTRACT

The objective of this paper is to demonstrate how the boosting approach can be used to define a data-driven board Balanced Scorecard (BSC) with applications to Latin American markets and S&P 500 companies. We compare our results using Adaboost with logistic regression, bagging, and random forests. We conduct tenfold cross-validation experiments on one sample of Latin American Depository Receipts (ADRs), on another sample of Latin American banks, and on the S&P 500 companies. We find that if the dataset is uniform (similar types of companies and same source of information), as is the case with the Latin American ADRs dataset, the results of Adaboost are similar to the results of bagging and random forests. Only when the dataset shows significant non-uniformity does bagging improve the results. Additionally, the uniformity of the dataset affects the interpretability of the results.

Using Adaboost, we were able to generate *alternating decision trees* (ADTs) that explained the relationship between corporate governance variables, performance and efficiency. We also proposed an algorithm to build a representative ADT based on cross-validation experiments. The representative ADT selected the most important indicators for the board BSC. Additionally, the thresholds of the representative ADT established targets or ranges of values to be used in the board BSC. As a final result, we propose a quantitative strategic management system combining Adaboost with the BSC for board-level or investment decisions.

1 Introduction

1.1 Quantitative analysis in finance

Quantitative evaluation of econometric models is usually done by evaluating the statistical significance of linear models. For example, previous studies on US securities (see the pioneering works of Altman [4], and Beaver [14], and also see [5–7; 11; 30; 33; 35; 52; 60; 61; 77; 88; 90; 95–97; 114]) have used linear discriminant analysis or logistic regression for the evaluation of financial distress, bankruptcy, and credit scoring systems. This analysis is based on estimating the parameters of an underlying stochastic system, usually assumed to be a linear system. One limitation of this methodology is that nonlinearities have to be incorporated manually. Another limitation is that the number of parameters that can be reliably estimated depends strongly on the amount of available data, and is often very small.

By contrast, machine learning methods such as decision trees [24], boosting [48] and support vector machines [89] avoid the question of estimating the parameters of the underlying distribution and focus instead on making accurate predictions for some variables given others variables. Breiman [23] contrasts these two approaches as the data modeling culture and the algorithmic modeling culture. According to Breiman [23], while most statisticians adhere to the data-modeling approach, people in other fields of science and engineering use algorithmic modeling to construct predictors with superior accuracy. The main drawback of algorithmic modeling, according to Breiman, is that although the models are easy to generate, are hard to interpret.

In this research, we apply algorithmic modeling to predict and interpret the determinant factors of corporate performance. We use Adaboost to define a board Balanced Scorecard (BSC), focusing on the conflict of interest between principal and agents. We concentrate on Latin American ADRs, banks domiciled in Latin American countries, and in the S&P 500 companies.

The paper is organized as follow. In the first part of this research we will study a sample of Latin American emerging market stocks (LAADR) represented in the US financial market through American

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Depository Receipts (ADRs)[1], Latin American banks (LABANKS), and S&P 500 companies. These data are described in Appendix 1. The study of corporate governance in emerging markets is especially important because these markets have become increasingly integrated into the major world financial centers, even though these markets have lax security regulations.

1.2 The principal-agent problem

1.2.1 Background

Many of the recent bankruptcy scandals in publicly held US companies such as Enron and WorldCom are inextricably linked to a conflict of interest between shareholders (principals) and managers (agents). This conflict of interest is called the principal agent problem in finance literature. The principal agent problem stems from the tension between the interests of the investors in increasing the value of the company and the personal interests of the managers.

One of the major areas where the agency conflict is expressed is in the compensation of the top executives of the firm. Before the 1970s, compensation was based mostly on salaries and bonuses that were linked to performance, but now most of the compensation is based on stock options. Jensen and Murphy [66] calculate that the average total remuneration of CEOs from S&P 500 firms has gone from $850,000 in 1970 to $9.4 million in 2002 (using 2002-constant dollars). The value of the options in the same period went from almost zero to $4.4 million. Jensen and Murphy [64; 65] as well as shareholder representatives suggested that executive compensation should include a larger options component. However, compensations committees tend to grant stock options to CEOs and top managers since stock options are not debited as a cost to the firm. Jensen and Murphy recognize the excess of these compensations committees and propose instead that the cost of granting options is the opportunity cost of not selling these options in the market. The Sarbanes-Oxley Act of 2002 introduced important provisions for executive compensation such as the prohibition of executive loans, the repayment of certain compensations by CEOs and CFOs when financial statements must be restated due to material noncompliance, and blackout period rules for insider trading. The Financial Accounting Standards Board (FASB) and the Securities and Exchange Commission (SEC) completed these rules requiring that if companies grant options to employees, those options should be registered in the financial statements as an expense for fiscal years beginning after June 15, 2005.

Several authors have studied resetting executives' options and its effect on performance [25] and as a reincentivization strategy [1]. Contrary to what is generally assumed, repricing of executive stock options does not reflect poor governance [31]. However, firms with agency problems and with insider-dominated boards are more to likely reprice executive stock options [28], while companies that have more outsiders directors grant more compensation packages to directors aligned with shareholders' interests such as equity-based compensation [99].

Another major area where the principal-agent problem is evident is insider ownership, because the separation of ownership and control is often seen as an opportunity for managers to accumulate wealth at the expense of shareholders [16; 63; 103]. Ang, Rebel and Lin [9], using a sample of small US companies, show how agency costs increase with a decrease in managerial ownership as proposed by Jensen and Meckling [63]. Based on previous study by Weston [110] who indicates that beyond board ownership of 20-30% a hostile bid cannot succeed, Morck, Shleifer and Vishny [87] find a curvilinear relationship in which the presence of insider ownership of less than 5% and more than 25% has a positive impact on the performance of US companies. These authors highlight the opposite effects of large insider ownership. On one hand, high proportion of insider ownership has a positive impact on performance because of insiders' incentive alignment with other shareholders (convergence-of-interests hypothesis) [26; 38; 62]. On the other hand, high proportion of insider ownership has a negative impact on performance because of the insider's bargaining power that may lead managers to make self-interested decisions (entrenchment hypothesis) [63]. Stulz [105] indicates–through a formal model–that the relationship between ownership and performance follows a roof-shaped curve. McConnell and Servaes [84] and Fuerst and Kang [50] empirically confirm the implications of this model. Other studies show mixed results [86].

The structure and size of the board of directors are also very important aspects of the principal-agent problem. The board of directors plays a high-level counsel and control role in any organization. However, it is necessary that the board of directors include outsiders (who are not part of the management team) and maintain a minimal level of ownership to ensure their interest in the performance of the company. A board of directors may fail due to a strong emphasis on the CEO's personal agenda, low equity ownership among the board of directors' members, an excessively large

[1] An ADR is a stock that represent a certain number of shares of a foreign company in the major US stock markets such as the NYSE.

board of directors, and a culture that discourages dissent [62].

1.2.2 The Board Balanced Scorecard

In response to the recent corporate scandals in the U.S., several organizations and researchers have proposed corporate governance scorecards. Gompers et al. [51] use 24 different provisions related to takeover defense and shareholder rights to create a governance index. They show that a trading strategy based on this index outperforms the market. Standard & Poor's [101] have developed a method which combines macro and micro variables and uses qualitative and quantitative analysis.[2] The German Society of Financial Analysts [104] has proposed a corporate governance scorecard for German corporations which is based on a "Code of Best Practice" following the German law. The latter two approaches use a normative framework based on "best practices" and require a lengthy due diligence process for each company under study.

Kaplan and Nagel [67] have proposed the creation of a board Balanced Scorecard which includes corporate governance variables. The Balanced Scorecard (BSC) is a well-known method for strategic planning and performance measurement widely accepted in business and academic communities. Large U.S. companies, such as General Electric and Federal Express, and non-profit and public organizations have implemented the BSC approach [8; 107]. According to Kaplan and Norton [68–72], the BSC is a management system that helps organizations define their vision and strategy, and translate them into specific actions. The BSC provides feedback on internal business processes and market conditions in order to review the strategy and future plans.

The BSC suggests that an organization should be evaluated from four perspectives:

1. **The financial perspective** emphasizes the long-term objectives of the company in terms of revenue growth and productivity improvement. The financial goals should be the final goals for the other perspectives.

2. **The customer perspective** emphasizes the lifetime relationship and service delivery with clients.

3. **The internal processes perspective** focuses on the use of clients' information to sell new products and services according to the clients' needs.

4. **The learning and growth perspective** is the foundation of the BSC. This perspective looks at the motivation, training, and capacity to innovate that employees need to have in order to implement the new strategy.

[2] Even though the Standard & Poor's corporate governance scoring has been very successful in emerging markets, Standard & Poor's corporate governance services decided to pull out of the U.S. market in September 2005.

The BSC is generally implemented at the corporate level, business unit level, and individual level. Kaplan and Nagel [67] propose that an effective BSC program should include three parts:

1. **An enterprise BSC** that presents the company strategy, with detailed description of objectives, performance measures, targets, and initiatives to be implemented by the CEO and managers throughout the organization.

2. **A board BSC** which defines the strategic contribution of the board, includes the strategic data necessary for the board operation, and offers an instrument to monitor the structure and performance of the board and its committees.

3. **An executive BSC** allows the board of directors and the compensation committee to evaluate the performance of the top managers of the organization. Epstein and Roy [42; 43] explain the importance of the board BSC as an instrument to monitor and implement the best-practices of corporate governance and also as a mechanism to evaluate the board of directors by the stakeholders.

The strategy of an organization, its main objectives, and its key business drivers define the indicators of the BSC. However, the choice of indicators is, in general, highly subjective and is often driven by the company management or industry practices. There are several proposals for more objective methods for quantifying board performance. YoungBlood and Collins [112] describe a method based on indicators using multi-attribute utility theory. Clinton et al [34] base their method on Analytic Hierarchy Process. However, these methods still require a mix of quantitative measure with a qualitative evaluation by managers or experts.

Our approach, following the algorithmic modeling methodology, is to select the board BSC and its indicators according to their statistical effect on value of companies in the given market segment. Instead of defining in advance a normative framework, we use a data-driven model where the relevant features are selected according to their positive impact on corporate efficiency for LABANKS and performance for

LAADR and S&P 500 companies. The main group of variables that we use are related to the principal agent problem because of their effect on company performance and efficiency. We use machine learning techniques to quantify this effect.

Adaboost [48] is the learning algorithm and interpretative tool of our board BSC. This model evaluates whether a company's performance or a bank's efficiency is above or below par as a function of the main corporate governance factors (executive compensation, insider ownership, and board of directors structure) and of selected accounting ratios that are known to be important in evaluating corporate governance. These features selected and quantified by Adaboost become the main indicators and targets of the board BSC.

We selected a broad group of corporate governance variables that we describe in the next sections. However, the methodology proposed to build a board BSC could be applied to different features or market conditions.

1.2.2.1. Measures of corporate governance factors and accounting indexes For the corporate governance variables, in the case of ADRs and banks we include the percentage of insider ownership (T_Insider) because the separation of ownership and control is seen as an opportunity for managers to accumulate wealth at the expense of the shareholders (see Table 1).

