EARNINGS FORECASTS ACCURACY: INTERNATIONAL EVIDENCE OF THE IMPACT OF THE COVID-19 PANDEMIC

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ABSTRACT

Covid-19 has brought an unprecedented climate of uncertainty to markets, industries and firms. The role of analysts is always important, but even more when there is a high degree of uncertainty, as investors demand more information and timely, accurate forecasts from analysts to help them make decisions. The main objective of this paper is to examine how the pandemic affected the forecast accuracy in countries from different geographical regions (Europe, Asia, North and Latin America). In addition, we analyzed to what extent other variables (company, macroeconomic and country variables) affect the prediction error and evaluated whether the pandemic modified this effect.

The results show that the forecast error was higher in 2020 than in 2019 and 2021. We observe that the crisis triggered by the pandemic has a significant impact on the error of analysts' forecasts issued 12 months before the year-end. However, this impact is no longer significant for forecasts made 3 months in advance. Other variables also explain the forecast accuracy, notably the sign of companies´ earnings, return on equity or the uncertainty avoidance.

We also find significant differences in the forecast errors between the countries in the sample, but these differences were observed in all three exercises under study. It means that these divergences across countries cannot be attributable to the Covid-19 pandemic.

Keywords: Covid-19, analysts' forecasts, forecast error, international analysis

JEL Classification: G01, G14, G17, O57, P52.

1. INTRODUCTION

Analysts play an important role in the functioning of the market. As Iturbe and Martínez-Pardo (2015, p. 102) note: *”the work of someone capable of professionally examining the information available on a given issuer, transforming it into earnings forecasts and target price estimates, and making it public in the form of an investment recommendation easily is understandable to an investor, even an inexperienced one, gives analysts a capacity to influence the markets, at the same time placing them in the focus of regulators, supervisors and investors”.* Analysts act as information intermediaries between issuing companies and investors, who rely on analysts' forecasts and recommendations as a basis for their investment decisions.

The work of analysts is always important, but even more when levels of uncertainty grow. In times of uncertainty, information is scarcer and less accurate, leading investors to demand more information from analysts, as well as timely and accurate forecasts to help them make decisions (Bhushan 1989; Moyer, Chatfield and Sisneros, 1989; O'Brien and Bhushan, 1990; Das, Levine and Sivaramakrishnan, 1998; Frankel, Kothari and Weber, 2006). However, uncertainty also affects analysts, who find it more difficult to obtain and process information to generate accurate forecasts. Amiram *et al*. (2018), for example, show that, when uncertainty is high, forecasts are more timely but less accurate, i.e. prediction error is higher.

Every crisis generates a certain level of uncertainty and, consequently, effects on analysts' forecasts and stock markets (Loh and Stulz, 2018). However, the Covid-19 crisis was an unprecedented crisis, very different from others, not only because of its health origin, but also because it was totally unpredictable and had a major impact on people's way of life and on all economic activities worldwide (Goldstein, Koijen and Mueller, 2021; Haddad, Moreira and Muir, 2021; Spiegel and Tookes, 2021). Covid-19 generated an unprecedented climate of uncertainty at all levels and, surely for analysts, who had to react to very intense levels of global uncertainty and insufficient information.

The literature identifies three sources of uncertainty that can affect analysts in their forecasting of corporate performance: market uncertainty, industry uncertainty and firm-level uncertainty. According to previous studies, analysts respond better to industry uncertainty (Kadan *et al.,* 2012), but they find it more difficult to incorporate general market information into their forecasts (Hann, Ogneva and Sapriza, 2012; Hugon, Kumar and Lin, 2016). Amiram *et al.* (2018) find that analysts' forecast accuracy is lower when market or firm-level uncertainty is high, but is not as affected by industry uncertainty.

In the case of Covid-19, uncertainty was high at all levels: market, industry and firm. Moreover, this was not a crisis that affected only one country, but all economies. In addition, the literature indicates that the influence of the accuracy of forecasts affects the level of economic stability of the country but also the business characteristics; therefore, it must be also taken into account, without forgetting that the crisis itself may have affected the impact of these aspects on the forecasts. Hence, it is interesting to study the effects of such a special and unforeseen crisis on analysts' forecasts. There is some previous study, such as the work of Hao *et al.* (2022), which analyzes the characteristics of analysts' forecasts after Covid-19 in the US.

