EVOLUTION OF THE IBEX-35 VS OTHER INTERNATIONAL INDICES: DETERMINANTS OF MARKET VALUE ACCORDING TO XGBOOST AND GLM MODELS.

EVOLUCIÓN DEL IBEX-35 VS OTROS ÍNDICES INTERNACIONALES: DETERMINANTES DEL VALOR DE MERCADO SEGÚN LOS MODELOS XGBOOST Y GLM

Juliánn Martínez-Vargas[1], Pedro Carmona and Pol Torrelles

Facultad de Economia, Universidad de Valencia, Valencia, Spain

Abstract

Purpose – The purpose of this paper is to study the influence of different quantitative (traditionally used) and qualitative variables, such as the possible negative effect in determined periods of certain socio-political factors on share price formation.

Design/methodology/approach - We first analyze descritively the evolution of the Ibex-35 in recent years and compare it with other international benchmark indices. Bellow, two techniques have been compared: a classic linear regression statistical model (GLM) and a method based on machine learning techniques called Extreme Gradient Boosting (XGBoost).

Findings - XGBoost yields a very accurate market value prediction model that clearly outperforms the other, with a coefficient of determination close to 90%, calculated on validation sets.

Practical implications - According to our analysis, individual accounts are equally or more important than consolidated information in predicting the behaviour of share prices. This would justify Spain maintaining the obligation to present individual interim financial statements, which does not happen in other European Union countries because IAS 34 only stipulates consolidated interim financial statements.

Social implications - The descriptive analysis allows us to see how the Ibex-35 has moved away from international trends, especially in periods in which some relevant socio-political events occurred, such as the independence referendum in Catalonia, the double elections of 2019 or the early handling of the Covid-19 pandemic in 2020.

Originality/value - Compared to other variables, the XGBoost model assigns little importance to socio-political factors when it comes to share price formation; however, this model explains 89.33% of its variance.

Keywords: Ibex-35, book value, market value, prediction models, Extreme Gradient Boosting.

[1] Corresponding author

Paper type: Research paper

Resumen

Propósito - El propósito de este artículo es estudiar la influencia de diferentes variables cuantitativas (tradicionalmente usadas) y cualitativas, como la posible influencia negativa en determinados períodos de ciertos factores sociopolíticos, sobre la formación del precio de

Diseño/metodología/enfoque – Primero analizamos de forma descriptiva la evolución del Ibex-35 en los últimos años y la comparamos con la de otros índices internacionales de referencia. A continuación, se han contrastado dos técnicas: un modelo estadístico clásico de regresión lineal (GLM) y un método basado en el aprendizaje automático denominado Extreme Gradient Boosting (XGBoost).

Resultados - XGBoost nos permite obtener un modelo de predicción del valor de mercado muy preciso y claramente superior al otro, con un coeficiente de determinación cercano al 90%, calculado sobre las muestras de validación.

Implicaciones prácticas – De acuerdo con nuestro análisis, la información contable individual es igual o más importante que la consolidada para predecir el comportamiento del precio de las acciones. Esto justificaría que España mantenga la obligación de presentar estados financieros intermedios individuales, lo que no ocurre en otros países de la Unión Europea porque la NIC 34 solo obliga a realizar estados financieros intermedios consolidados.

Implicaciones sociales – El análisis descriptivo permite ver cómo el Ibex-35 se ha alejado de las tendencias internacionales, especialmente en periodos en los que se produjo algún hecho sociopolítico relevante, como el referéndum de autodeterminación de Cataluña, el doble proceso electoral de 2019 o la gestión inicial de la pandemia generada por el Covid-19

Originalidad/valor - En comparación con otras variables, el modelo XGBoost asigna poca importancia a los factores sociopolíticos cuando se trata de la formación del precio de las acciones; sin embargo, este modelo explica el 89,33% de su varianza.

JEL Classification: F17, C53, M41, D53, E65, G15

Management area: Capital Markets and Banking

1. Introduction

In an increasingly globalized economic environment, there are certain political or sociological events that transcend the countries in which they have a direct impact, such that the main international stock market indices follow similar trends and cycles. However, there may also be country-specific issues for which the domestic impact is greater than that on other markets, due to the additional risks perceived by investors.

We are currently witnessing a period of notable convulsion in international financial markets; particularly in the Spanish market, where various domestic issues have negatively affected investment. Events causing a major international impact include Brexit, which sparked a social and political crisis; the tariff war between the United States and China or the European Union; and more recently, the Covid-19 pandemic, which triggered an economic crisis as well as a health crisis. On top of all this, there are the internal problems arising from the crisis in financial institutions caused by the resolution of Banco Popular; the Catalan independence movement; and the no-confidence motion brought against the government, which resulted in a change in political direction.

Thus, if we observe the evolution of the main benchmark indices within our sphere, such as the American Dow Jones, the French CAC-40 and the British FTSE-100, and compare them with the main benchmark index in Spain—namely, the Ibex-35—things seem to have gone much worse in Spain. This may be because global issues have had a greater impact here or because domestic issues have had an additional negative effect that is hobbling Spanish companies.

Against this backdrop, we seek to analyse the evolution of the Ibex-35 and compare it with that of the main benchmark indexes in our sphere to check whether significant differences can be observed. If such differences do emerge, we will attempt to pinpoint when they occur in order to identify the socio-political events in that period that may be behind them. We will then use statistical analysis to determine the relationship between these market values and a number of different quantitative variables sourced from financial individual and consolidated reports, as well as some qualitative variables related to these events. By so doing, the aim is to obtain a good prediction model that shows the importance of each of these variables. To bolster the rigour of our findings, we compare two different techniques: on the one hand, a classic linear regression model; and on the other, a more recent method based on modern machine learning techniques, called Extreme Gradient Boosting.

The sample under analysis is composed of the 35 companies that made up the Ibex-35 in the first six months of 2020. The information analysed covers the last 11 six-month periods since the close of 2015. Results confirm that there are indeed important differences between the

evolution of the Ibex-35 and the other international benchmark indices. It is shown that the only six-month periods in which there was a degree of normality were the second six months of 2016 and both periods in 2018. In the statistical study, the XGBoost fitted prediction model reveals the variables obtained from the individual accounts of the parent company are more important than those obtained from consolidated accounts.

2. Literature review

The value of a company is normally determined by the cash flows that it will be able to generate with the exploitation of its activity. Furthermore, in an efficient capital market in which investors make their decisions rationally, the shares price is a good estimator of the present value of future cash flows. Thus, if the existence of a relationship between the accounting information and share price is demonstrated, it would be verified that this information is useful to estimate the future cash flows that the entity will generate and, therefore, to determine the value of the company (Ansón et al., 1997).

Several studies confirm that there are many variables that can explain the market price of shares and most use the economic-financial information presented by the company accounts, which is sometimes combined with other variables such as the sector to which the company belongs, its size, its life cycle, etc. However, they are not the only factors that influence share price formation; there are also others related to aspects external to the management of the company.

With regard to the first group, Ball and Brown (1968) carry out the first work in which the usefulness of accounting information is verified for the formation of market prices. In the same vein, Easton et al. (1992), Warfield and Wild (1992) and Ohlson and Penman (1992), identified a low correlation between the accounting data and the returns of the shares, although it increases as the time interval studied increases.

Chan et al. (1991) analyze various financial ratios and find that cash flow has the most significant positive impact on Tokyo Stock Exchange stock returns during 1971-1988.

Miralles and Miralles (2002) analized the Lisbon Stock Exchange during 1991-1999 and using a factorial model they found that the profitability of the liquid asset and of the total investment are the most influential factors in the market value.

Gallizo et al. (2006) carry out an empirical study of American listed companies, attempting to identify a relationship between share price and accounting information variables such as cash-flow per share and book value. Classifying the selected companies by size, dividend policy and profitability, they conclude that cash-flow is the most relevant variable in smaller companies in a growth phase with a more restrictive dividend policy to ensure greater self-financing capacity.

Book value and profit-generating capacity turned out to be the most influential variables for large companies well established in the market.

In another study focusing on different European banks, Muñoz and Fernández (2014) examine variables such as asset quality, capital adequacy, operational efficiency and liquidity level, as well as non-financial variables such as a good corporate governance rating, and conclude that an improvement in these variables has a positive and significant impact on Tobin's Q (the ratio between a company's market value and the replacement cost of its assets).

A similar concept that is widely used is the P/B ratio (Price to Book Value). This ratio plays a major role in the literature analysed and is also an indicator widely used by securities investment professionals.

In the Spanish context, Crespo (1991) finds that in the Madrid Stock Exchange during 1985-1990 the price of the shares depends on the economic and financial profitability and the structure of indebtedness.