The next group of variables that we include for LAADR and LABANKS are those related to the structure of the board of directors (outsiders on the board of directors [PartOutBOD], natural logarithm of the size of the board of directors [LnDIR], and the double role of the CEO as chairman of the board of directors and manager [ChairmanCEO]). Among these variables, outsiders on the board of directors seem the most important. Fama [44] and Fama and Jensen [46] explain how the separation between control and security ownership can be an efficient structure because professional outside directors may limit the power of agents to expropriate the residual claimants' interest. The size of the board of directors is also a relevant variable, according to Yermack [111] and Fuerst and Kang [50], because the size of the board of directors has an inverse association with firm value in the case of large US industrial corporations. Lipton and Lorsch [80] and Jensen [62] recommend that companies limit board membership to no more than seven or eight members. Additionally, Jensen [62] suggests that companies should separate the CEO role from the chairman role because of the need for independence. If the CEO is also chairman of the board, the dual role may have a negative impact on performance. Even more, Jensen recommends including active investors who hold a large equity or debt position in a company and take part in their strategic decisions. Institutional ownership (InstPart) is another variable that we include because large institutional shareholders act as active monitors of managers' actions. Results might be ambiguous if there is insider ownership or hidden investment, because large shareholders may manage the firm for their own benefit only, and not for the benefit of the majority of small shareholders.

For LAADR and LABANKS, we also include corporate governance indicators at the country level according to La Porta et al. [75]: efficiency of the judicial system [EfficiencyJudicialSystem], rule of law [RuleOfLaw], risk of expropriation [RiskOfExpropriation], risk of contract repudiation [RiskOfContractRepudiation], corruption [Corruption], quality of accounting system [Accounting], and legal system [English/French]. Based on these indicators, La Porta et al. [75] found that French-civil law countries have the weakest, and common-law (English) countries have the strongest legal protection of investors. We include these variables because we wanted to separate the effect of country variables from the effect of company variables.

For S&P 500 companies we include insider ownership, and variables related to executive compensation for the top five senior managers. The variables of executive compensation are total compensation for officers (TotalCompExec) and CEOs (totalCompCEO), value of options for officers (OptionAllValExec), CEOs (TotalValOptCEO), and directors (OptionsDirectors), value of stock options for officers (OptionAllValExec), fees paid for attendance to board of directors meeting (TotalMeetingPay), annual cash paid to each director (PayDirectors), dummy variables to indicate if directors are paid additional fees for attending board committee meetings (DcommFee), and annual number of shares granted to non-employee directors (StockDirectors). The discussion about the link between executive compensation and performance is very extensive. Himmelberg et al. [59] and Palia [91] do not find any important association between Tobin's Q[3] as a proxy for performance and equity incentives granted to managers. On the contrary, Hillegeist and Penalva [58] find that those firms with higher options incentives show better performance than the other US firms that were studied. The contradictory results of previous research as well as the importance of executive compensation in corporate governance policies led us to extend our analysis to the study of how total and stock options compensation for the top five officers,

[3] Tobin's Q is the ratio of the market value of assets to the replacement cost of assets.

Table 1. Corporate governance variables at the country level are from La Porta et al. [75]. These variables are English, French, RuleOfLaw, Corruption, EfficiencyJudicialSystem, RiskOfExpropriation, RiskOfContractRepudiation, and Accounting.

Indicator	Definition	Type of companies
TobinQ	Tobin 's Q, which is the ratio of the market value to the replacement cost of assets. We use a proxy for Tobin's Q as the ratio of book value of debt plus market value of common stocks and preferred stocks to total assets	LAADR,S&P 500
PartOutBOD	% outsiders on the board of directors	LAADR,S&P 500, LABANKS
LnDIR	Natural logarithm of board size	LAADR LABANKS
InstPart	% institutional ownership	LAADR LABANKS
T_Insider	% insiders' ownership. In the case of LAADR and the Latin American banks, insider ownership is defined as ownership of a company by the CEO, managers, or relatives of the CEO, and members of the board of directors.	LAADR, S&P 500, LABANKS
ChairmanCEO	1 if CEO is chairman, 0 otherwise	LAADR LABANKS
TotalCompCEO	Total compensation for CEOs. It includes the same items as TotalCompExec (thousands of dollars).	S&P 500
TotalValOptCEO	Value of options for CEOs (thousands of dollars).	S&P 500
TotalCompExec	Total compensation for officers. It includes the following items: salary, bonus, other annual, total value of restricted stock granted, total value of stock options granted (using Black-Scholes), long-term incentive payouts, and all other total (thousands of dollars).	S&P 500
OptionStockValueExec	Value of stock options granted to the executive during the year as valued using S&P's Black Scholes methodology (thousands of dollars).	S&P 500
OptionAllValExec	The aggregate value of all options granted to the executive during the year as valued by the company (thousands of dollars).	
DexecDir	Dummy variable to indicate if officer was also a director for the reference year.	S&P 500
OptionsDirectors	Number of options and additional options granted to each non-employee director during the year (thousands).	S&P 500
StockDirectors	Stock shares (including restricted stock) granted to each non-employee director (thousands).	S&P 500
PayDirectors	Annual cash retained paid to each director (thousands of dollars).	S&P 500
TotalMeetingPay	Fees paid for attendance to board of directors meeting (thousands of dollars).	S&P 500
DcommFee	Dummy variable to indicate if directors are paid additional fees for attending board committee meetings.	S&P 500
SPindex	Standard and Poor's index membership. It indicates if companies are part of S&P500 (SP), S&P midcap index (MD), S&P smallcap index (SM), or is not part of a major US index (EX).	S&P 500
LnMarketCap	Natural logarithm of market capitalization, used to measure firm size	LAADR, S&P 500
KS or KD	Ratio of long term assets (property, plant and equipment) to sales (KS) for LAADRs and S&P 500 companies, and to deposits (KS) for LABANKS. This ratio is considered for its effect in the reduction of the agency conflict because these assets can be monitored very easily and they can become collateral for the development of new projects.	LAADR, S&P 500, LABANKS
YS	The ratio of operating income to sales	LAADR, S&P 500, LABANKS
DebtRatio	The ratio of debt to total assets, used as a capital structure variable. Emerging markets are much less liquid than those of developed countries. Hence, firms may give more importance to debt, rather than equity, as a source of capital.	LAADR, S&P 500, LABANKS
Equity index	Index of equity according to country of residence. This is a measure of size applied to LABANKS.	LABANKS
Efficiency	The ratio of operating expenses to sales. This is the efficiency ratio and works as a proxy for market power. It also indicates cash flow available for management use. Similarly, this efficiency ratio may also reveal agency costs or agency conflicts. (This is different from the DEA technical efficiency indicator).	LAADR, S&P 500, LABANKS
IK	The ratio of capital expenditures to long term assets (stocks of property, plant and equipment)	LAADR, S&P 500, LABANKS
AvgParticipation	Measure of ownership concentration. This is calculated as the average of the participation of the three largest shareholders per firm	LAADR,LABANKS
English	If the firm is domiciled in a country whose legal regime is part of the common law or English law legal family according to La Porta et al. (1998)	LAADR,LABANKS
French	If the firm is domiciled in a country that is part of the Napoleonic or French legal family according to La Porta et al.	LAADR,LABANKS
RuleOfLaw	Law and order tradition according to the agency International Country Risk (ICR). Scores are from 0 to 10. Lower values indicate that a country is characterized by less tradition of law and order.	LAADR,LABANKS
Corruption	Indicator of level of government corruption according to ICR. Low levels indicate higher corruption, such as solicitation of bribery by government officials	LAADR,LABANKS
EfficiencyJudicialSystem	Index about the level of efficiency of the legal system according to the agency Business International Corp. Scale is from zero to ten. Lower values correspond to lower efficiency levels.	LAADR,LABANKS
RiskOfExpropriation	Risk of confiscation or nationalization according to ICR. Scale is from zero to ten. Lower values imply higher risks.	LAADR,LABANKS
RiskOfContractRepudiation	Risk of modification of a contract by economic, social or political reasons as defined by ICR. Lower values correspond to higher risks.	LAADR,LABANKS
Accounting	Index based on 1990 annual reports according to their inclusion or omission of 90 items. These items are classified into the following categories: general information, income statements, balance sheets, fund flow statement, accounting standards, stock data and special items. For each country, a minimum of three companies were studied.	LAADR,LABANKS

CEOs and directors of a broad sample of US firms affect performance.

We have selected a group of accounting variables for all companies that are well-known for their predictive power, and also are indirect indicators of corporate governance variables. These accounting variables are: the logarithm of market capitalization (LnMarketCap) for ADRs and S&P 500 companies, and an equity index per country as a proxy for size for Latin American banks[4]; long-term assets to sales ratio (KS) for ADRs and S&P 500 companies, and long-term assets to deposits (KD) for banks for their effect in the reduction of the agency conflict[5]; debt to total assets ratio (DebtRatio) as a capital structure indicator[6]; operating expenses to sales ratio (Efficiency) as an efficiency or agency cost indicator[7]; operating income to sales ratio (YS) as a market power proxy, and to indicate cash available from operations; and capital expenditures to long-term assets ratio (IK)[8] as a proxy for the relationship between growth and the possibility of investing in discretionary projects. A large IK ratio may indicate agency problems if managers are developing new projects that may increase their power, but do not add market value to the company. We use region and sector as indicators of the geographical area and industrial sector in which the company operates.[9] For S&P 500 companies sectors we also include Standard and Poor's index membership (SPindex).

1.2.2.2. Measures of company performance We use Tobin's Q as the measure of performance for ADRs and S&P 500 companies.[10] Tobin's Q, as a measure of the value of intangibles of a firm, is the ratio of the market value of assets to the replacement cost of assets. This is a measure of the real value created by management.[11] A higher value of Tobin's Q indicates that more value has been added or there is an expectation of greater future cash flow. Hence, the impact of management quality on performance is captured by Tobin's Q. Any difference of Tobin's Q from one indicates that the market perceives that the value of total assets is different from the value to replace their physical assets. The value of internal organization, management quality, or expected agency costs is assumed to explain the difference. Values of Tobin's Q above one indicate that the market perceives the firm's internal organization as effective in leveraging company assets, while a Tobin's Q below one shows that the market expects high agency costs. We use a proxy for Tobin's Q as the ratio of book value of debt plus market value of common stocks and preferred stocks to total assets.[12] Tobin's Q is a measure of the value of intangibles of a firm.[13]

For Latin American banks, we use an efficiency measure based on data envelopment analysis (DEA) instead of Tobin's Q because some of the banks under study are not public companies or participate in very illiquid markets. Additionally, efficiency indicators calculate the agency costs to the firm. Conflicts between managers and shareholders may arise when operating costs increase in relation to a fixed output.

The rest of the paper is organized as follows: Section 2 introduces the main methods (logistic regression, bagging, random forests, efficiency calculations, boosting, and the generation of a representative ADT) used in this paper; section 3 explains in detail our experiments; section 4 presents the methodological findings; section 5 discusses the results from a financial perspective, and section 6 presents the conclusions.

2 Methods

This part of the paper describes a first attempt in applying the algorithmic modeling approach to the determination of a board BSC, comparing the results of Adaboost to logistic regression, random forest, and bagging, and evaluating its accuracy as well as its inter-

[4]We used the equity index instead of equity value because efficiency is calculated country by country. We are interested in the effect of the relative size by country on efficiency instead of its absolute value.