Given the impact of Covid-19 was different in different geographical regions, the main aim of the study is to examine the impact of Covid-19 on earnings forecast error, not for a single country, but for a broad set of countries from different geographical areas: Europe, Asia, North and Latin America. We base on forecasts issued 12 months before earnings publication and forecasts made 3 months in advance. Twelve months before 2020 earnings publication, the outbreak of Covid-19 in China was already known, but the extent of the consequences of the pandemic on lifestyle and the economy was not yet foreseeable. In the case of forecasts made 3 months in advance 2020 earnings release, analysts were already aware of the serious consequences of the pandemic at all levels.

The results obtained show that the forecast error made 12 months before the fiscal year end was higher in 2020 than in the previous and subsequent years, due to the crisis triggered by Covid-19. However, the forecasts accuracy issued 3 months before year-end 2020 is not significantly different from that observed in 2019 and 2021, which is probably due to the fact that analysts were already able to adjust their forecasts, at least in part, to the effects of the new situation on business performance at that time.

In addition, we analyzed to what extent other variables (company, macroeconomic and country variables) affect the prediction error and evaluated whether the pandemic modified this effect. The results show that economic situation of the company or the uncertainty avoidance in each country also explain the prediction error, and that the pandemic crisis particularly affected the forecast error of loss-making companies.

The study contributes to the literature by providing new evidence on how the Covid-19 induced crisis, different from previous crises, and affects the accuracy of analysts' forecasts in a global environment of nine countries. To our knowledge, there are no previous studies on this aspect that consider a global environment including countries from different geographical areas, with different levels of economic stability and different cultures. In consequence, companies from different regions deal with uncertainty in different way, as confirmed in previous studies, see for example, Capstaff, Paudyal and Rees (2001), who indicate that the degree of accuracy of analysts' forecasts differs between countries.

Our findings have important implications for the usefulness of analysts' forecasts. Crisis situations affects forecasts accuracy and, therefore, their usefulness. So, it is important to take this into account in investment decisions based on forecasts.

The paper is structured as follows. It starts with an introduction. Then, the second section reviews the previous literature. Following, the sample and methodology are described in the third and fourth sections, respectively. The results of the study are presented in the fifth section and, finally, a sixth section is devoted to the main conclusions reached. Bibliographical references are listed in a final section.

2. PREVIOUS LITERATURE

The exchange of financial assets on the stock markets involves companies whose shares are listed, financial analysts and investors. Investors search the market for financial assets that best suit their financial needs, risk profiles and, above all, their expectations. To this end, they have various sources of information available to them, of which, according to Hirst, Koonce and Simko (1995), analysts' reports are the most influential in investment decision-making.

The primary role of financial analysts is to analyze the company's financial situation and make a diagnosis. They are important information intermediaries between companies and investors and their estimates and recommendations influence market expectations (see Schipper, 1991; Abarbanell, Lanen and Verrecchia, 1995; Ramnath, Rock and Shane, 2008). In crises, uncertainty increases considerably and this fact makes the role of analysts even more relevant (Cervera, 2015).

Any economic crisis affects stock markets and the actors involved in them: companies, investors and analysts, among others. Business activity and corporate earnings fall and an atmosphere of uncertainty is generated, leading investors to demand more information from analysts, as well as timely and accurate forecasts. However, the analyst is also affected in the performance of his or her job, since, as Maslar, Serfling, and Shaikh (2021) argue, the uncertainty surrounding economic downturns makes it disproportionately difficult for external market participants to assess the company's prospects.

Amiram *et al.* (2018) analyze changes in the key characteristics of analysts' forecasts (timeliness, accuracy and information) during periods of high uncertainty. They conclude that during such periods, forecasts are more timely and informative, but less accurate. In addition, they distinguish three sources of uncertainty: market, industry and firm. They confirm that high levels of market uncertainty are the most difficult for the analyst, affecting both the timeliness and accuracy of forecasts. Other studies, such as those by Hann, Ogneva and Sapriza (2012) and Hugon, Kumar and Lin (2016) obtained similar results.

As it is well known, the crisis generated by Covid-19 was very different from all previous crises. This crisis caused by the pandemic, it could not have been predicted. It was so unexpected and its effects went far beyond the consequences of an economic crisis. It negatively affected people's way of life, economic activities, the supply of raw materials, stock markets, etc. It generated an environment of high uncertainty at all levels that affected markets, companies, investors and, surely, analysts. The impact of Covid-19 has triggered the development of numerous research projects to study the effects of a crisis as different from previous ones as it was unforeseen.