Ruiz and Espitia (1996) examine the relevance of dividend payments and conclude that in the Spanish stock market during 1980-1992, unlike in other markets, the distribution of dividends positively affects the market price since the investor is willing to pay more for these shares. The market price drops after the ex-dividend date.

Menendez (2000) finds that the variables size, equity valuation and profit valuation are the main determinants of the investment return shares in the Spanish Stock Exchange during 1993-1998.

García and Rueda (2002) conduct an analysis of the main companies listed on the Madrid Stock Exchange during the period 1986-2000, finding a positive relationship between financial returns and the P/B ratio, and establishing that this ratio is useful for predicting long-term returns. In the same vein, and in the Madrid Stock Exchange, Laínez and Cuellar (2002) find that a part of the P/B ratio is determined by historical variations in the company's net asset market value.

Finally, in a study that used accounting variables in line with us and same companies sphere, Villanueva et al. (2011) analyze the correlation between the market price and the book value of the shares of the Ibex-35 companies. The authors conclude that the variables book value, profitability and the PER ratio (price-earnings ratio) explain the market price of these companies' shares.

With regard to the second group, that is, those that take into account factors external to the management of the company, Gitman and Joehnk (1997) and Malkiel (1995) conclude that in order to determine the value of shares, investors do three analyses to help them establish the cash flows they can expect to receive from their purchase:

1. Analysis of the economic situation (fiscal and monetary policy, inflation, consumer spending, business investments, foreign trade and exchange rates) and their potential effects on stock returns.
2. Analysis of the industrial sector in which the company operates and its position with respect to the main competitors.
3. Fundamental analysis of the company's financial situation, management, behaviour of the sector to which the company belongs, the risks it faces and their impact on the growth of the company.

Morales (2016), in a paper on share price formation in the Mexican Stock Exchange, uses a sample of 21 companies labelled sustainable (certified for their environmental governance and corporate and social responsibility) and establishes 12 explanatory variables related to profitability and 8 related to macroeconomic factors. The main conclusion of the study is that macroeconomic variables have the greatest influence on the share price of these companies.

Menéndez et al. (2012) analyze using panel data whether different indicators based on accounting information, efficiency and productivity levels and the macroeconomic environment evolution explain the market risk of Spanish companies. The results show that productivity and the macroeconomic environment variables play an important role in explaining the risk of non-financial companies.

Sevillano and Jareño (2017) analyze the sensitivity of business profitability of Ibex-35 listed companies to changes in international factors such as the return of the international market (USA), the international interest rate (USA), the oil price and two financial indicators of great relevance in the USA Stock Exchange (CFSI and VIX).

Amat (2015) explains how political stability, legal certainty and the existence of a favourable legal framework for economic activity have a positive effect on the stock markets. Conversely, a lack of any of these factors—for example, political instability—drives up the risk of the investments, which prompts investors to look towards other opportunities and adversely affects the share price of the companies in this market. Thus, some studies have attempted to demonstrate the extent to which these political factors can affect the stock markets; for example, in the United States, several studies were carried out in the 1970s, notably that by Niederhoffer et al. (1970), who concluded that the Republican Party's electoral victories had a positive effect on the stock market.

In contrast, it is worth mentioning the study by Döpke and Pierdzioch (2006), who find no significant differences in market prices between the mandates of liberal and conservative

governments in Germany. Nevertheless, a positive impact on the popularity of the government can be observed when markets are bullish.

In another attempt to identify the influence of politics on the stock markets, Rodríguez and Vargas (2012) use voting intention polling data during pre-election periods to analyse the impact on the Peruvian stock market of the possible victory of a certain candidate. They report a positive influence on investors' expectations in the first elections, whereas the second elections had a negative effect because by that time investors had a worse view of the candidate.

To end this section, in terms of the statistical methodology used in the study, the Generalized Linear Model (GLM) is the natural extension of the classic Linear Model first proposed by Nelder and Wedderburn (1972), but we will focus more on developing and describing Extreme Gradient Boosting (XGBoost), since it is a more recent model and provides results that are clearly superior, as we will see. This variant of boosting has proven to be better when working with structured data and only a few variables, as is the case in our study. Zieba et al. (2016) apply and compare different methods—statistical models and machine learning models—concluding that XGBoost yields better results.

Maciej et al. (2016) used and compared different methods, both statistical-based and Machine Learning, concluding that boosting models obtained better results. Xia et al. (2017) projected an innovative boosted tree for credit scoring model based on XGBoost. Besides, they point out that XGBoost model for credit scoring performs better to the formerly existed credit scoring system. Santhanam et al. (2017) observed that XGBoost is the most appropriate model to analyze the characteristics that influence clients' retaining for software-as-a-service firms. Similarly, recent studies focused on bank failure in the eurozone (Climent et al., 2019) and the United States (Carmona et at., 2019) have shown the high predictive power of this method.

3. Empirical analysis

The empirical study consists of two parts: First, a descriptive analysis of the evolution of the Ibex-35 in relation to other international indices, identifying the periods where the main differences have occurred in order to determine which socio-political factors may have had an effect. In the second part, we conduct a statistical analysis to identify the factors that have the greatest influence on the market value of the Ibex-35 companies, noting that the Extreme Gradient Boosting model yields significantly better results than those obtained from a classic linear regression model.

3.1. Selection of companies

To select the sample of companies, we used the Ibex-35, taking into account that it is composed of the 35 most liquid stocks traded on the Spanish stock market. As these stocks are reviewed every six months, we have selected those that were in the index at the beginning of 2020.

The information analysed starts with the accounting data for year-end 2015 and is obtained for each six-month period until the second half of 2020 (Spanish companies are requested to half-yearly reporting with individual and consolidated information)[2]. The data thus consists of 11 six-month periods, which, multiplied by the 35 companies, initially yields a total of 385 cross sectional observations.

The economic and financial data have been obtained from the companies' annual accounts and their interim reports, which are available on the Comisión Nacional del Mercado de Valores (Spanish Stock Exchange Commission, hereinafter the "CNMV") website. We have considered both individual and consolidated data, but there is one company, ArcelorMittal, which is headquartered in Luxembourg, and does not submit individual interim reports as it is not mandatory there (IAS 34: Interim Financial Reporting). In addition, the interim data for the first six months of 2016 are not available for Masmóvil—either individual or consolidated—since this information was not provided to the CNMV until 2017; similarly, we do not have its share price at 31-12-2020 because it was excluded in November 2020 after the takeover bid launched by KKR, Cinven and Providence.

Furthermore, for the purposes of the statistical study, we did not have at the time of carrying out the research the accounting data for year-end 2020 as it had not yet been made available.

Table A1 shows the seven sectors represented in the Ibex-35, as well as the subsectors and the number of companies in each one.

3.2. Selection and definition of variables

Based on the literature review carried out and in line with the objectives of this study, a number of variables that may explain market value have been selected. As a novelty, we split these variables to use both individual and consolidated information.

In selecting the quantitative variables (Table A2), we have drawn on the studies by Ohlson (1995), Crespo (1991), García and Rueda (2002), Gallizo et al. (2006) and Villanueva et al. (2011), which use variables sourced from financial information to explain market value. The most commonly used of these include book value and financial and economic profitability. We

[2] Listed companies also provided quarterly information but only on the group and its publication is not mandatory from 2021 (art. 6.14(2) of Law 5/2021).

have also included indebtedness, as it explains the risk the company faces vis-à-vis third parties: Gitman and Joehnk (1997) and Malkiel (1995) refer to this in their studies on the fundamental analysis carried out by investors.

In an effort to improve the model, we have decided to add other variables of a non-financial nature, taking into account the contributions of Gitman and Joehnk (1997) and Malkiel (1995), which refer to the analysis of the sector, or the studies by Niederhoffer et al. (1970), Rodríguez and Vargas (2012) and Amat (2015), which examine political factors as a relevant issue for investors' expectations. In this way, we also use two qualitative variables; the first indicates the sector to which each company belongs *(values from 1 to 7 as shown in Table 1)*, since there may be specific trends in each sector that can affect the share price of the companies therein but do not have an impact on other sectors of the economy. The second identifies the socio-political factors: when a possible relevant influence is detected in the six-month period, the variable takes the value of 1, and 0 otherwise.

3.3. Previous descriptive analysis

3.3.1. Relevant socio-political factors

In Table 1 we summarize the most relevant events at the national and international level from 2016 to 2020, to see if they coincide in time with certain changes in stock values.

[Table 1 near here]

Table 2 depicts the distribution of these events over the periods under analysis.