[5]Assets can be monitored very easily and they can become collateral either for the development of new projects or to finance new acquisitions.

[6]Harvey et al. [55] find that in emerging market companies with extreme managerial agency costs shareholders benefit from intensively monitored debt.

[7]If operating costs are too high in relation to industry peers or previous years, it might be due to excessive perquisite consumption or other direct agency costs.

[8]Operating expenses to sales ratio and operating income to sales ratio are calculated only for ADRs and S&P 500 companies because these ratios are highly correlated with the efficiency indicator calculated for the banking sector. The capital expenditures to long-term assets ratio is also calculated only for the ADRs and S&P 500 companies.

[9]Sectors of activity for the S&P 500 companies is by the Global Industry Classification Standard, and for ADRs is by the North American Industrial Classification System (NAICS).

[10]Tobin's Q is the preferred indicator of performance in corporate governance studies such as in La Porta et al. [76]

[11]The intangibles can also refer to other factors such as intellectual capital or the value of information technology. In this paper we control for differences among countries, and economic sectors where companies may have similar technology. So we assume that Tobin's Q reflects management quality.

[12]Several papers [32; 93; 94] indicate that this proxy is empirically close to the well-known Lindenberg and Ross [79] proxy. For international stocks, the information to calculate the Lindenberg and Ross proxy is very limited.

[13]The discrimination between the contribution to performance of top management and other intangibles assets such as intellectual capital requires a more detailed analysis.

pretability. Here we create a predictive model for evaluating whether a company's performance or a bank's efficiency is above or below par as a function of the main corporate governance factors and of selected accounting ratios that are known to be important in evaluating corporate governance risk. A second objective of this research is to evaluate the use of Adaboost as a predictive and interpretative tool to select and measure the main features used in a board BSC.

In the next subsections, we introduce logistic regression, bagging, random forests, Adaboost, and efficiency calculations.

2.1 Learning methods

2.1.1 Logistic regression

The logistic regression models the posterior probabilities of L classes using linear regression. The model is a series of ordinary regressions where L-1 logit transformations or log-odds are the dependent variables:

$\log \frac{Pr(C=1|X=x)}{Pr(C=L|X=x)} = \beta_{10} + \beta_1^T$ x

$\log \frac{Pr(C=2|X=x)}{Pr(C=L|X=x)} = \beta_{20} + \beta_2^T$ x

...

$\log \frac{Pr(C=L-1|X=x)}{Pr(C=L|X=x)} = \beta_{(L-1)0} + \beta_{L-1}^T$ x

Taking the exponential of the log-odds, we can calculate the probabilities of each class as follows:

$Pr(L=k|X=x)=\frac{e^{\beta_{l0}+\beta_l^T x}}{1+\sum_{r=1}^{L-1} e^{\beta_{r0}+\beta_r^T x}}$, r = 1, ..., L-1

The summation of these probabilities equal one. Logistic regression results are better interpreted using the odds ratios which can be computed by raising the e number to the power of the logistic coefficients [56].

2.1.2 Bagging and random forests

Bagging was proposed by Breiman [21] as a method that reduces the variance of a prediction function. Bagging or bootstrap aggregation averages the prediction of classifiers by the generation of different bootstrap samples. Each bootstrap sample is generated by obtaining uniform samples with replacement from the training set. Bagging has been shown to be particularly effective for reducing the variance of decision trees [24].

Each sample S_i where $i = 1, .., n$ generates a classifier C_i using the initial prediction function. The final classifier $C*$ is an average of all the classifiers obtained from the bootstrap samples:

$C* = 1/n \sum_{i=1}^{n} (C_i)$

Random forests is a variant of bagging decision trees also proposed by Breiman [22], and for which free computer code is available. We chose this algorithm because it presents the best publicly available combination of decision trees and bagging.

This algorithm generates multiple trees (θ_i) from the training data and from a random vector (x) sampled independently and with the same distribution for any tree that is part of the forest. As a result each tree generates a classifier $h(x, \theta_i)$. The majority vote of all the trees determine the predicted class. When the number of trees is very large, the generalization error for forests converges. Breiman [22] indicates that the accuracy of random forests is as good as Adaboost or better.

2.1.3 Adaboost

Adaboost is a general discriminative learning algorithm invented by Freund and Schapire [48].

The basic idea of Adaboost is to repeatedly apply a simple learning algorithm, called the *weak* or *base* learner, to different weightings of the same training set. In its simplest form, Adaboost is intended for binary prediction problems where the training set consists of pairs $(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)$, x_i corresponds to the features of an example, and $y_i \in \{-1, +1\}$ is the binary label to be predicted. A *weighting* of the training examples is an assignment of a non-negative real value w_i to each example (x_i, y_i).

On iteration t of the boosting process, the weak learner is applied to the training set with a set of weights $w_1^t, \ldots, w_m^t$ and produces a prediction rule h_t that maps x to $\{0, 1\}$. [14] The requirement on the weak learner is for $h_t(x)$ to have a small but significant correlation with the example labels y when measured using the *current weighting of the examples*. After the rule h_t is generated, the example weights are changed so that the weak predictions $h_t(x)$ and the labels y are decorrelated. The weak learner is then called with the new weights over the training examples, and the process repeats. Finally, all of the weak prediction rules are combined into a single *strong* rule using a weighted majority vote. One can prove that if the rules generated in the iterations are all slightly correlated with the label, then the strong rule will have a very high correlation with the label – in other words, it will predict the label very accurately.

The whole process can be seen as a variational method in which an approximation $F(x)$ is repeatedly changed by adding to it small corrections given by the weak prediction functions. In Figure 1, we describe Adaboost in these terms. We shall refer to

[14] Mapping x to $\{0, 1\}$ instead of $\{-1, +1\}$ increases the flexibility of the weak learner. Zero can be interpreted as "no prediction."

$F(x)$ as the *prediction score* in the rest of the document. The strong prediction rule learned by Adaboost is sign$(F(x))$.

A surprising phenomenon associated with Adaboost is that the test error of the strong rule (percentage of mistakes made on new examples) often continues to decrease even after the training error (fraction of mistakes made on the training set) reaches zero. This behavior has been related to the concept of a "margin," which is simply the value $yF(x)$ (Schapire et al. 1998). While $yF(x) > 0$ corresponds to a correct prediction, $yF(x) > a > 0$ corresponds to a *confident* correct prediction, and the confidence increases monotonically with a.

$F_0(x) \equiv 0$
for $t = 1 \ldots T$
$w_i^t = e^{-y_i F_{t-1}(x_i)}$
Get h_t from *weak learner*
$$\alpha_t = \frac{1}{2} \ln \left(\frac{\sum_{i:h_t(x_i)=1, y_i=1} w_i^t}{\sum_{i:h_t(x_i)=1, y_i=-1} w_i^t} \right)$$
$F_{t+1} = F_t + \alpha_t h_t$

Figure 1. The Adaboost algorithm. This algorithm improves prediction increasing the weight of the misclassified observations in each iteration.

2.1.4 Alternating decision trees

Similarly to Bagging, Adaboost is often used with a decision tree learning algorithms as the base learning algorithm [49]. We use Adaboost both to learn the decision rules constituting the tree and to combine these rules through a weighted majority vote. The form of the generated decision rules is called an *alternating decision tree* (ADT) [47]. In ADTs each node can be understood in isolation.

We explain the structure of ADTs using one of the trees (see Figure 2) that we obtained using data from Latin American ADRs. The problem domain is corporate performance prediction, and the goal is to separate stocks with high and low values based on 17 different variables. The tree consists of alternating levels of ovals (*prediction nodes*) and rectangles (*splitter nodes*) (hence the word "alternating" in the name). The first number within the ovals defines contributions to the prediction score, and the second number (between parentheses) indicates the number of instances. In this example, positive contributions are evidence of high performance, while negative contributions are evidence of corporate financial problems. To evaluate the prediction for a particular company we start at the top oval (0.042) and follow the arrows down. We follow *all* of the dotted arrows that emanate from prediction nodes, but we follow *only one* of the solid-line arrows emanating from a splitter node, corresponding to the answer (yes or no) to the condition stated in rectangle. We sum the values in all the prediction nodes that we reach. This sum represents the prediction score $F(x)$ above, and its sign is the final, or strong, prediction. For example, suppose we had a company for which

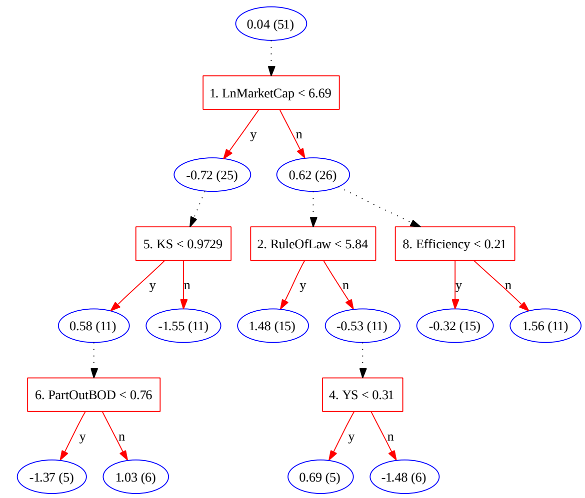

Figure 2. Representative ADT of LAADR. The tree has ovals (*prediction nodes*) and rectangles (*splitter nodes*). The sum of first values in all relevant prediction nodes is the prediction score.

LnMarketCap=6, KS=0.86, RuleOfLaw=7.02, and PartOutBOD=0.76. In this case, the prediction nodes that we reach in the tree are 0.042, -0.7181, 0.583, and 1.027. Summing gives a score of 0.9339, i.e., a very confident indicator that the company has a high market value.

This example demonstrates how alternating decision trees combine the contributions of many indicators to generate a prediction. The ADT in the figure was generated by Adaboost from training data. In terms of Adaboost, each prediction node represents a weak prediction rule, and at every boosting iteration, a new splitter node together with its two prediction nodes is added to the model. The splitter node can be attached to any previous prediction node, not only leaf nodes. Each prediction node is associated with a weight α that contributes to the prediction score of every example reaching it. The weak hypothesis $h(x)$ is 1 for every example reaching the prediction node and 0 for all others. The number in front of the conditions in the splitter nodes of Figure 2 indicates the iteration number on which the node was added. In general, lower iteration numbers indicate that the decision rule is more important. We use this heuristic to analyze the ADTs and identify the most important factors in corporate performance. Additionally, the final score that we obtain for each company using Adaboost can be normalized between -1 and 1 and become our corporate governance score.

2.1.5 Representative ADTs

A common complaint about boosting and the alternating decision tree algorithm (see section 2.1.3) is that the ADTs generated do not have a clear interpretation, especially if they are very different as it may happen after cross-validation. Considering these problems we propose an algorithm to calculate a representative ADT that extracts the common features among several trees.

The Representative ADT algorithm looks for the most frequent nodes among a set of ADTs with same positions, features and thresholds. The selected nodes are ranked according to a rank coefficient obtained by the multiplication of the average iteration and the inverse of the frequency of nodes that share the same characteristics. A low value of this coefficient indicates that the node is more important because is present in many nodes of the original set of ADTs and/or appears in the first iterations. The algorithm selects the most important nodes. In case that the algorithm selects two nodes with the same position, the node with lower priority is put under the root (see Figure 3).