Regarding the effects on firms and investors, it is worth highlighting the study of Ding *et al.* (2021), which assessed the connection between corporate characteristics and the reaction of stock returns to Covid-19 cases based on data from 61 economies. The results showed that the Covid-19 effect was milder for firms with stronger financials before 2020 (more cash and undrawn credit, less total and short-term debt, and higher profits), less exposure to Covid-19 through global supply chains and customer locations, more corporate social responsibility activities, and less entrenched executives. In addition, stocks of companies controlled by families, large corporations and governments outperformed, while those of companies with greater involvement of hedge funds and other asset management firms underperformed. During the pandemic, stock markets viewed small percentages of managerial ownership positively, but high percentages negatively.

Other studies investigated the effect of Covid-19 on stock markets, specifically on the volatility caused by the uncertainty surrounding the pandemic. Albulescu (2021), for example, focused on the US stock market. He showed how the health crisis increased the volatility of the S&P 500. Zaremba *et al.* (2020) explored the impact of government interventions aimed at curbing the spread of Covid-19 on stock market volatility, including 67 countries around the world. They concluded that non-pharmaceutical interventions significantly increased stock market volatility and that information campaigns and the cancellation of public events were the actions that contributed most to increased volatility.

As for analysts and their forecasts, some previous studies on the impact of Covid-19 have also been developed. Hao *et al.* (2022), for instance, examined the characteristics of financial analysts' forecasts after the Covid-19 outbreak in the United States. They found a significant change in forecasts as a consequence of market uncertainty. They concluded that forecasts were more timely and frequent during the pandemic, but less accurate.

Our research focuses on the study of the impact of Covid-19 on the earnings forecast error for a wide set of countries from different geographical regions: Europe, Asia, North and Latin America. Covid-19 made analysts' work more difficult. First, it severely disrupted the economy, but not all firms were equally affected as commented by Ding *et al.* (2021). Second, both the quantity and quality of information declined, as in other economic crises (Brockman, Liebenberg and Schutte, 2010; Aaron *et al*., 2021; Hope *et al.,* 2022), creating a climate of uncertainty that made it difficult to assess firm's prospects.

Moreover, it also increased the uncertainty surrounding the policy decisions, both health and economic, that had to be taken in all countries and which differed from one country to another. In this respect, Chourou, Purda and Saadi (2021) pointed out that the increase in forecast accuracy and dispersion as the uncertainty of government economic policies increased. Nor can we forget that the handling of uncertainty and the way in which it affected individuals and their way of acting and deciding was not always the same, as shown in studies by Hofstede (1980) and Hofstede, Hofstede and Minkov (2010), which considered uncertainty avoidance as a cultural variable that differs from country to country.

In a view of the above, on the one hand we consider it interesting to investigate how the pandemic affected the forecast accuracy in countries from different geographical regions. On the other hand, we cannot forget various factors that previous studies have found to affect forecast error, such as the number of analysts following the company, recent changes in earnings or the countries to which the companies belong, among others (Sánchez-Ballesta and García-Meca, 2005).

We are therefore also interested in how company, macroeconomic and country variables explain the prediction error, also taking into account that the relationship between them and analysts' prediction error may have changed during the crisis. In consequence, we formulate the following hypotheses in its alternative form:

H1: The crisis triggered by Covid-19 significantly affected the earnings forecast error

H2: The crisis triggered by Covid-19 modified the effect of company, macroeconomic and country variables on the forecasting error.

3. SAMPLE

To test our hypothesis, we selected a sample of companies listed on the main stock market indices of nine countries. In order to include companies from different geographical areas, we include European companies (from Spain, France, Germany and the United Kingdom); American companies (from the United States, Canada and Brazil) and Asian companies (from Japan and Hong Kong).

The sample is composed of a total of 690 companies for a three-year analysis period, 2019 to 2021, with a total of 2,070 observations, distributed by country and stock market index as shown in Table 1. The country with the highest representation is Japan (32%) and the lowest representation are Spain (5%) and the United States (4%). By geographical areas, Asia with 42%, Europe with 32% and America with 26%.