[Table 2 near here]

3.3.2. The Ibex-35 in the context of other benchmark indices

In this section we want to observe the evolution of this index in relation to other international benchmark indices such as the American Dow Jones, the Italian FTSE MIB, the British FTSE 100, the French CAC-40, the Chinese A50 and the Japanese Nikkei.[3] Although there are some events that have a contagion effect due to the globalization of markets, they do not have the

[3] For comparative purposes, we cannot include indices such as the German Dax, which is referred to as a total return index. Unlike most indices which discount distributed dividends, total return indices assume that they are reinvested and they form part of the index.

same degree of impact in each country given the national social, economic and political characteristics.
Figure 1 depicts the evolution of these indices by points and the Ibex-35 (red line) is the only one that has gone down during the period considered.

[Figure 1 near here]

The same trends can be seen more clearly in Figure 2, where we see the percentage change relative to the start of the period analysed in this study.

[Figure 2 near here]

If we look at the percentage change in the indices over the previous six-month period (Figure 3) the results are consistent with the above statements.

[Figure 3 near here]

In short, it seems evident that the values of the Ibex-35 diverge from the trends shown by other markets, particularly in periods in which some relevant socio-political event has occurred. Below, we attempt to quantify these effects in order to incorporate into the statistical study a qualitative variable that captures these circumstances.

3.3.3. Effect of relevant socio-political factors on Ibex-35

In this section, we seek to analyse how socio-political factors have affected the market value of Ibex-35 companies. Table 3 shows the change between the initial and final share price of the six-month period in which any of the relevant events identified occurred. It also provides some perspective on this change relative to the Mean-7. The most notable drops initially appear to have occurred in the periods 16-1 and 20-1, but when compared with the mean, the worst six-month period in this regard is 17-2.

[Table 3 near here]

In order to determine the relevance of a factor, we note when the six-month change in the Ibex-35 in that period is at least 3 points below the Mean-7, bearing in mind that the mean also

includes the values of the Ibex-35. From there, we then have to make the following assessments regarding some specific periods:

- First six-month period of 2017, in which the resolution of Banco Popular is ordered by the Single Resolution Board. Although this factor may have had a negative impact on financial institutions, overall its effect has been positively offset by the other companies. Therefore, we rule out this factor as having had a relevant negative impact, although as it occurred in the last month of the six-month period, its effects may have partially carried over to the following period.
- First six-month period of 2018, in which the no-confidence motion was brought against the president of the government. There is a negative impact on the Ibex-35 values but the trend is very close to the mean of the main international indices in that period (-4.19% vs -3.10%), meaning this factor can be deemed not relevant.
- Second six-month period of 2020: although we observe the relevance of the small positive effect of the announcement of the first vaccine against Covid-19 on the Ibex-35, we cannot include this event in the subsequent statistical analysis as we do not yet have the financial information for year-end 2020.

The other socio-political factors that we had put forward as possible causes of the comparatively worse performance of the Ibex-35 are indeed related to poorer performance than the other benchmark indices, since a clear difference is observed in the variations. We thus label them as relevant in the statistical analysis seeking to explain the share price formation for these companies.

3.4. Statistical Analysis

3.4.1. Methodology applied

Using a set of predictors of an accounting and financial nature, we seek to construct a reliable predictive regression model that can help identify the variables that play a major role in Ibex-35 companies' share price formation. Our objective is to develop a predictive model and validate its predictive power on a hypothetical dataset that is different from the training set, using machine learning techniques. We use XGBoost, which belongs to the gradient boosting family of algorithms, because it provides very good results in the context of regressions. Models based on the boosting technique adaptively combine an extremely large number of relatively simple decision tree models to obtain a very accurate result in their combined predictions, far better than that of the individual trees that make up the final combined model.

In particular, this technique can be used both in classification contexts and in regression situations, and the results are often much better than those obtained using more traditional statistical procedures, such as ordinary least squares or logistic regressions. Specifically, its success lies in the fact that the boosting algorithms sequentially combine many very simple models (*weak learners*), yielding very accurate predictions that are actually an average of the predictions of all these simple models combined. Accordingly, as reported by James et al. (2017), the results typically have very low variance, which ensures the reliability of the predictions.

Chen and Guestrin (2016) describe XGBoost as a scalable and effective implementation of the gradient boosting technique developed by Friedman (2001) and Friedman et al. (2000). The decision trees are developed sequentially; and each tree grows out of the information obtained from the previously generated trees but attempts to correct the errors of the previous tree. Each tree is fitted to a version of the original dataset that has been modified by the errors left to resolve. Therefore, the construction of each tree largely depends on the trees that have already been built (Hastie et al. 2009). As James et al. (2017) point out, in each iteration this algorithm fits a new tree using the current residuals instead of the values of the dependent variable. The algorithm then adds this new decision tree to the fitted model to update the residuals, thereby sequentially improving the model. In short, XGBoost continues adding new trees until it is no longer possible to improve the prediction results, with each successive model attempting to correct the errors of the previous model and makes it possible to overcome the limitations of the individual trees, which typically provide fairly unsatisfactory prediction results. Climent et al. (2019) and Carmona et al. (2019), using classification trees, have applied this method to predict bank failure in the eurozone and the United States, respectively. However, in our study, the XGBoost technique is applied using regression trees.

Model fit

Since the sample is not very large—we only have 350 observations—and since we do want to use all the observations to obtain the best model with the highest predictive power, we have decided to estimate this predictive power on a hypothetical independent dataset, which in machine learning is known as cross-validation technique. In this way, we can make use of all the observations to fit the best model and apply the aforementioned cross-validation procedure to obtain a very accurate estimate of the results on a hypothetical independent test set. Therefore, it is a way to validate the model internally without sacrificing part of the sample data for subsequent validation.

Specifically, we decided to carry out the cross-validation with 10 subsets or folds (*k=10*). Thus, the training process of the XGBoost algorithm consists of fitting 10 models on 9 different subsets (each with 90% of the observations). The final goodness of fit estimate is then calculated from the mean of the results obtained on the remaining 10% of each of the 10 subsets.

After completing the whole cross-validation process, an additional model is estimated with 100% of the observations. This constitutes the final model and, if appropriate, is the one that would be taken to production. Therefore, a total of 11 models will be estimated (*k+1= 10+1*), and we will obtain the indicators of goodness of fit on both the final model and on the cross-validation ones. It is worth noting that generally the goodness of fit indicators that would be obtained in an independent test set are very similar to the estimations of the cross-validation. These model performance metrics are much more conservative than those extracted from the final model fitted with all the data. It is not good practice to provide information only on the final model when working with such complex and powerful algorithms, because they could memorize part of the data during the training process and provide overly optimistic results, giving rise to what is known as over-fitting. Therefore, the results for the performance of the model must always be taken from the cross-validation sets.

The XGBoost algorithm has been implemented using the *R* statistical programming environment (R Core Team, 2021) and the *H2O* library (LeDell et al., 2020).

3.4.2. Comparison of XGBoost model and GLM

In addition to the algorithm explained in the previous section, we have also applied a traditional statistical method—namely, ordinary linear regression, framed within GLM (generalized linear models)—in order to determine whether there are important differences in their predictive power.

Figures 4 and 5 show the comparison between the predictions from the cross-validation of both models and the actual market values included in the available data. By using the predictions obtained with cross-validation, we can ensure that these predictions are in line with the results that would have been obtained on an independent test set and, ultimately, that the performance metrics of the models are reliable and can be generalized.

[Figures 4 and 5 near here]

Figure 6 also compares the distribution of the residuals from cross-validation—that is, the difference between predicted and actual values—for both models using box plots.

[Figure 6 near here]

In addition, Figure 7 shows the cumulative distribution of the absolute values of the cross-validation residuals for both models.

[Figure 7 near here]

Some noteworthy conclusions can be drawn from the figure:

- The XGBoost model presents practically no errors greater than 30, while GLM presents residuals close to 50.
- With the XGBoost model, errors greater than 20 represent less than 10% of the total, whereas with GLM, 10% of the absolute values of the residuals exceed 25.

In short, the analysis of the residuals confirms the greater predictive power of the XGBoost model compared to GLM.

To finish assessing the goodness of fit, Table 4 shows the different metrics used, focusing on the RMSE (root mean square error) calculated for both the training set and the cross-validation sets).

[Table 4 near here]

All observations from the dataset are included in the training set and the error is calculated on these data; that is, the data used to calculate the performance metrics are the same as those used to train the model. The results are very optimistic and should not be taken as a reference. Cross-validation sets are used to produce a reasonable estimate of the results on a hypothetical test set that has not been used to fit or train the model; their results are more conservative and at the same time more realistic, so we will take them as a reference to assess the goodness of fit of the fitted models.