Figure 3. The Representative ADT algorithm.

The Representative ADT algorithm selects the most important features of a group of ADTs according to an internal ranking procedure.

Input:
Set of n cross-validation samples

1. For each feature i, select the node j that has the maximum number of cases over all the n cross-validation samples with the threshold k ($freq_{i,j,k}$) and calculate the rank[a] of the feature i:

$rank_{i,j,k} = \frac{avgIter_{i,j,k}}{freq_{i,j,k}}$
where $iter_{i,j,k,m}$ is the iteration when feature i is selected in node j with threshold k, and in sample m. The average iteration is:

$avgIter_{i,j,k} = \sum_{m=1}^{n}(iter_{i,j,k,m})/freq_{i,j,k}$

The thresholds values are simplified using the most significant two digits when written in scientific notation.

2. Select the first V nodes with the lowest $rank_{i,j,k}$ and with $avgIter_{i,j,k} \leq A$. If the node has a feature that already exists in another node, include it only if it is in at least 60% of the ADTs.[b]

3. Put a node under the root, if there is another node with higher priority in the same location.

Output:
The representative ADT

[a] A low value of $rank_{i,j,k}$ shows that it is a more important node because in most cases the feature is included in early iterations.

[b] Based on previous tests, we chose to work with values of V and A equal to seven and ten respectively.

The features and their relationship of the representative ADT is used to identify key business drivers, strategic objectives and indicators of the BSC (see section 1.2.2). In a first step, the features and thresholds of the representative ADT become the indicators and targets of the BSC. If the representative ADT has several levels, then the relationship among the nodes also determine the relationship among the indicators of the BSC. In a second step, the indicators are transformed into objectives of the BSC and of the board strategy map. This second step requires a dialogue among managers where the results of the representative ADTs are reviewed according to the priorities of senior management.

2.2 Measuring efficiency of Latin American banks

We conduct the evaluation of performance of the Latin American banks using an efficiency measure because some of the banks under study are not public companies or participate in very illiquid markets. The present banking literature gives significant importance to efficiency evaluation of financial institutions, applying parametric and nonparametric frontier analysis techniques to a specific company as part of an industry, or to a firm's branches. Frontier analysis, based on optimization methodologies, selects the ”best practice” firms or areas of a firm, obtains an efficient score, and recognizes those areas where there is overuse of inputs or underproduction of outputs within complex operations. Regulators use these techniques [12] to recognize the efficiency gain of a merger between two financial institutions. Frontier analysis can also be used to relate the level of risk that the firm is taking to its overall efficiency, and to establish ”benchmarks” for financial institutions based on a ”best-practice” frontier. These ”benchmarks” can be established by regulators and also by managers who want to assure that the firms they run are competitive nationally or internationally in comparison with the rest of the industry [15].

From an economics point of view, the study of efficiency has been influenced by Leibenstein [78] and his concept of X-efficiency. The economic concept of efficiency includes technical efficiency and also implies allocative efficiency, where the firm must choose an optimal combination of input and output that minimizes costs or maximizes output based on the production technology as well as relative market prices. X-efficiency refers to technical efficiency. Examples of this approach appear in the early nonparametric frontier models [29] and in some of the early parametric frontier models such as in Aigner et al. [2].

The frontier approaches used to measure efficiency can be based on:

1. Nonparametric methods:

   (a) Data Envelopment Analysis (DEA): is a linear programming technique to measure X-efficiency where the set of best-practice (frontier) observations are those for which no other (combination of) firm(s) has as much of every output (given input) or as little of every input (given output). The institutions subject of study receive a score based on how efficient they are in relation to the best-practice institution. The drawback to this method is that it assumes that there is not random error that leads to overestimating inefficiency.

2. Parametric methods:

   (a) Stochastic Frontier Approach (SFA) or the Econometric Frontier Approach: imposes a functional form such as the cost function and recognizes the random error.

   (b) Thick Frontier Approach (TFA): similar to SFA, but the estimations are based on the best performers in the data as estimators of the best-practice cost function for the whole group.

   (c) Distribution Free Approach (DFA): handles a cost function as the two previous techniques do, but assumes that there is an average efficiency and that the random error term tends to be eliminated.

These efficiency studies in the financial sector have been conducted mainly in the U.S.A. [20; 41; 85; 106], and on a smaller scale in Europe [10; 53; 82], Canada [100], Saudi Arabia [3], Tunisia [27], Turkey [113], and India [19].[15] In Latin America, efficiency studies in the banking sector have been scarce [106]. Pastor, Perez and Quesada [92], and Berger and Humphrey [15] have compared international studies on banking efficiency. We are not aware of previous studies that have addressed the relationship between efficiency, and corporate governance structure in Latin America.

[15] See Hall [54] for a collection of articles on bank efficiency from 1973 until 1998 for many countries.

DEA measures the performance of each producer relative to the best observed practice among k producers. The DEA frontier is a piecewise linear combination that connects the set of best-practice observations, creating a convex production possibilities set. The rest of the firms that are not in the frontier are ranked accordingly. DEA calculation implies the minimization of a weighted sum of inputs in relation to a weighted sum of outputs:

$$\min_{u,v} \frac{v_T x_0}{u^T y_0}$$

subject to

$$\frac{v_T x_i}{u^T y_i} \geq 1$$
$$u, v \geq 0$$

where:
i= 1,...,0,...k
(x_0, y_0): input-output vector of the firm that is evaluated
(x_i, y_i): input-output vector of ith. firm in the sample
u: vector of weights given to output
v: vector of weights given to input

This minimization problem can also be expressed as a linear programming problem:

$$\min_{u,v} v_T x_0$$

subject to

$$u^T y_0 = 1$$
$$v_T x_i \geq u^T y_i \quad \text{where i= 1,...,0,...k}$$
$$u, v \geq 0$$

and then as the dual linear programming "envelopment" problem:

$$\max_{\theta,\gamma} \theta$$

subject to

$$X\gamma \leq x_o$$
$$\theta y_o \leq Y\gamma$$
$$\gamma \geq 0$$

X is an n by k input matrix, Y is an m by k output matrix, γ is a k by 1 intensity vector, and x_i and y_i are the columns of the input and output matrix respectively.

θ is a radial measure of technical efficiency. An optimal firm will have its efficiency measure (θ) equal to one. If it is more than one, it can still increase its output with the same unit of input. This version of DEA is output oriented, assumes constant returns to scale and was proposed by Charnes, Cooper, and Rhodes [29] (see also [81]).

We calculate efficiency for the Latin American banking sector using the DEA with different variations (input-oriented or output-oriented; constant, non-decreasing or variable returns to scale) and stochastic DEA. We used only output-oriented constant returns to scale as our measure of banking efficiency which results are consistent with the results obtained by the other methods. As input, we use interest-paying deposits and non-interest expenses which may include personnel, administrative costs, commissions, and other non-interest operating costs. As output, we use total income which includes interest and non-interest income. Banks are ranked according to this measure country by country. If a bank shows a great level of inefficiency, a potential agency conflict might be present.

3 Experiments

The data we used in our experiments are from Latin American ADRs (LAADR), Latin American banks (LABANKS), and S&P 500 companies. These data are described in Appendix 1. We conducted a logistic regression using Tobin's Q and the DEA technical efficiency indicator as the dependent variables for LAADR and LABANKS respectively. As independent variables we used the following:

1. Corporate governance variables: In the case of ADRs and banks we include the presence of insider ownership (T_Insider), variables related to the structure of the board of directors (outsiders on the board of directors (PartOutBOD), natural logarithm of the size of the board of directors (LnDIR), and the double role of CEO as chairman of the board of directors and manager (ChairmanCEO)), institutional ownership (InstPart), and corporate governance indicators at the country level according to La Porta et al. [75] (efficiency of the judicial system (EfficiencyJudicialSystem), rule of law (RuleOfLaw), risk of expropriation (RiskOfExpropriation), risk of contract repudiation (RiskOfContractRepudiation), corruption (Corruption), quality of accounting system (Accounting), and legal system (English/French)). For S&P 500 companies we include insider ownership, and variables related to executive compensation for the five top senior managers. The variables of executive compensation are total compensation for officers (TotalCompExec) and CEOs (totalCompCEO), value of options for officers (OptionAllValExec), CEOs (TotalValOptCEO), and directors (OptionsDirectors), value of stock options for officers (OptionAllValExec), fees paid for attendance to board of director meetings (TotalMeetingPay), annual cash paid to each director (PayDirectors), dummy variable to indicate if directors are paid additional fees for attending board committee meetings (DcommFee), and annual number of shares granted to non-employee directors (StockDirectors).
2. Accounting variables: Logarithm of market capitalization (LnMarketCap) for ADRs and S&P 500 companies, and an equity index per country; long-term assets to sales ratio (KS) for ADRs and S&P 500 companies, and long-term assets to deposits (KD) for banks; debt to total assets ratio (DebtRatio); operating expenses to sales ratio (Efficiency); operating income to sales ratio (YS); and capital expenditures to long-term assets ratio (IK) (see Appendix 2).

The logistic regression includes a dummy variable for industrial sectors. We calculated the efficiency indicators for each country because of the differences between accounting systems in the countries under study. Hence, efficiency of banks is calculated in relation to their peers in their country.

For the logistic regression analysis and for all the learning algorithms, we eliminated variables that indicated multicollinearity. For LABANKS the variables eliminated were risk of contract repudiation, legal system, region, corruption, and debt ratio. For LAADR, we eliminated risk of expropriation, risk of contract repudiation, and region. For S&P 500 companies, we eliminated total compensation of officers, and CEOs.

We used Adaboost to classify stocks above and below the median. In the LAADR sample, the median is very close to one. So, the results can be interpreted as the classification between those stocks with a market value of its assets above (Tobin's Q greater than one) or below (Tobin's Q smaller than one) its costs of replacement. For LABANKS, the classification is between more efficient and less efficient banks. The results of ADTs must be interpreted as companies with positive scores that have high Tobin's Q or in the case of banks are efficient, while companies with negative scores have low Tobin's Q or are inefficient banks.

We performed tenfold cross-validation experiments to evaluate classification performance on held-out experiments using Adaboost. For LAADR and LABANKS we run our experiments with 10 iterations. For S&P 500 companies, we run 300 iterations. We used the MLJAVA package, which implements the alternating decision tree algorithm described in Freund and Mason [47].[16] We ranked the variables as an average of the iteration when each variable is selected, weighted by their frequency (see section 2.1.5).

To evaluate the difficulty of the classification task, we compared our method, Adaboost, with random forests using the software Random Forests V5.0.[17] We run our experiments with 1000 trees. We also used four variables for LAADR and LABANKS, and eight for S&P 500 companies randomly selected at each node in order to reduce the test error.

To check for the possibility that the Adaboost results could be improved because of the characteristic instability of Adaboost, we run bagging on top of Adaboost (bagged boosting). We created ten folds for testing and training. We obtained 100 bootstrap replicates of each testing fold. We averaged the score of the bootstraps of each fold to get the estimated class. Finally, we averaged the test error of the ten folds. We also compared ADTs with a single tree classifier and with a stumps averaged classifier trained using boosting. We evaluated the differences between the average of the test error of Adaboost with the test errors of the rest of the learning algorithms using the t-test.