Table 1: Sample

Country (stock index)	Firms	Observations	%
Brazil (BOVESPA)	90	270	13%
Canada (TSX)	60	180	9%
France (CAC)	40	120	6%
Germany (DAX)	40	120	6%
Hong Kong (HANG SENG)	69	207	10%
Japan (NIKKEI)	225	675	32%
Spain (IBEX)	35	105	5%
United Kingdom (FTSE)	101	303	15%
US (DOW JONES)	30	90	4%
TOTAL	**690**	**2,070**	**100%**

Table 2 shows the descriptive statistics (minimum, maximum, mean and standard deviation) of some variables selected to characterize the sample: total assets, earnings and equity. The descriptive statistics by country for the year 2021 are shown in Appendix 1.

Table 2: Sample characterization

	millions of euros	**Min.**	**Max.**	**Mean**	**Standard dev.**
2019	Assets	29	309,952,268	3,312,605	20,172,611
	Earnings	-111,188	1,868,085	45,626	133,841
	Equity	-8,617	19,846,225	499,375	1,468,701
2020	Assets	157	335,579,019	3,507,033	21,313,381
	Earnings	-992,524	2,058,899	30,979	129,644
	Equity	-18,316	20,564,787	492,518	1,451,694
2021	Assets	105	358,421,843	3,762,919	22,704,362
	Earnings	-577,900	4,957,716	44,944	233,534
	Equity	-21,054	23,404,547	542,260	1,601,759

The data for the variables used in the study are obtained from the EIKON database in the case of actual financial data and I/B/E/S in the case of forecast data.

4. METHODOLOGY

The aim of this study is to examine which variables had a significant impact on analysts' forecasting error and to what extent the crisis triggered by Covid-19 affected this impact in itself, or in conjunction with the previous variables. To this end, we focus on assessing whether or not the forecasts accuracy made from the earnings finally achieved by companies in the year 2020, the year of the pandemic, were significantly different from the prediction errors in the previous and subsequent years.

Of all the predictions made for the annual earnings throughout the year, we focused on the one made 12 months before the year-end, when in 2020 we were not yet aware of the significance that the pandemic would have for companies and the economy in general. Additionally, we used the predictions that were made 3 months before the year-end, but when there was already awareness of the importance of Covid-19 in all areas. In the second one, it is foreseeable that analysts would have incorporated new information on the matter in their forecasts.

Thus, we work with the deviations of the forecasts (made 12 and 3 months before) with respect to the result of the exercise, calculated according to expression (1), for the years: 2019 (pre-pandemic), 2020 (pandemic) and 2021 (post-pandemic):

$$D_{mit} = [FE_{mit} – AE_{it}] / \left| AE_{it} \right| \qquad (1)$$

where:

D_{mit} is the deviation of the forecasted earnings *m* months before year-end from the actual earnings for company *i* in year *t*,

FE_{mit} is the forecasted earnings based on consensus analysts forecast *m* months before year-end for company i in year t,

$AEit$ is the actual earnings for company i in year t,

$\left| AEit \right|$ is the absolute value of the actual earnings for company i in year t.

m= 12 or 3 months before year-end; *i* = 1 to 690 companies; *t* = 2019 to 2021.

First, we performed a descriptive analysis of the calculated deviations, in order to find out their sign. Next, in order to examine whether the prediction errors, in absolute value, are significantly different in the three years analyzed, we apply the non-parametric Friedman test, which does not require the normality of the data.

We apply the Friedman test twice, once to find out if there are significant differences in $D_{12,i,t}$ in absolute value ($\left| D_{12,i,t} \right|$), between the three years analyzed (2019, 2020 and 2021), and once to find out if there are significant differences in $\left| D_{3,i,t} \right|$.

In order to analyze whether the behavior of the deviations is homogeneous across countries or not in each of the years under study, we apply the Kruskal Wallis test three times (2019, 2020 and 2021) for the $\left| D_{12,i,t} \right|$ variable, and three times for the $\left| D_{3,i,t} \right|$ variable.

Finally, in order to examine what variables explain the analysts' deviations and to what extent the crisis triggered by Covid-19 influences their effect on the forecasts error, we carry out two multivariate linear regressions (one with $\left| D_{12,i,t} \right|$ as the dependent variable and the other with $\left| D_{3,i,t} \right|$), according to expressions (2) and (3).