It should be noted that with many machine learning algorithms, there are substantial differences between the results of the training sets and those from the cross-validation sets, whereas with classic regression methods the results are very similar. However, in any case, for both the training set and the cross-validation set, the errors obtained with the GLM are greater than those of the XGBoost model.

Furthermore, if we look at the coefficient of determination (r^2), we find that the XGBoost model can explain 89.33% of the variance in market value, while the GLM only explains 58.04%.

Finally, we seek to confirm these results by performing two statistical tests of differences between the errors of the cross-validation sets for the two models (T-test and Wilcoxon test), where the null hypothesis is that there are no statistically significant differences between the two models. According to the values obtained (Table 5), the null hypothesis should be rejected and it can be concluded that at a level of significance lower than 1% there are statistically significant differences between the GLM and the XGBoost model, with the latter proving far superior.

[Table 5 near here]

In short, the XGBoost model yields better results than the GLM and its predictive power based on the analysed variables is fairly satisfactory.

3.4.3. Most relevant variables in the XGBoost model

Figure 8 shows the importance of each of the variables in relation to the dependent variable (market value), identified using the XGBoost algorithm.

[Figure 8 near here]

First, it should be noted that the most important variable is the book value—both individual and consolidated–followed by the sector and individual indebtedness. Bearing in mind that investment analysis companies usually rely on consolidated book value for their interpretations and forecasts of market value, over and above the individual value of the parent company, we are surprised to find that—at least in the analysed companies during the period considered—the individual book value carries more weight. Moreover, if we look at the order of importance of the variables, we see the same pattern repeated, in that the variables reflecting individual financial information are always ahead of those that refer to consolidated information.

A priori, it could be stated that the consolidated accounting information is more useful than individual due to the impact that internal operations may have on the structure and their amounts. However, authors such as Chambers (1968) consider that the individual information of a group of companies would be more reliable and more understandable than the information

from the consolidation process due to, among other issues, that the parent undertaking owning a share of the capital stock of subsidiaries is strictly limited to that share of the capital, or that the subsidiary company creditors only have rights on its assets and not on another subsidiary or parent company of the consolidation group.

At this point it is worth recalling that IAS 34 and Regulation (EC) No 1606/2002 are more exacting when it comes to consolidated financial information than with individual financial information, as they do not require the preparation of individual interim financial statements. The results indicate that we should still assign importance to the individual interim financial statements.

Below, we graphically depict and analyse the relationship between market value and each of the variables that have turned out to be the most relevant. We will use the partial dependence plots obtained from the model fitted using the XGBoost algorithm. These plots illustrate the marginal effect of each separate variable on the predicted market value. The x-axis shows the values that the analysed variables can take and the y-axis shows the prediction for the market value. Partial dependence plots are a global interpretation method, as they consider all observations and present the global relationship of a variable with the predictions of the dependent variable obtained using the algorithm.

In Figure 9 we can see that the market value reacts to movements in individual book value.

[Figure 9 near here]

In Figure 10, we can see that there is also a positive relationship between market value and consolidated book value, although in this case, as indicated by the graph of the relevance of the variables, the influence is somewhat weaker.

[Figure 10 near here]

Regarding indebtedness, Figure 11 does not show, as might be expected, a clear negative relationship; rather, market value remains stable when the level of debt increases. Therefore, it seems that current levels of debt do not pose a threat to market value. This could be explained by the low interest rates during the analysed period and the fact that they are not expected to rise while the effects of the current health and economic crisis persist.

[Figure11 near here]

Figure 12 analyses the last of the most relevant variables, the sector. It is interpreted differently because it is a non-continuous variable.

[Figure 12 near here]

4. Conclusions

Different studies confirm that there are many variables that can explain the market price of shares, and that they may differ depending on the industry in which the company operates or its life cycle. Some of these variables correspond to the financial information presented by the company, while others relate to different business decisions. But these are not the only factors: there are also issues external to companies that can have a beneficial impact on share price, such as political stability, legal certainty and a legal framework favourable to economic activity.

In light of the comparison between the Ibex-35 and some of the international benchmark indices, we can confirm that it is the worst performing index at year-end 2020 relative to year-end 2015, registering a fall of 15.41%, while the others remain at similar levels or have even risen considerably, such as the Dow-30 (+75.65%), the China A50 (+65.30%) and the Nikkei 225 (+44.19%).

The different graphs allow us to see how the Ibex-35 has moved away from international trends, especially in periods in which some relevant socio-political event occurred, such as the independence referendum in Catalonia, the double elections of 2019 or the early handling of the Covid-19 pandemic in 2020.

To explain share price formation, we have compared two statistical models, concluding that the most up-to-date techniques based on algorithms such as XGBoost yield significantly better results in terms of predictive power than classical linear regression methods.

Compared to other variables, the XGBoost model assigns little importance to socio-political factors when it comes to share price formation; however, this model explains 89.33% of its variance, so it may be possible that the unexplained part is influenced by such factors, or by business decisions that are not reflected in the financial information. Nevertheless, the statistical study has confirmed the relevance of the financial information and the sector to which the company belongs. The effects of some of these socio-political factors may be transferred ex post to book values and on certain sectors, and thus might be correlated with the market price although with a certain lag.

According to our analysis, individual information is equally or more important than consolidated information in predicting the behaviour of share prices. This would justify Spain maintaining the obligation to present individual interim financial statements, which does not happen in other European Union countries because IAS 34 only stipulates consolidated financial statements.

We have also observed how the sector to which the Ibex-35 companies belong influences market value. The technology and telecommunications sector stands out as the one generating the greatest increase in share prices, while the opposite is true of the financial services sectors and basic materials, industry and construction, although the latter presents lower volatility than the rest.

Lastly, despite the importance of indebtedness and the fact that it does have some influence, this variable has not proven to be a determining factor in share price formation, probably due to the low interest rates in recent years and the expectations that they will not rise following the economic crisis triggered by Covid-19. The crisis sparked by the pandemic, whose negative effects have been felt worldwide, seems to have hit Spain harder, or at least the Ibex-35 companies. This is probably due in part to the early handling of the pandemic, but, above all, to its greater impact on all companies related to tourism, an essential sector in our production model. In fact, the recovery after the announcement of the first vaccine has also been well below average. In future extensions of this study, it would be interesting to better assess these effects, and also to compare the results before and after the covid-19 crisis, but to do so we will have to wait for the financial information for the latest six-month periods to become available.

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[Tables A1 and A2 near here]

TABLES, FIGURES AND APPENDIX

Table 1
Most relevant socio-political factors in the period 2016-2020

Nº	Data	Description
1	*Jun. 23, 2016*	Referendum on the United Kingdom's continued membership of the European Union. This is not an exclusively external issue; indeed, it has major implications for the companies that make up the Ibex-35, given that some of them have interests in the UK.
2	*Jun. 07, 2017*	A European body, the Single Resolution Board, orders the resolution of Banco Popular in order to safeguard the general interest: it suddenly loses all its value and adds a further element of uncertainty to investments in this type of institution.
3	*Oct. 01, 2017*	Catalan independence referendum. The main international media reported on the clashes that occurred when trying to prevent this illegal referendum from taking place. The resulting uncertainty prompted a mass exodus, with many of the companies based in this region deciding to relocate their headquarters.
4	*May./Jun., 2018*	No-confidence motion against the president of the Spanish Government. The no-confidence motion was carried with the support of various different parties and represented a radical shift in Spanish politics.
5	*Apr. 28, 2019*	General Elections. No party emerged from these elections with a clear majority, and the resulting parliamentary fragmentation led to a period of negotiations. The failure to reach an agreement meant that general elections were called again.
6	*Nov. 10, 2019*	Repetition of General elections. Following the new election results, the party composition of parliament remained broadly similar, but in this case the formation of a coalition government made up of two progressive parties was immediately announced.
7	*Mar. 14, 2020*	Covid-19 pandemic and lockdown. The health crisis caused by the pandemic meant that governments had to take a series of measures to control its spread, which had a very negative impact on the global economy. The OECD identified Spain as the developed country worst hit by the recession with an 11% drop in GDP in 2020, followed by Argentina (-10.5%), the United Kingdom (-9.9%) and Italy (-8.9%).
8	*Nov. 09, 2020*	Announcement of the effectiveness of the first vaccine against Covid-19. The positive expectations generated by the announcement had a notable influence on international markets, with gains in the major stock market indexes.