For LABANKS and LAADR, considering that we had very limited amount of information, we calculated representative ADTs using the nodes that were present in at least 60% of the trees. For the S&P 500 companies, we automated the calculation of representative ADTs with stumps averaged classifier trained using boosting and we followed the procedure described in section 2.1.5).

We propose that the formulation of the BSC can be enriched with the boosting approach in order to identify the key business drivers and strategic objectives, establish their indicators and targets, and the relationship between these indicators. We use the main features and their thresholds selected by the representative ADTs as the indicators and the targets of the board BSC.

In this paper we restrict our analysis to the board BSC for the S&P 500 companies. Although we could use a similar methodology to develop the enterprise BSC and the executive BSC. We mostly concentrate on the financial perspective and the internal process perspective because these are the perspectives mainly affected by the corporate governance variables.

[16]If interested in using MLJAVA, please contact `yfreund@cs.ucsd.edu`

[17]A working version of Random Forests V5.0 can be obtained from ⟨http://stat-www.berkeley.edu/users/breiman/RandomForests/⟩.

3.1 Results

The evolution of the training and testing errors are in Figure 4. The single tree boosting behaves similarly to Adaboost, and the stumps boosting shows a poorer performance for LAADR, while it shows a better performance for LABANKS during the first 10 iterations. In the case of S&P 500 companies, Adaboost is the dominant algorithm. The receiver operating character-

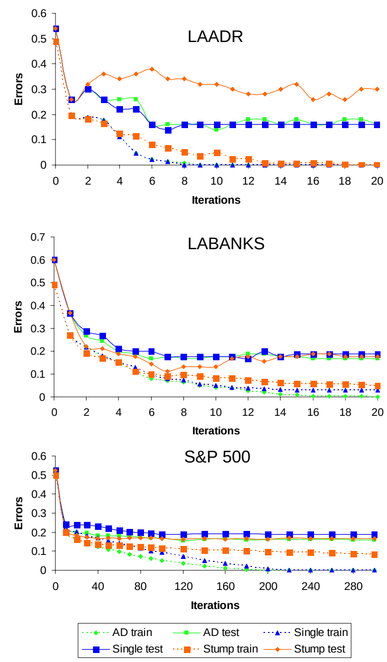

Figure 4. Training and testing error across algorithms as described in section 3 by group of companies.

istic (ROC) curve for LABANKS and S&P 500 companies generated using Adaboost shows a larger proportion of true positives versus false positives in comparison to the LAADR case (see Figures 5). The results of the testing errors for the learning algorithms used are shown in Table 2. As both our LAADR and LABANKS datasets are very small (51 examples in LAADR and 104 examples in LABANKS), evaluating the statistical significance of the different models and the comparison of their test errors is difficult. Acknowledging these limitations, we present the results of the t-test. The t-test indicated that there was a significant difference between the test errors of Adaboost and random forests for LAADR. There were no differences of the test errors for the rest of the tests in both samples. In the case of S&P 500 companies, the test errors of single tree, bagged boosting, and random forests show a significant difference with Adaboost. Random forests presents the lowest test error for S&P

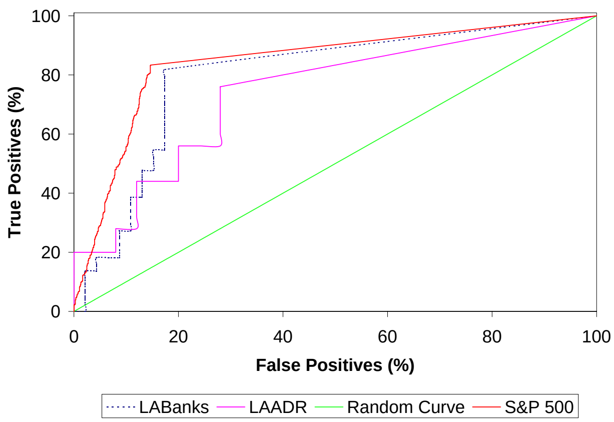

Figure 5. ROC curves by group of companies. y-axis presents the percentage of positive observations adequately classified (true positive) and x-axis presents the percentage of negative observations misclassified (false positives).

500 companies, and it is followed by bagged boosting.

Most of the S&P 500 subsets defined by the main accounting variables and economic sectors when only the corporate governance variables are included (Table 3) show a significant reduction of the testing error. The most important reduction of the testing error is observed in sectors 1 and 3, and when companies have a market capitalization and an efficiency ratio above the median.

Table 2. Testing errors and standard deviations of learning algorithms when all variables are included.

	LAADR		LABANKS		S&P 500	
	Test error	St. dev.	Test error	St. dev.	Test error	St. dev.
Adaboost	14.0%	16.5%	17.8%	9.4%	16.1%	2.1%
Single tree	16.0%	12.7%	17.8%	11.9%	18.7% **	1.8%
Stumps	32.0%	19.3%	13.3%	11.5%	16.8%	2.6%
Bagged boosting	22.0%	23.9%	13.33%	8.66%	14.01% **	0.50%
Random forests	32.0% *	16.87%	16.67%	17.57%	11.50% **	4.56%
Logistic regression	23.7%	18.5%	20.1%	13.2%	16.9%	2.9%
Number observations	51		104		2278	

*: 5%, **: 1% significance level of t-test difference between test errors of algorithms and Adabooost

Tables 4 and 5 indicate the importance of each variable according to Adaboost and random forests. The results of both algorithms coincide in terms of what the most important variables are. Four top variables of the LAADR dataset and six top variables of S&P 500 companies according to Adaboost are ranked between the top six variables in random forests. In the case of LABANKS, four variables chosen by Adaboost are ranked between the top five variables according to random forests. Considering the similarity of the most important variables selected by random forests and Adaboost, we discuss the ADTs.

Table 3. Testing errors and standard deviations of Adaboost for S&P 500 companies aggregated by variables (below and equal or above the median). Only corporate governance variables are used to make the prediction. Number of observations in parenthesis.

Subsets	S&P 500		
	Test error		St. dev.
All observations (2278)	35.81%		2.58%
Debt ratio < median (1139)	32.02%		6.20%
Debt ratio ≥ median (1139)	31.50%	*	4.20%
Efficiency < median (1139)	29.91%	**	3%
Efficiency ≥ median (1139)	29.54%	**	2.55%
Cap. Expenditures / L.T. Assets < median (1139)	31.15%	**	2.99%
Cap. Expenditures / L.T. Assets ≥ median (1139)	33.72%		3.63%
L.T. assets / sales < median (1139)	34.34%		5.70%
L.T. assets / sales ≥ median (1139)	32.21%	*	2.99%
Log market cap. < median (1139)	31.51%	**	3.02%
Log market cap. ≥ median (1139)	28.77%	**	5.03%
Operating income / sales < median (1139)	29.82%	**	5.05%
Operating income / sales ≥ median (1139)	31.32%	**	3.79%
Sector 1 (energy & materials) (419)	20.98%	**	3.67%
Sector 2 (industrials & consumer discretionary) (782)	30.51%	*	6.27%
Sector 3 (consumer staples & health care) (542)	25.36%	**	5.71%
Sector 4 (financials & information technology) 492	30.21%	**	4.50%
Sector 5 (telecomm.services & utilities) (43)	25.00%		26.35%

*:5%,**:1% significance level of t-test difference between test errors of subset and all observations

The results of bagged boosting cannot be interpreted in terms of the impact of each variable on performance and efficiency because of the large number of trees generated.

The odds ratios of logistic regression also confirm the importance established by Adaboost and random forests of the following variables: long-term assets to sales ratio and corruption for LAADRs; long-term assets to deposits ratio, insider ownership, and risk of expropriation for LABANKS; and long-term assets to sales ratio, and debt ratio for S&P 500 companies.

4 Methodological findings

The tenfold LAADR test errors do not show any significant difference between Adaboost and the other learning algorithms according to the t-test, with the exception of random forests, which shows a higher test error of 32%. For the tenfold LABANKS and S&P 500 cross validation, Adaboost has a 17.8% and 16.1% test error respectively. Bagged boosting and random forests reduces the Adaboost test error for LABANKS and for S&P 500 companies. The inverse situation happens in the case of LAADR companies.

It seems that the advantage of using bagging over Adaboost depends on the uniformity of the dataset. LAADR and S&P 500 companies are more uniform samples than LABANKS. LAADR only includes com-

Table 4. Results for LAADR and LABANKS. This table reports statistics and results of predicting Tobin's Q for LAADR and efficiency for LABANKS using logistic regression, Adaboost, and random forest. Country corporate governance variables are from [75]. RF: Random forests. z-score for Random Forests [23] is the raw importance score divided by standard deviation. Q25: 25th. percentile. Q75: 75th percentile. Logistic regression includes dummy variables to control for sector. Variables that do not show any relevance are not included such as legal system, accounting, number of insiders in board of directors, and chairman as CEO. Corporate governance variables are in gray.

	LAADR								LABanks							
	Statistics				Logit	Boost	RF		Statistics				Logit	Boost	RF	
	Q25	Median	Q75	Mean	Odds ratios	Rank	z-score	Rank	Q25	Median	Q75	Mean	Odds ratios	Ranks	z-score	Rank
LnMarketCap (Nat. log market capitalization)	5.44	6.73	7.49	6.57	0.00	1	26	1	(Not used)							
Equity index	(Not used)								0.04	0.16	0.50	0.30	0.00	2	35	1
IK (Capital expenditures/ long-term assets)	0.05	0.08	0.13	0.10		10	6	3	(Not used)							
Efficiency (Operating expenses / sales)	0.10	0.16	0.23	0.16		6	5	4	(Not used)							
YS (Operating income / sales)	0.13	0.23	0.35	0.25	0.00	3			(Not used)							
Debtratio(Debt / total assets)	0.46	0.59	0.80	0.61			2	5	0.89	0.92	3.23	77.96				
KS (L.T. assets/sales)	0.73	1.44	2.20	1.82	53157	4										
KD (LT ass./deposits)									0.04	0.06	0.10	0.11	2.08E+12	1	33	2
TobinQ (Tobin's Q: performance)	0.91	1.04	1.44	1.38					(Not used)							
EfficiencyJudicialSystem (Effic. legal system)	6.00	6.00	7.25	6.50		9			6.00	6.25	6.75	6.43	0.46	9	12	4
RuleOfLaw (Law and order tradition)	5.35	5.35	7.02	5.82	0.03	2	6	2	2.50	6.32	6.67	5.27	0.63	7	8	6
Corruption (Level of government corruption)	4.77	5.30	5.30	5.21	82222.46				5.00	5.18	6.02	5.45				
RiskOfExpropiation (Risk confiscation)	6.95	7.29	7.50	7.09					5.91	6.57	7.50	6.67	0.47	3	10	5
RiskOfContractRepudiation (Contract change)	6.30	6.55	6.80	6.33					4.91	5.18	6.30	5.68				
PartOutBOD (% outsiders as directors)	60.0%	77.0%	87.0%	68.1%	0.00	5	2	6	75.0%	94.4%	100.0%	84.8%	2.53	7	3	9
Avg Participation	(Not used)								0.50	0.93	1.00	0.75	0.16	6	4	8
LnDir (Natural log number directors)	1.95	2.20	2.30	2.08	1.04E+11	7			1.79	2.20	2.40	2.10	0.41	5	12	3
InstPart (% institutional equity ownership)	15.0%	44.0%	71.0%	43.2%	27.76	8			(Not used)							
T_Insiders (% insider's equity ownership)	0.0%	0.0%	2.0%	10.4%			0.02	7	0.0%	0.0%	1.2%	8.8%	0.53	4	4	7

panies of large Latin American countries that fully obey the registration requirements of the SEC, including complying with US GAAP, while LABANKS includes banks of different size and following different accounting standards of Latin American countries. If the dataset is an agglomeration of several different datasets, such as in LABANKS or a combination of companies of diverse sectors such as in S&P 500, bagging can improve the results; however if the dataset is uniform such as in LAADR, bagging does not show any improvement over Adaboost. Therefore, stability is not a property that only depends on the learning algorithm; it also depends of the uniformity of the dataset.