Previously, we have checked that the assumptions required by multiple linear regression models are met. Thus, we have checked the normality of the residuals, using the Kolmogorov-Smirnov and Shapiro-Wilk tests, which led us to accept the hypothesis of normality; the non-autocorrelation of the residuals, using the Durbin-Watson test, which indicates that there is no strong autocorrelation; the homoscedasticity or equality of variances, using the Levene test; the non-multicollinearity, using the VIF parameter (Variance Inflation Factor), which indicate that there is some collinearity, but it is moderate; and, finally, the linearity of the independent variables and the dependent one, obtaining the Deviation from linearity statistic, which leads us to accept that the relationship between the means is linear and that the linearity assumption is fulfilled.

$$\left| D_{12,i,t} \right| = \alpha_0 + \alpha_1\, Crisis_t + \alpha_2\, Analysts_{it} + \alpha_3\, PoL_{it} + \alpha_4\, Liq_{it-1} + \alpha_5\, Indebt_{it-1} + \alpha_6\, ROE_{it-1} + \alpha_7\, VarGDP_{ct} + \alpha_8\, Inflation_{ct} + \alpha_9\, MarketReturn_{ct} + \alpha_{10}\, MarketCapit_{ct} + \alpha_{11}\, Uncertainty_c + \alpha_{12}\, Stringency_{12,c,t} + \alpha_{13\text{-}18}\, Crisis_t\ x\ X + e_{it} \qquad (2)$$

$$\left| D_{3,i,t} \right| = \beta_0 + \beta_1\, Crisis_t + \beta_2\, Analysts_{it} + \beta_3\, PoL_{it} + \beta_4\, Liq_{it-1} + \beta_5\, Indebt_{it-1} + \beta_6\, ROE_{it-1} + \beta_7\, VarGDP_{ct} + \beta_8\, Inflation_{ct} + \beta_9\, MarketReturn_{ct} + \beta_{10}\, MarketCapit_{ct} + \beta_{11}\, Uncertainty_c + \beta_{12}\, Stringency_{3,c,t} + \beta_{13\text{-}18}\, Crisis_t\ x\ X + e_{it} \qquad (3)$$

X = Analysts, PoL, Liq, Indebt, ROE, Uncertainty.
i = 1 to 690 firms
t = 2019 to 2021
c = 1 to 9 countries (stock markets)

where:

$\left| D_{12,i,t} \right|$ is the deviation of the earnings forecast made 12 months before year-end from the actual earnings for year *t* for company *i,* calculated according to equation *(1)* and expressed in absolute value.

$\left| D_{3,i,t} \right|$ is the deviation of the earnings forecast made *3* months before year-end from the actual earnings for year *t* for company *i,* calculated according to equation *(1)* and expressed in absolute value.

$Crisis_t$ is a dichotomous variable taking value 1 for the year 2020, the year in which the Covid-19 pandemic was triggered, and 0 for 2019 and 2021.

$Analysts_{it}$ is the number of analysts who follow company *i* in period *t* and who issue earnings forecasts.

PoL_{it} is a dichotomous variable that takes a value of 1 if company reached profit for year *t* and a value of 0 if company reached loss.

Liq_{it-1} refers to the liquidity of company *i* in year *t-1* and is defined as the ratio of current assets to current liabilities.

$Indebt_{it-1}$ refers to the indebtedness of firm *i* in year *t-1* and is defined as the ratio of liabilities to equity.

ROE_{it-1} refers to the return on equity for firm *i* in year *t-1* and is defined as the ratio of earnings to equity.

$VarGDP_{ct}$ is the absolute value of the percentage change in GDP for country *c* in year *t* compared to year *t-1*.

$Inflation_{ct}$ is the inflation rate for country *c* in year *t*.

$MarketReturn_{ct}$ is the return on the stock market index *c* in which the company is listed for year *t*.

$MarketCapit_{ct}$ is the capitalization of the stock market index *c* in which the company is listed to total capitalization of nine stock markets indexes for year t.

$Uncertainty_{c}$ is the logarithm of the uncertainty avoidance index for country *c* proposed by Hofstede (1980)

$Stringency_{12,c,t}$ is the logarithm of the Stringency Index for January 1 of year t in country *c* calculated in The Oxford Coronavirus Government Response Tracker (OxCGRT) project.