Table 2.
Distribution over time of the most relevant socio-political factors

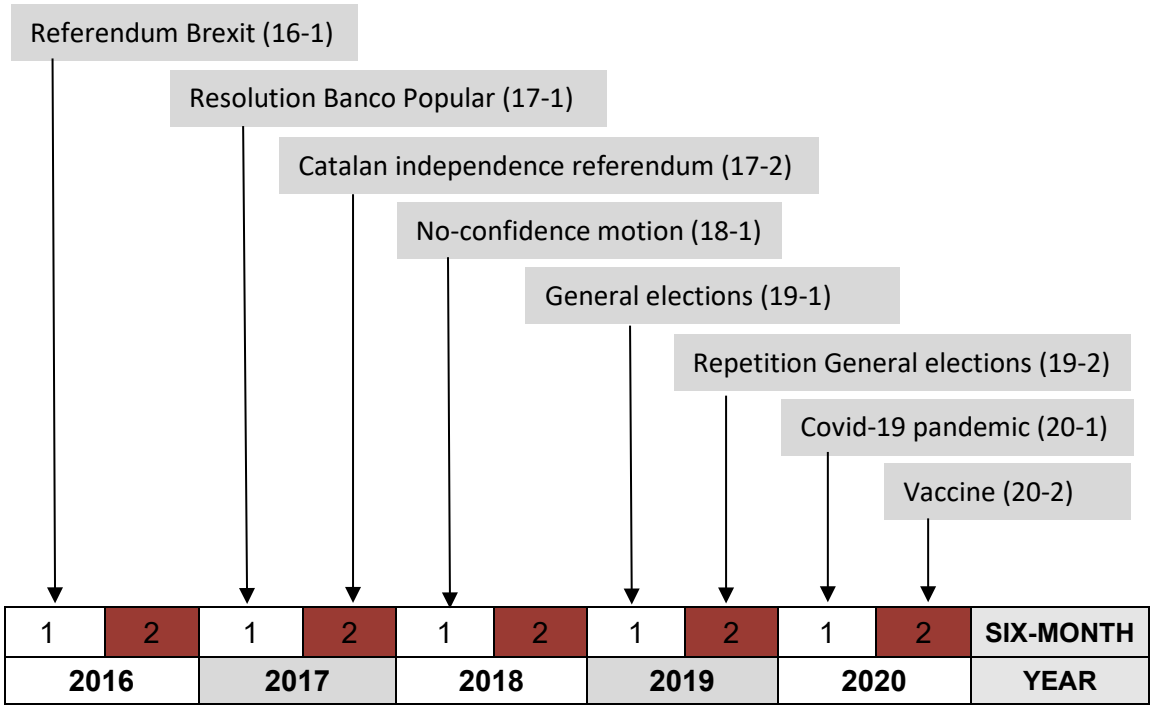
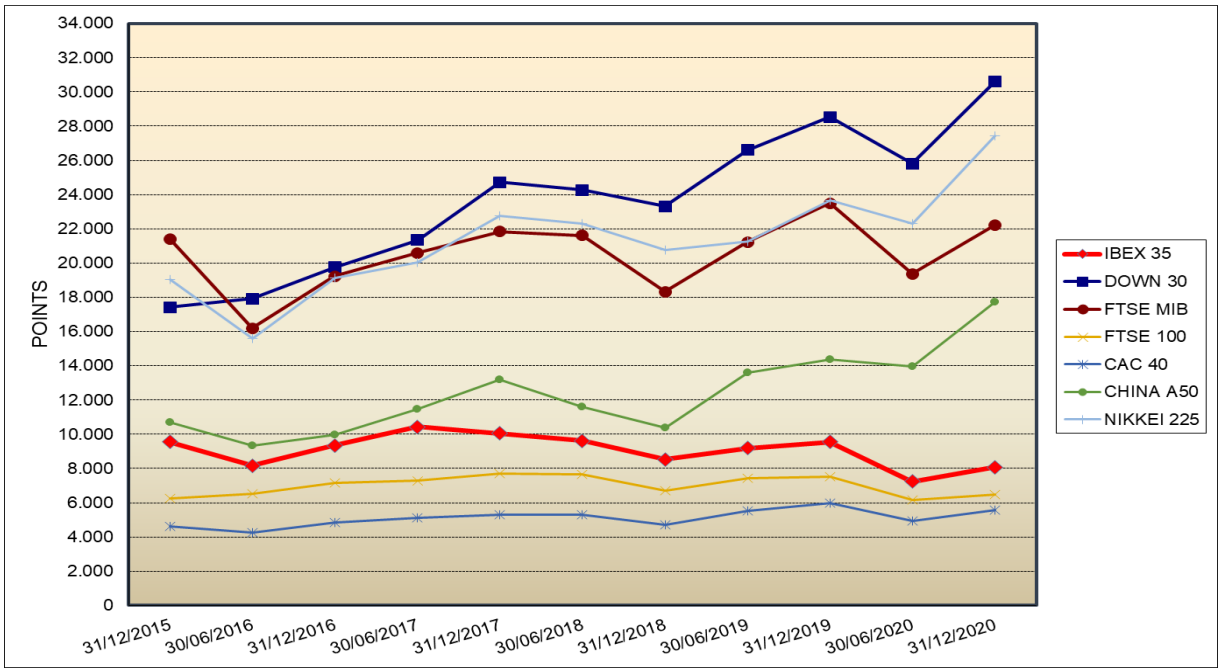
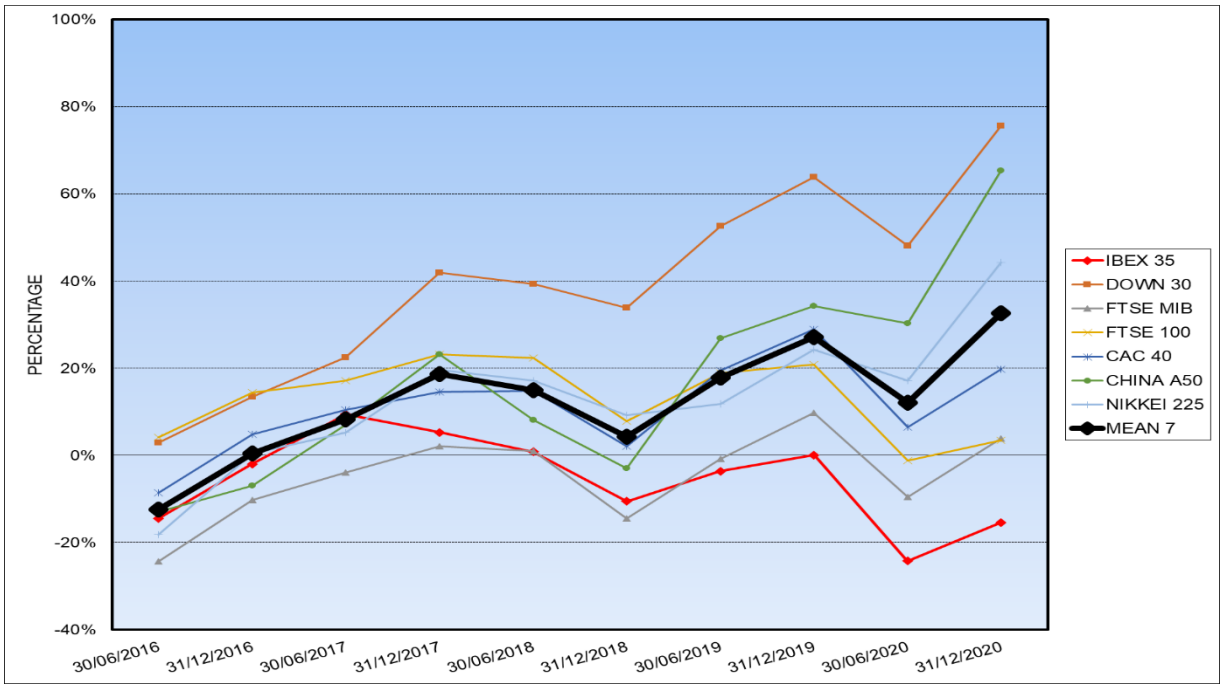


Figure 1
Benchmark indices 31-12-2015 to 31-12-2020



Note(s): Taking 31st December 2015 as the starting point, all the indexes are up at the end of the period under analysis (particularly the Dow 30, Nikkei 225, and the China A50), except for the Ibex-35, which is down by about 1,500 points. We can also see the overall rise in all indices during 2019, drastically interrupted in the first six months of 2020 as a result of the economic effects of the Covid-19 outbreak.