The logistic regression analysis offered some insight about the relevance of the most important variables; however it was not possible to capture the interaction of these variables with the limited amount of data that we had. In contrast, Adaboost helped to rank the variables according to their importance, and also modeled their interaction.

In synthesis, in most of the cases Adaboost performed in a similar way to other learning algorithms such as bagging and random forests, and had the capacity to generate a score that evaluated the effect of corporate governance variables on performance (corporate governance score). Additionally, Adaboost also allowed us to interpret the results because of the limited number of trees that were generated in contrast to the requirements of the other methods.

5 Financial interpretation

Comparing the ADTs of LAADR and LABANKS (see Figures 2 and 6), the main distinctive variable is the size of the company measured by the logarithm of market capitalization for ADRs and equity index for LABANKS. In S&P 500 companies this is also the most important variable according to random forests and Adaboost respectively. This result coincides with the classical study of Fama and French [45] in USA, which indicated that size is a key factor to explain the rate of return of stocks. ADRs and banks around or above the median perform better than the rest. Large companies in emerging markets are likely to be oligopolies or monopolies in their area of activity. The efficiency of smaller banks is also affected when there is a high country risk of expropriation. However, the performance of LAADR improves in countries with a weak rule of law. Large Latin American companies probably perform better in environments with a weak tradition of law and order because of the close family relationships that help them to influence government decisions in their favor. The benefits of these government private sector connections seem to be less important for the small banks sector.

In countries with a strong rule of law and order, large companies may still have an important agency conflict that affects their performance if the cash available for operations is too high, as a large operating income to sales ratio indicates. An excessive amount of cash may allow managers to spend it on projects that

Table 5. Results for S&P 500 companies. This table reports statistics and results of predicting Tobin's Q for S&P 500 companies using logistic regression, Adaboost, and random forest. RF: Random forests. z-score for Random Forests [23] is the raw importance score divided by standard deviation. Q25: 25th. percentile. Q75: 75th percentile. Logistic regression includes dummy variables to control for sector. Sector 3 (consumer staples and health care) according to Adaboost and sectors in general for random forests is the 7th. most important variable. Corporate governance variables are in gray.

	S&P 500							
	Statistics				Logit	Boost	RF	
	Q25	Median	Q75	Mean	Odds ratios	Ranks	z-score	Rank
LnMarketCap (Nat. log market capitalization)	7.97	8.66	9.48	8.81	0.36	5	83.75	2
IK (Capital expenditures/ long-term assets)	0.14	0.20	0.30	0.24	0.03	3	69.85	6
Efficiency (Operating expenses / sales)	0.12	0.22	0.34	0.24	0.00	1	80.28	3
YS (Operating income / sales)	0.11	0.17	0.25	0.19	0.00	2	89.22	1
Debtratio(Debt / total assets)	0.41	0.57	0.69	0.56	11.18	6	79.65	4
KS (L.T. assets/sales)	0.72	1.03	1.50	1.32	4.26	4	70.43	5
TobinQ (Tobin's Q: performance)	1.43	2.03	3.16	2.74	NA			
T_Insiders (% insider's equity ownership)	0.1%	0.3%	1.8%	3.27%	1.15		32.34	10
totalMeetingPay (Total payment per meeting)	0	7	11	7.73	1.03		22.87	17
TotalCompExec (Total compensation)	1572	2673	4782	4345.00		9	32.04	11
optionStockValueExec (Value stock option)	466.9	1174	2687	2677.00	1.00		25.12	15
payDirectors (Annual cash pay to directors)	19	26	35	27.90	1.04	8	52.66	8
optionAllValExec (Total value options)	543.8	1436	3088	2972.00	1.00		31.45	13
optionsDirectors (Number options directors)	0	3	10	9.42	1.00		32.54	9
stockDirectors (Number of stocks directors)	0.00	0.00	0.84	0.71	1.15	7	31.76	12
totalCompCEO (Total compensation CEO)	2012.00	4215.00	8300.00	8166.00			30.06	14
totalValOptCEO (Total value options CEO)	542.30	1919.00	4741.00	5340.00	1		24.84	16

benefit them directly instead of increasing the value of their companies. A large operating expenses to sales ratio may also indicate an agency conflict. Among the medium and large companies, 58% have an excessive efficiency ratio in relation to the threshold level found by Adaboost. The performance of small and medium

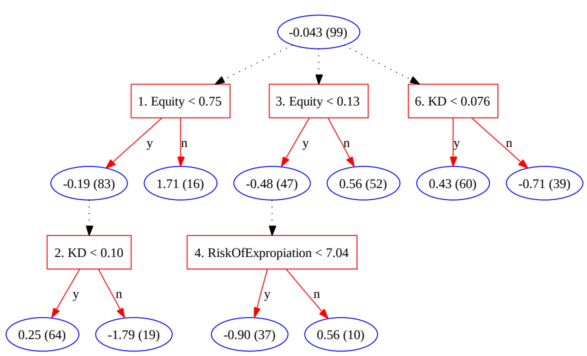

Figure 6. Representative ADT of LABANKS. The tree has ovals (*prediction nodes*) and rectangles (*splitter nodes*). The sum of first values in all relevant prediction nodes is the prediction score. The representative ADT is calculated selecting nodes present in at least 60% of the trees obtained from tenfold cross-validation.

size companies improves if the proportion of long-term assets to sales is below 0.97 (below the median) for LAADR companies. For Latin American banks, the efficiency improves when the long-term assets to deposits ratio is below 0.076 (close to the median). These indicators are important to reveal agency problems. The long-term assets are easy to monitor, and can become collateral to finance new projects. However, if the level of long-term assets is too high, it may indicate inefficiency and overspending.

According to the ADT for LAADR, the composition of the board of directors is important for smaller companies which have a capital sales ratio below 0.97. In these cases, the participation of outsiders on the board of directors above a level of 75.5% is a relevant factor to improved performance. The finance literature indicates that outside directors supervise managers [102; 109]. Weisbach [109] finds that outsider-dominated boards are more likely to remove CEOs than firms with insider-dominated boards, especially when firms show poor performance.[18] Denis and Sarin [40] find that companies that increase the proportion of outsiders on the board of directors or reduce ownership concentration have above average returns in the previous year. However, Yermack [111], MacAvoy et al. [83], Hermalin and Weisbach [57], and Bhagat and Black [17; 18] find little correlation be-

[18] In the case of Italy this situation is different. Volpin [108] finds that the probability of turnover and its relationship to performance is lower for executives who are part of the family of the controlling shareholder. Rosenstein and Wyatt [98] find that announcements of outside directors are related to positive excess returns.

tween composition of board of directors and performance. One possible explanation for these results is that the CEO hires outside directors; hence, directors do not dissent [38]. This hypothesis is reinforced by Core et al. [36], who find that CEO compensation is a decreasing function of the share of inside directors, and is an increasing function of the share of outside directors chosen by the CEO.

Inside directors also play an important role in the board of directors for strategic planning decisions, reviewing functional performance by areas and, in some cases, evaluating if there are important differences between the CEO's perspective and what is happening in the firm on a daily basis.[19] Baysinger and Butler [13] propose that an optimal board of directors should have a combination of inside, independent, and also affiliated directors. Bhagat and Black [18] suggest that boards should not be composed only of independent directors because of their findings that board independence does not improve performance, and because inside directors may bring the additional benefits explained above. This may explain why the ADT suggests that the maximum participation of outsiders in the board of directors of LAADR companies should be 75.5%.

Insider ownership does not seem to affect the performance of LAADR companies. This can be understood in terms of the information published in the proxy statements of ADRs. These reports are not under the same strict control that the financial statements are. As a result, it is possible that many firms did not include relevant information about managers, ownership structure and board composition due to the need to protect shareholders against potential kidnapping or assault. Hence, only the major shareholders are registered. In the case of LABANKS, according to Adaboost and logistic regression, insider ownership is the third and fourth most important variable in explaining efficiency. This is not the case for S&P 500 companies according to Adaboost and random forests. Furthermore, the mean of insider ownership for S&P 500 companies (3.27%) is much lower than the same value for LABANKS (8.8%) and LAADR (10.4%).

Management with a high level of ownership are likely to be able to steer corporate decisions toward their own interests at the expense of corporate interests. This could be the case of strong family groups that control a company. These family groups may use their great bargaining power to make corporate decisions that benefit companies where they have a great interest. For example, banks may direct an important part of their loan portfolio to companies where managers or insiders have a significant interest. If the investment is successful, managers benefit. Otherwise, government and depositors assume the loss, as occurred in the financial crisis of the Andean countries during the nineties. Jensen and Meckling [63] in their classic work described this behavior where large investors as equity holders will benefit when the firm takes an excessive risk because of the potential benefit on the upside, while the other stakeholders, such as the creditors, bear all the risk. Hermalin and Weisbach [57] had already proposed that agency costs increase with ownership, such as in the case of family firms. La Porta el al. [74] also mention that the agency problem in these companies is that the dominant family owner-manager may expropriate minority shareholders. Hence, there is a strong incentive to be a large shareholder in developing countries. However, expropriation is expensive; the cost of expropriation might be bigger than its potential benefit in the case of controlling shareholders, which explains why La Porta et al. [76] find that firms with higher cash-flow ownership by the controlling shareholder have higher valuation measured by Tobin's Q. La Porta et al. also find that firms in countries with better shareholder protections (common law countries) have higher valuation. Large management ownership may avoid the risks of takeovers and reduce the pressure of the board over managers [39].

In the case of LAADR and LABANKS, the limited impact of size of board of directors, the double role of CEO as manager and chairman of the board of directors, and composition of board of directors (percent of outsiders) on performance and efficiency using logistic regression or ADAboost are findings similar to what previous studies have indicated in USA. Bhagat and Black [18] do not find that board independence leads to improved profitability after controlling for firm size, board size, industry effects, CEO stock ownership, ownership by outsiders, and size and number of outside 5% blockholders.

In our sample of S&P 500 companies, we present the representative ADT when we include all variables (Figure 7), and only the corporate governance variables (Figure 8) for all companies and aggregated by sectors of economic activity.

The representative ADT for all variables has selected mostly accounting ratios. The efficiency ratio (operating expenses / sales) is the most important variable to determine performance according to the top panel of Figure 7. If the efficiency ratio is below 0.17 in the top panel of Figure 7, performance deteriorates. This counterintuitive result is explained because sector 1 (energy and materials) and 2 (industrials, and con-

[19] Klein [73] found that inside director participation in investment committees correlates with better firm performance.

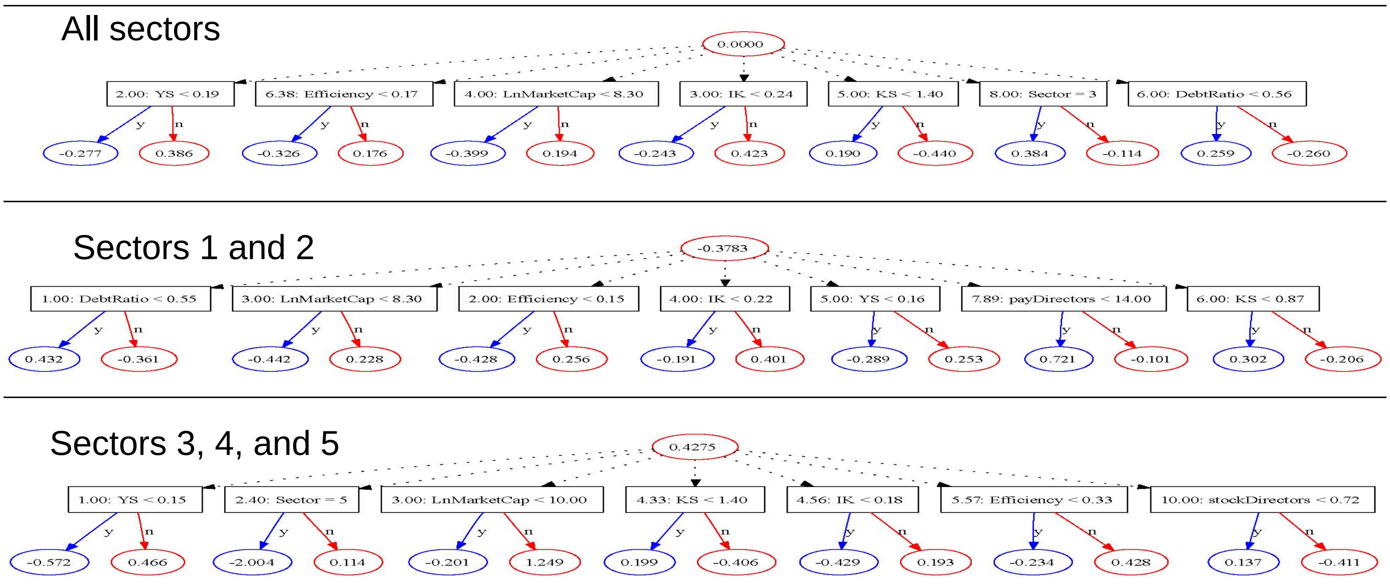

Figure 7. S&P 500: representative ADTs with all variables by sectors. This figure includes representative ADTs when all variables are considered (top panel), sectors 1 and 2 (medium panel), and sectors 3, 4, and 5 (bottom panel). First number in each rectangle is average iteration. Section 2.1.5 describes the procedure to calculate representative ADTs.

sumer discretionary)[20] are the sectors with the largest presence (52.2%) among the S&P 500 companies, and a large proportion of these companies (84.5%) with an efficiency ratio below 0.17 has a low Tobin's Q or show poor performance. The representative ADT with all variables for these sectors (medium panel of Figure 7) has an efficiency node similar to the top panel of Figure 7, while the representative ADT of sectors 3, 4, and 5 (bottom panel of Figure 7) has an efficiency node with a threshold of 0.33 which is a much higher value than what is observed in the previous two graphs. Considering that companies of sectors 1 and 2 are mostly of an industrial type or capital intensive, they may have higher fixed costs than the rest of the industries. So, if the operating expenses / sales ratio is too low, it may indicate that the operating expenses are not enough to cover an efficient level of operation, and performance deteriorates.

[20]Energy includes energy equipment and services. Materials includes chemical industries, construction materials, containers and packaging, metals and mining, and paper and forest products. Industrials include capital goods; commercial services and supplies; and transportation. Consumer discretionary includes automobiles and components; consumer durables and apparel; hotels, restaurants and leisure; media, and retailing.

5.1 Interpreting the S&P 500 representative ADTs with all variables

There is no indication that a large YS ratio or capital expenditures to long-term assets ratio (IK) may lead to corporate governance problems (IK above the mean improves results). The representative ADT establishes a limit to the long-term assets to sales ratio (KS). Companies that are in the top quartile according to the KS ratio show a lower performance than the rest of the companies.

The limitation of this ADT is that the accounting variables dominate, even when we separate our sample between sectors (medium and bottom panel of Figure 7). Only companies of sectors 1 and 2 show two corporate governance variables as relevant: annual cash pay to directors (payDirectors) and stock shares granted to directors (stockDirectors).

In order to capture the effect of corporate governance variables, in the next section we present a representative ADT that includes only these variables.

5.2 Interpreting the S&P 500 representative ADTs with only corporate governance variables

The representative ADT for all companies with only the corporate governance variables (top panel of Fig-

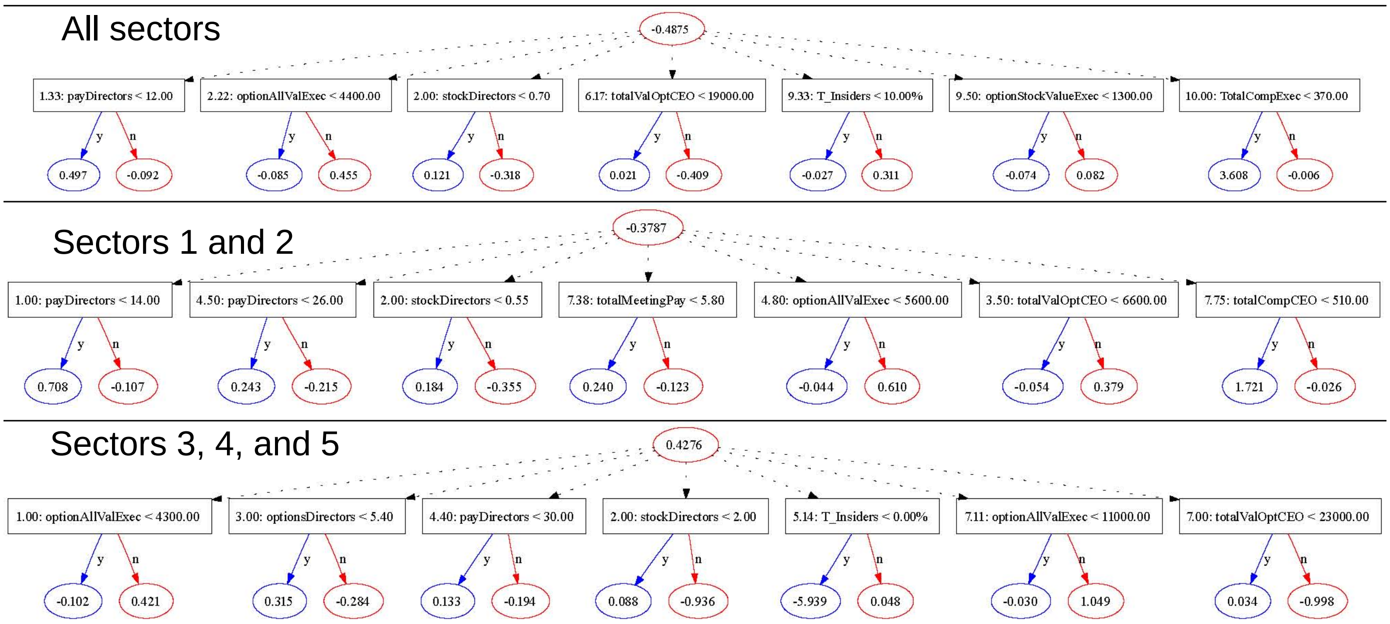

Figure 8. S&P 500: representative ADTs with only corporate governance variables by sectors. This figure includes representative ADTs when all variables are considered (top panel), sectors 1 and 2 (medium panel), and sectors 3, 4, and 5 (bottom panel). First number in each rectangle is average iteration. Section 2.1.5 describes the procedure to calculate representative ADTs.

ure 8) captures most of the variables (payDirectors, optionAllValExec, stockDirectors, and TotalValOptCEO) or rules associated with high corporate performance in all companies. This ADT suggests that the compensation policy should have a larger variable component granting more options to top officers (companies in the top quartile), with very broad limits for the value of the options to CEOs (companies in the fourth quartile), and with a small cash payment to directors (companies in the first quartile). Additionally, this ADT recommends that insider ownership should at least be 10%. When we separate the representative ADTs by sectors of economic activity, the compensation policy varies. For sectors 1 and 2, the representative ADT (medium panel of Figure 8) suggests a policy that grants very limited cash compensations to CEOs (companies in the first quartile), and the rest of the compensation should largely be based on options. For the rest of top officers, the value of the options granted should also be high (companies in the fourth quartile). This ADT suggests that the compensation of directors should have a larger components of stocks (companies in the third quartile) and a smaller annual cash payment (less than the median).

In the case of companies of sectors 3, 4, and 5, the representative ADT (bottom panel of Figure 8) indicates that the compensation policy should have a larger amount of stocks, and cash payment to directors, and options for top executives including the CEO (companies in the fourth quartile) than in sectors 1 and 2. Additionally, the representative ADT shows that insiders ownership improves performance.

The discrepancies between the two policy recommendations by sectors is explained by the main business processes of each economic sector. Companies of sectors 1 and 2 take major investment decisions that involve direct participation of the CEO as well as the strategic direction of the board of directors, such as the development of a new factory or the exploration of a new oil region. Companies may motivate with large compensations, especially based on options, the involvement of CEOs and directors. However, once these investment decisions are taken the role of middle managers becomes more relevant, and CEO compensation can be restricted. [21] The profit of companies of sectors 3, 4 and 5, especially in the case of financial services, information technology and telecommunica-

[21] Jensen and Murphy [66] consider that there is a major misalignment between corporate performance and compensation paid to executives, especially CEOs. In recent years, there are well-known stories of CEOs who have been paid large compensations regardless of their performance. Michael Ovitz, former president of The Walt Disney Corp., received $140 million as his severance package when he was fired by unhappy shareholders after 14 months at the company. Core et al. [37] also find that CEOs have greater compensation in companies with greater agency problems.

tions, are driven by the quality of customer service and continuous technology update. Therefore, their success may significantly depend on the motivation of top officers and middle managers through flexible remuneration (options), while establishing a limit to the options granted to directors.

If the rules suggested by the top panel of Figure 8 are effective to improve company performance, the flexible part of executives' compensation might be reduced in some sectors, however it should not disappear as a result of the recent FASB rule which establishes that companies should register as expense any options granted to employees.

5.3 From Adaboost to the Board Balanced Scorecard

We include the variables that the representative ADTs selected for all companies (top panels of Figures 7 and 8) in the board strategy map and in the board BSC suggested by Kaplan and Nagel [67].