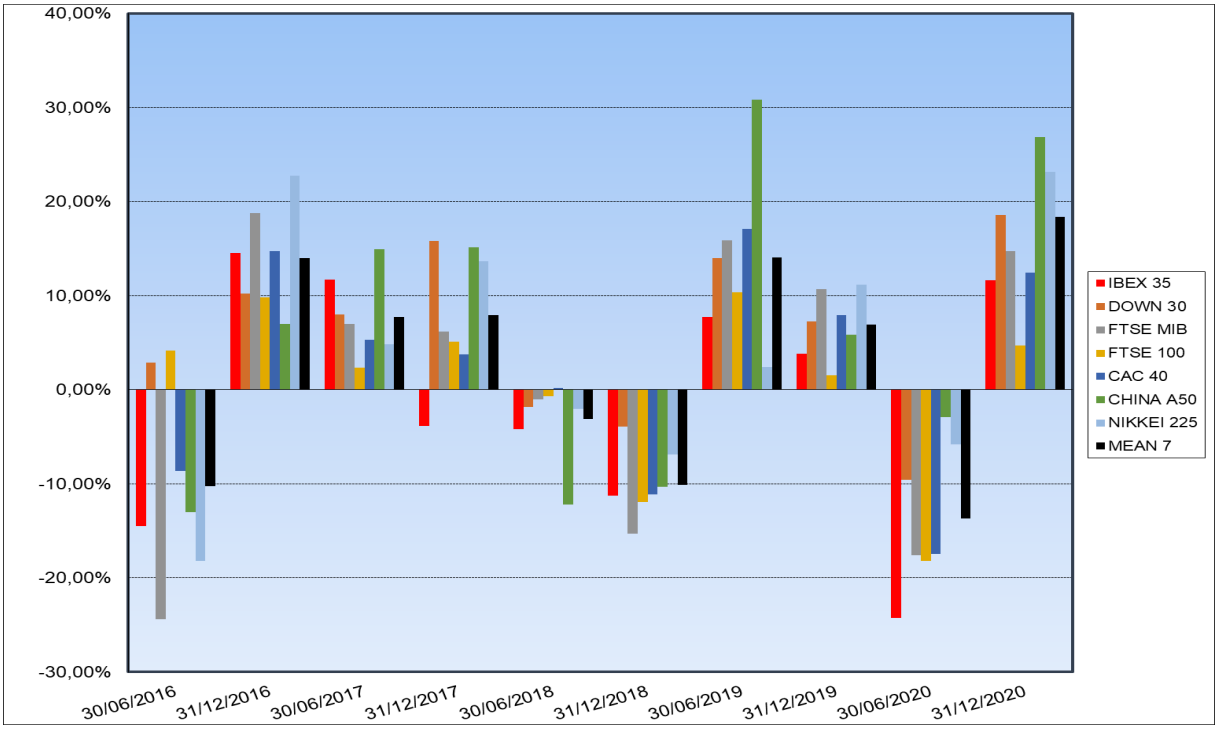
Figure 2
Change in indices base date 31/12/2015



Note(s): At year-end 2020, while all the indices have gone up—to a greater or lesser extent—relative to 2015, the Ibex-35 (red line) has gone down, with a drop of -15.41% in the last period analysed. The

continuing distance from the mean (black line) in these years can also be clearly seen, starting in the second six-month period of 2017, growing in the second six months of 2019 and reaching the maximum in both periods of 2020. Therefore, we might suspect that socio-political factors such as the independence referendum in the latter half of 2017, the elections in 2019 and the domestic handling of Coronavirus had negative effects.

Figure 3
Six-month percentage change in indices

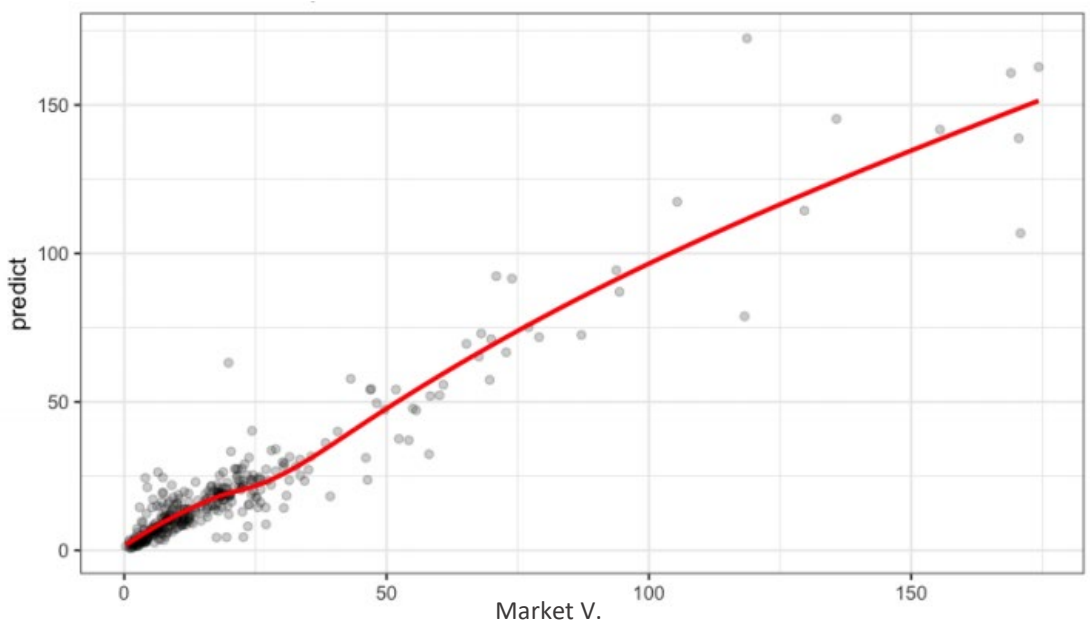


Note(s): It is worth highlighting the two six-month periods of 2019, where after three consecutive periods of downward movement, the values of the Ibex-35 make a slight recovery, albeit well below the Mean-7, coinciding with the abovementioned electoral processes. Something similar happens with the recovery in the midst of the pandemic in the second half of 2020, after the announcement of the first vaccine. In the first six-month period of 2016 and of 2020, we see a drop greater than that in the Mean-7, while in the second six-month period of 2017, the IBEX was the only index registering a negative change.

Table 3
Six-month change in the Ibex-35 in relation to socio-political events

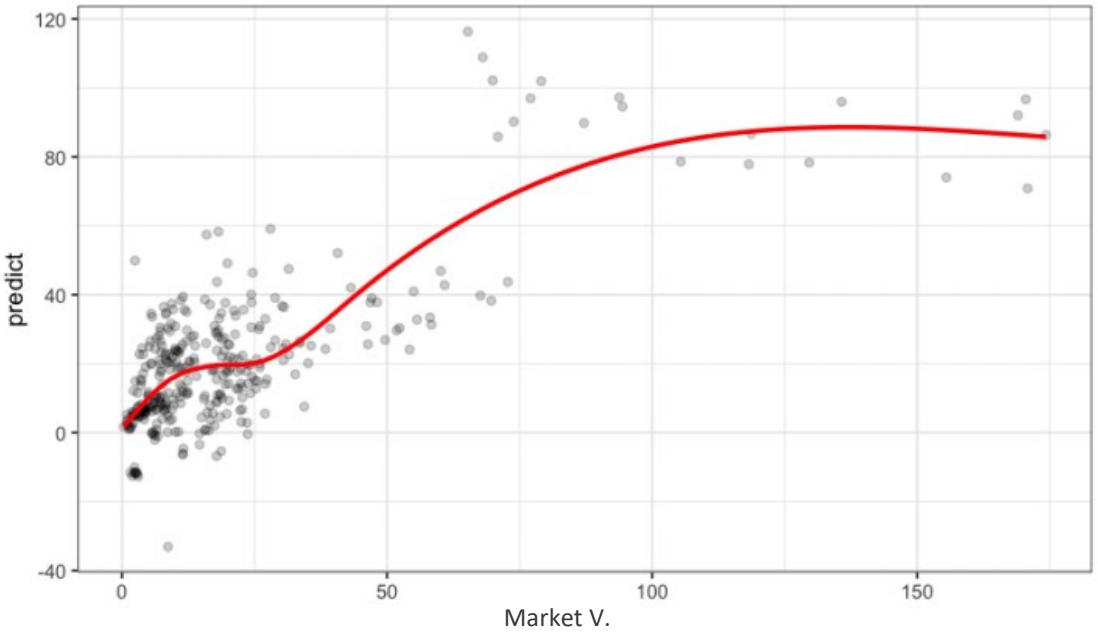
Socio-political Factors	Six-month	Initial share price	Final share price	Variation Ibex	Effect	Variation Mean-7	Difference	Relevance
Referendum BREXIT	16-1	9.544,20	8.163,30	-14,47%	↓	-10,22%	-4,25%	YES
Resolution B. Popular	17-1	9.352,10	10.444,50	11,68%	↑	7,74%	3,94%	NO
Cataluña referendum	17-2	10.444,50	10.043,90	-3,84%	↓	7,97%	-11,80%	YES
No-confidence motion	18-1	10.043,90	9.622,70	-4,19%	↓	-3,10%	-1,09%	NO
General elections 28A	19-1	8.539,90	9.198,80	7,72%	↑	14,05%	-6,33%	YES
General elections 10N	19-2	9.198,80	9.549,20	3,81%	↑	6,90%	-3,09%	YES
Covid-19 pandemic	20-1	9.549,20	7.231,40	-24,27%	↓	-13,68%	-10,59%	YES
Vaccine ad	20-2	7.231,40	8.073,70	11,65%	↑	18,34%	-6,69%	YES

Figure 4
Cross-validation predictions vs actual data (XGBoost)



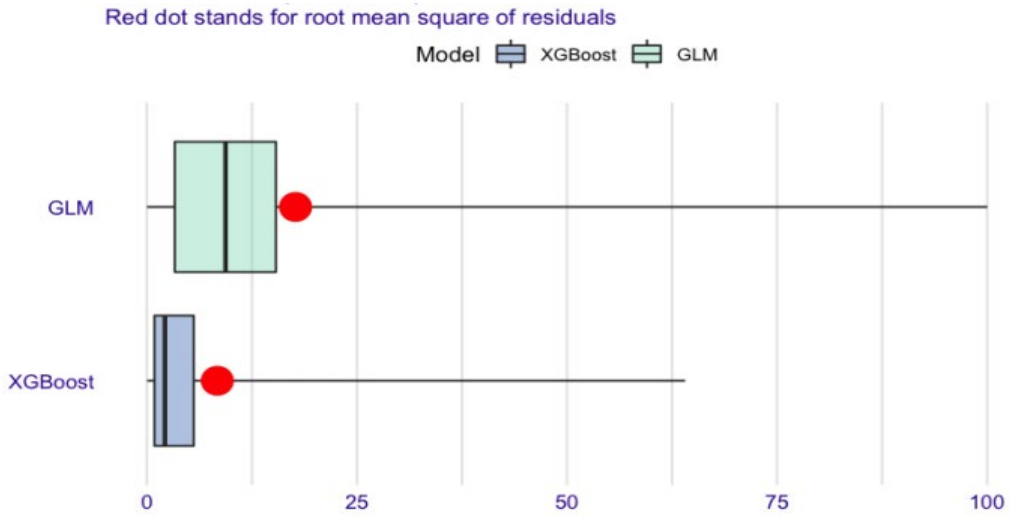
Note(s): The fit observed in the plot of the XGBoost model resembles a diagonal straight line, in which the values on the vertical axis (predictions) show close alignment with those on the horizontal axis (actual values). Therefore, the figure graphically depicts that the prediction results obtained with the XGBoost algorithm are very good.

Figure 5
Cross-validation predictions vs actual data (GLM)



Note(s): In the graph of the fit of the GLM model, a more irregular figure can be seen, in which the alignment between the real values and the predictions is less clear. It can thus be inferred that the goodness of fit of this model is worse than that of the XGBoost.

Figure 6
Distribution of the cross-validation residuals



Note(s): The red dot indicates the square root of the arithmetic mean of the squares of the residuals of the fitted model. The comparison between the two models allows us to affirm that the XGBoost model presents residuals in the cross-validation sets with a median close to 0 and a mean below 10, while the GLM shows notably higher values.

Figure 7
Cumulative distribution of the absolute value of cross-validation residuals

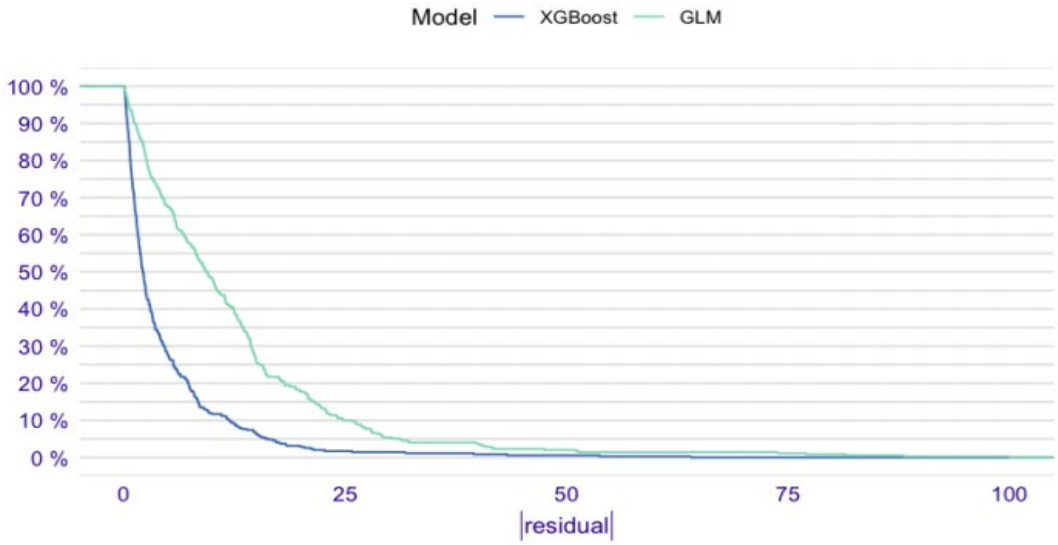


Table 4
Model fit results

	XGBoost	GLM
RMSE (Training set)	0,2590	16,5603
RMSE (Cross-validation set)	8,3771	17,6857
r^2	0,8933	0,5804

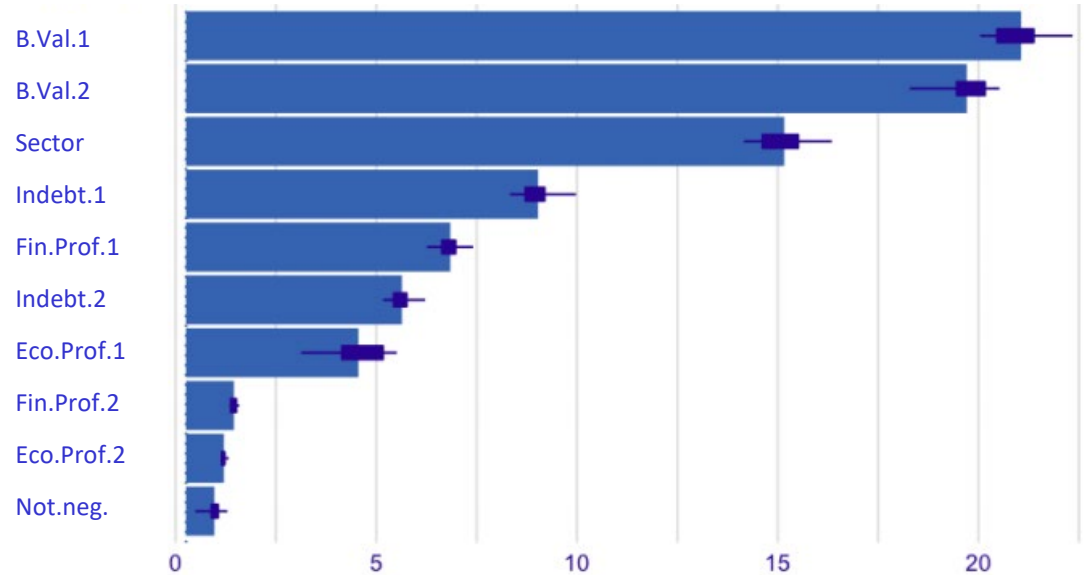
Note(s): In the cross-validation sets coincides with the red dot depicted in Figure 6.

Table 5
Analysis of the statistical significance of the residuals from validation sets

	P-value
T-test (parametric)	0,0002048
Wilcoxon test (non-parametric)	0,0004871

Note(s): The null hypothesis is that there are no statistically significant differences between the two models.