The board strategy map (Figure 9) shows the interrelationship between the objectives of each perspective. An important element of the board strategy map and the board BSC is the perspective of ”stakeholder” instead of ”consumer” as was proposed in the original BSC. The reason to include the ”stakeholder” perspective is that the stakeholders (shareholders, financial analysts, etc.) are the consumers or clients of the board of directors.

We have expanded the board strategy map proposed by Kaplan and Nagel [67] to incorporate new objectives that were consistent with the main variables selected by Adaboost. The new objectives that emerged are ”Balanced capital structure” in the financial perspective; ”Independent ownership structure” in the internal perspective, and ”Ensure corporate governance best-practices” in the stakeholder perspective. The board BSC (Figure 10) incorporates the new indicators and its targets according to the representative ADTs presented in Figures 7 and 8. The indicators are the most important variables selected by the representative ADTs and their targets are the threshold levels calculated for each variable. Finally, we can say that Adaboost and BSC complement each other. Adaboost selects what are the most important features or variables that should be used as indicators and therefore helps to choose the key drivers and objectives of the BSC. Additionally, Adaboost is able to calculate the targets for every metric. The BSC puts in perspective the findings of Adaboost. The BSC, as a strategic management system, integrates the four perspectives already described, and offers a framework that connects the variables recognized by Adaboost in a logical order towards the maximization of shareholders' return.

6 Conclusions

In this research we proposed a method that ranked variables according to their level of importance in the ADTs, and generated representative ADTs with the most important variables. We applied this methodology to small and large samples from different countries and economic conditions. Specifically, we worked with S&P 500 companies, and Latin American ADRs and banks. This research showed that Adaboost performed similarly to logistic regression, random forests, and bagging with stable datasets. Additionally, we showed how Adaboost and representative ADTs can be used as an interpretative tool to evaluate the impact of corporate governance factors on performance and efficiency. Representative ADTs were particularly useful to understand the non-linear relationship between the variables that affected performance and efficiency.

We demonstrated that the representative ADT is a useful tool to select and establish the relationship among the most important indicators of the BSC. Additionally, the thresholds of the representative ADTs established targets or ranges of values of the indicators that managers could follow to improve corporate performance. With this combined tool, managers can concentrate on the most important strategic issues and delegate the calculation of the targets to an automated system supported by Adaboost.

The use of ADTs in finance requires time-series or cross-sectional data in order to calculate meaningful nodes. Indicators that do not have enough information cannot be quantified using Adaboost. So, the initial versions of a BSC still require an important participation of the board of directors, middle and senior management. However, as the planning team or the company creates its own database, then Adaboost can select the relevant indicators and their targets. As the first part of this research showed, Adaboost also worked adequately with small datasets. However, the variance of the test error increased as the size of the dataset decreased. So, we suggest that companies that use Adaboost to build BSCs use large datasets (industrial surveys or compensation surveys) or build their own internal dataset using the company's historical information.

Comparative regional studies always have a major problem in terms of how to integrate data coming from different sources, and generally with different standards. We saw that this problem was implicit in the LABANKS dataset. We think that the research

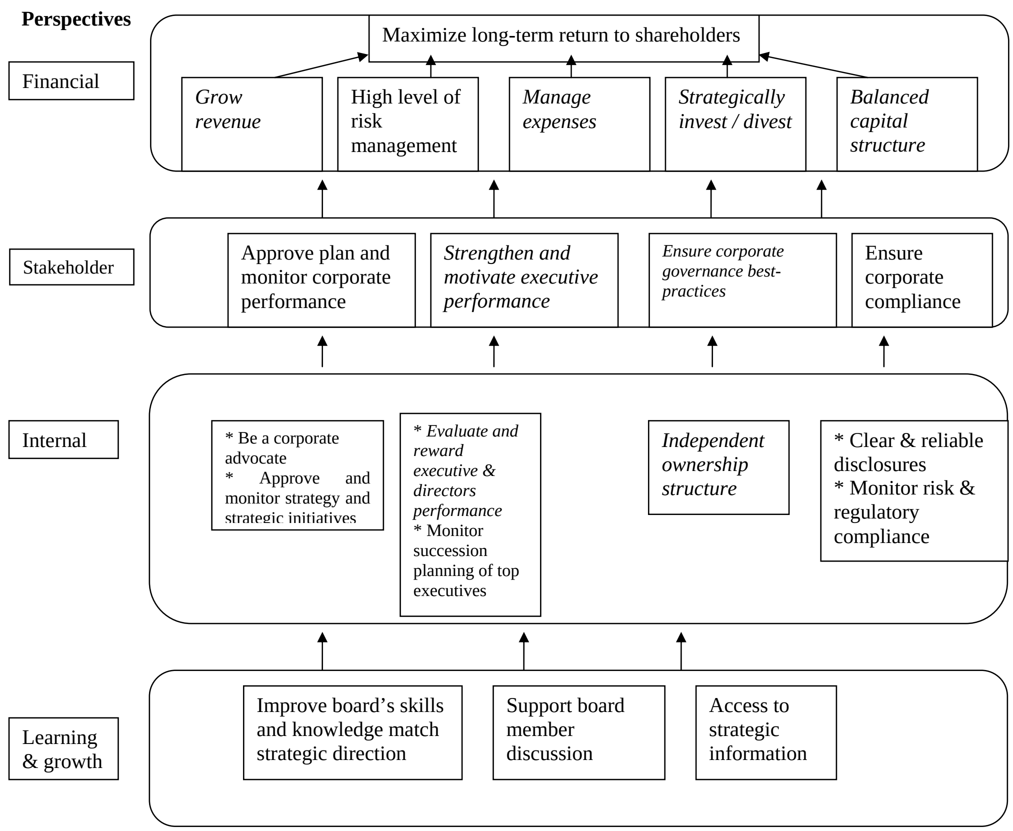

Figure 9. S&P 500: representative Board Strategy Map. This figure shows the causal relationship among corporate variables. Adapted from [67]. Italics are the objectives selected or modified by representative ADTs

Board's strategic objectives		Indicators	Target(s)	Scores		Owners
High-level objectives	**Specific objectives**			**Yes**	**No**	
Financial:						
Maximize long-term total return shareholders	Grow revenues	Operating income / sales (YS)	> 0.19	-0.277	0.386	Executive management
	Manage expenses	Operating expenses / sales (Efficiency ratio)	> 0.17	-0.326	0.176	
	Strategically invest/divest	Long-term assets/sales (KS)	< 1.4	0.19	-0.44	
		Capital expenditures / Long-term assets (IK)	> 0.24	-0.243	0.423	
	Balanced capital structure	Debt ratio	< 0.56	0.259	-0.26	
Internal:						
Evaluate and reward directors' performance	Reduce fixed payment	Annual cash pay to directors (payDirectors)	< $12K	0.497	-0.092	Compensation committee
	Limit options payment to directors	Number stocks granted to directors (stocksDirectors)	< 700	0.121	-0.318	
		Total value options CEO's (totalValOptCEO)	< $19M	0.021	-0.409	
Evaluate and reward executive's performance	Increase options payments to top officers	Value of all options to officers (optionAllValExec)	> $4.4M	-0.085	0.455	
		Value stock options to officers (OptionStockValueExec)	> $1.3M	-0.074	0.082	
		Total compensation officers (TotalCompExec)	< $370K	3.608	-0.006	
Independent ownership struct.	Limit insiders' ownership	% insiders' ownership (T_Insiders)	> 10%	-0.027	0.311	Governance comm.

Figure 10. S&P 500: representative Board Scorecard. Adapted from [67]. The board scorecard assigns indicators to the objectives selected in the Board strategy map. The indicators of the financial perspective are from the representative ADT that includes all variables (Figure 7) and the indicators of the internal perspective are from the representative ADT that includes only the corporate governance variables (Figure 8). The targets come from the rectangle and the scores from the ovals of the representative ADTs. K is thousands and M is millions.

of emerging markets can be improved by enlarging the dataset and running the learning algorithms in subsets aggregated by regions or corporate governance systems.

This research can also be extended using Adaboost for the design of the enterprise BSC, and including other perspectives of those reviewed in this study. Initially, the corporate governance variables do not seem to be very relevant to predicting corporate performance. However, when the results of these variables were interpreted together with the accounting variables using representative ADTs, the effect of corporate governance on performance became evident as the BSC demonstrated. A similar situation may happen with the variables of the other perspectives. The recent cases of US bankruptcies have demonstrated that when companies are doing very well, corporate governance variables do not seem to be relevant. However, in moments of financial distress, corporate governance variables play a very important role in improving performance and efficiency. In this respect, a future development of this research would also be the evaluation of the abnormal return of two portfolios with top and bottom tier companies based on the suggestions of the representative ADTs / board BSC.

Finally, the combination of Adaboost with the BSC can be used as a quantitative strategic management system of corporate or market leading indicators that continuously updates itself for board-level decisions of directors or for investment decisions of portfolio managers.

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Appendix 1: Data

LAADR: We used a sample of 51 stocks domiciled in Latin America (LAADR) (Argentina, Brazil, Chile, Colombia, Peru, Mexico and Venezuela) that have issued ADRs of level II and III for the year 1998. Level I ADR are least restricted in their required compliance with US regulations, so we have not included them in our analysis. Level II ADRs correspond to foreign companies that list their shares on NASDAQ, AMEX, or NYSE. These companies must fully obey the registration requirements of the SEC, including complying with US GAAP. Level III ADRs refer to foreign companies that issue new stocks directly in the United States. This means that they have the same compliance requirements as a US public company, and are therefore the most regulated. We chose ADRs from countries on the list of emerging markets database (EMDB) of the International Finance Corporation (IFC).[22]

We obtained the financial information from COMPUSTAT for the year 1998. The information on the value of market capitalization is from CRSP, and is compared with information from the NYSE. We extracted corporate governance information – such as list of directors, executives, and major shareholders – from the proxy statements published at Disclosure, Edgar, and companies' websites for the year 1998. In the case of LAADR, insider ownership is defined as ownership of a company by the CEO, managers, or relatives of the CEO, and members of the board of directors.

LABANKS: We also used a list of 104 Latin American banks, called LABANKS. LABANKS consists of banks domiciled in Argentina, Brazil, Chile, Colombia, Peru, Ecuador and Bolivia representing about 80% of the total assets of the private sector in the major Latin American countries. [23]

[22] Standard and Poor's acquired this database in January 2000, and it became the Standard and Poor's EMDB.

[23] We were not able to include Venezuela's banks because the President of the Venezuelan Banking Association declined to supply any information to our research team and asked member banks not to supply any corporate information to us due to the increased risk of kidnapping that its members would be subject to if this information were distributed.

We obtained the banks' corporate information from Internet Securities Inc., central bank, regulator and company websites. We collected financial as well as corporate information similar to that collected for ADRs. Our sample of banks is restricted by the availability of corporate finance information.

Most of the financial information is from 2000. A few companies that were merged or disappeared in 1998 were included using the financial statements of 1997. The corporate information is gathered from the period 1998-2000. Considering that the information about ownership structure is relatively stable, we do not foresee any major consistency problem.

S&P 500: The main sources of data for S&P 500 companies were ExecuComp for executive compensation information and Compustat North America for accounting information. These two datasets are products of Standard & Poor's. We restricted our dataset to S&P 500 companies with available data from 1992 to 2004. We eliminated observations that did not have enough information to calculate Tobin's Q or incomplete executive compensation information.