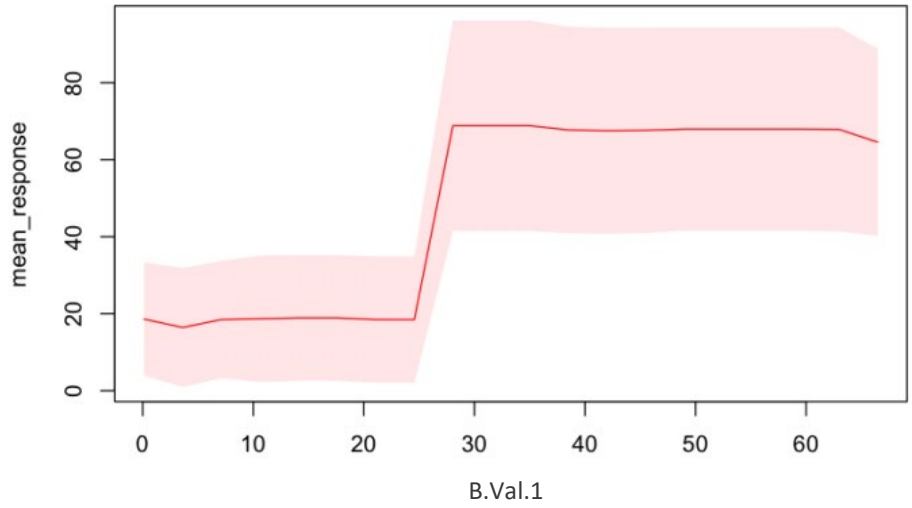
Figure 8
Importance of the variables according to the XGBoost model



Note(s): The variables reflecting individual financial information are always ahead of those that refer to consolidated information.

Figure 9

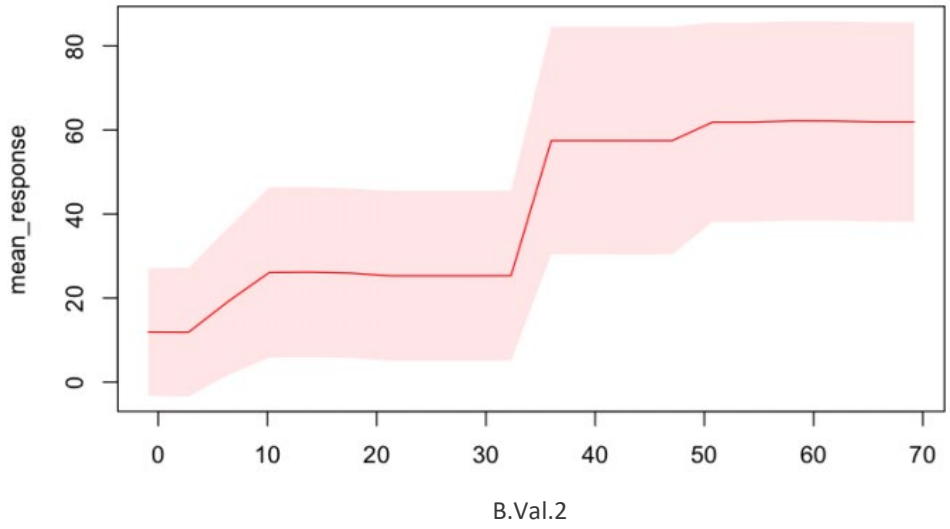
Partial dependence plot of market value and individual book value



Note(s): There is a positive relationship between the two; as expected, an increase in book value leads to an increase in market value.

Figure 10

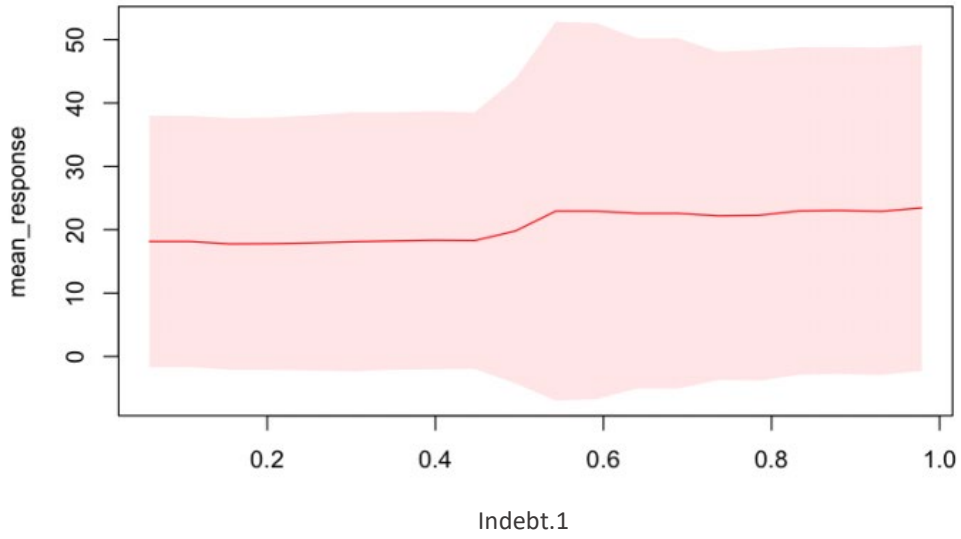
Partial dependence plot of market value and consolidated book value



Note(s): The relationship between market value and consolidated book value is positive too, but the influence is somewhat weaker.

Figure 11

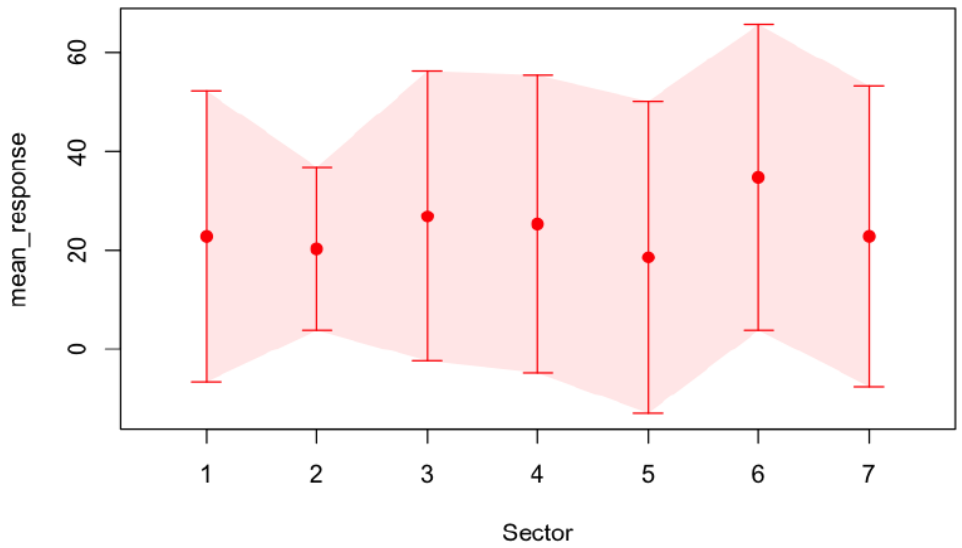
Partial dependence plot of market value and indebtedness



Note(s): The market value remains stable when the level of debt increases and vice versa.

Figure 12

Partial dependence plot of market value and sectors



Notes: Whereas sector 6 (Technology and telecommunications) is the one that drives prices up the most, sector 2 (Basic materials, industry and construction) and sector 5 (Financial services) are the ones that lead to a decrease. Volatility is similar in all sectors except sector 2, where it is lower.

Table A1
Distribution of companies by sectors and subsectors

SECTOR	SUBSECTOR	Nº	Nº
1. Oil and energy	1.1 Oil 1.2 Electricity and gas	1 5	**6**
2. Basic materials, industry and construction	2.1 Mineral, metals and transformation 2.2 Manufacture and assembly of equipment 2.3 Construction	3 1 3	**7**
3. Consumer goods	3.1 Alimentation and drinks 3.2 Textile, clothing and footwear 3.3 Paper and graphic arts 3.5 Pharmaceutical and biotechnological products	1 1 1 1	**4**
4. Consumer services	4.1 Leisure, tourism and hospitality 4.3 Information media and publicity 4.4 Transportation and distribution	1 1 2	**4**
5. Financial services	5.1 Banks and savings banks 5.2 Insurance	6 1	**7**
6. Technology and telecommunications	6.1 Telecommunications y others 6.2 Electronics and software	3 2	**5**
7. Real estate services	7.2 REIT	2	**2**
TOTAL		**35**	**35**

Table A2
Quantitative variables

RATIO	MODE	VARIABLE	DESCRIPTION
Book value	Individual	**B.Val.1**	Equity / no Shares
	Consolidated	**B.Val.2**	(Equity – Non-controlling interests) / no Shares
Indebtedness	Individual	**Indebt.1**	Liability / (Liability + Equity)
	Consolidated	**Indebt.2**	Liability / (Liability + Equity)
Economic profitability	Individual	**Eco.Prof.1**	Net income / Asset
	Consolidated	**Eco.Prof.2**	Net income attributable to equity holders of the parent / (Asset - Non-controlling interests)
Financial profitability	Individual	**Fin.Prof.1**	Net income / Asset
	Consolidated	**Fin.Prof.2**	Net income attributable to equity holders of the parent / (Asset - Non-controlling interests)