$Stringency_{3,c,t}$ is the logarithm of the Stringency Index for September 30 of year t in country *c* calculated in The Oxford Coronavirus Government Response Tracker (OxCGRT) project.

$Crisis_{t}$ *x X* is the product of the dichotomous variable *Crisis* times *X*, where *X* equals *Analysts, PoL, Liq, Indebt, ROE, Uncertainty.*

As can be seen, the dependent variables ($\lvert D_{12,i,t} \rvert$ and $\lvert D_{3,i,t} \rvert$) are the absolute value of the forecast deviation 12 and 3 months before the year-end with respect to the earnings actually achieved by the firms.

As for the explanatory variables, firstly, we include the variable *Crisis* in order to examine whether the Covid-19 crisis in itself influenced the deviations to be higher than in other years. We cannot forget that this is a supervening crisis whose effects on the economy, in general, and on companies´ earnings, in particular, could hardly have been foreseen when the year 2020 began. It is, therefore, likely that analysts were unable to incorporate this information into their forecasts, especially those made 12 months in advance, and the forecast errors were higher, which means that the expected sign of the α_1 (in equation 2) and β_1 (in equation 3) coefficients is positive. However, in 2021, even with some uncertainty associated with the pandemic, analysts were already able to consider in their forecasts the foreseeable impact of Covid 19 on earnings. Therefore, for the purpose of measuring the impact on the prediction error, we have only considered 2020 as the crisis period.

Taking into account studies such as Basu, Leeseok and Ching-Lih (1998), Duru and Reeb (2002) and Ang and Ciccone (2002), which found a significant and negative association between the number of analysts following a firm and the forecast error, we include the variable *Analysts*, whose coefficients, α_2 and β_2, we expect to be negative.

The *PoL* variable intends to capture the possible impact of the sign of corporate earnings on the prediction error, on the assumption that it is easier to make forecasts when firms are making a profit than when they are making a loss. For this reason, given how the variable has been defined, the expected sign of the coefficients α_3 and β_3 is negative.

We also include in the regression three economic-financial indicators that measure the liquidity (*Liq*), the indebtedness (*Indebt*) and the return on equity (*ROE*) of the company with a one-year lag, to examine to what extent the initial economic-financial situation of the company affects the analysts' forecasts accuracy. Assuming that it is more difficult to forecast earnings for firms that are in a worse situation, we expect the coefficients of the *Liq* and *ROE* variables to be negative (α_4, β_4, α_6 and β_6), and that of the *Indebt* variable (α_5 and β_5) to be positive.

On the other hand, it should also be highlight that the economic stability of the environment in which the company operates may affect the forecasts and the errors made. It is logical to think that, in a situation of economic stability, it is easier to forecast with fewer errors than in a context of instability. In this regard, Goedhart, Raj and Saxena (2010) conclude that analysts tend to underreact to negative gross domestic product news, leading to less accurate forecasts when economic growth declines. For this reason, we have introduced the variable *VarGDP* expecting that when instability is greater and, therefore, this variable reaches higher values, the deviations of the forecasts will be greater, i.e. we expect the sign of the coefficients α_7 and β_7 to be positive. We also include *Inflation* as a macroeconomic variable expecting that the sign of the coefficients α_8 and β_8 will be positive, as more inflationary environments are more unstable and more difficult to forecast.

The explanatory variables related to the stock market index in which the companies are listed, namely return (*MarketReturn*) and capitalization (*MarketCapit*), are included to control for the effect that the market may have on the prediction error. Larger and more profitable markets may attract more analyst interest, potentially leading to more accurate forecasts. A priori, both variables can be expected to have a favorable influence on forecast deviations, so the expected sign of their coefficients (α_9, β_9, α_{10} and β_{10}) is negative; the higher the profitability and capitalization, the lower the deviation. Other variable relative to the stock index which may influence on forecast error is the volatility, since when volatility is high it is more difficult to forecast the earnings. Nevertheless, we do not include it on the model because of the high correlation with other variables (see Appendix 2)

Uncertainty variable refers to the uncertainty avoidance index proposed by Hofstede (1980) as a national culture dimension. It can be defined as the extent to which the members of a culture feel threatened by ambiguous or unknown situations. Cultures with high indexes (strong uncertainty avoidance) tolerate uncertainty worse, have more fear of the unknown and, therefore, prefer the rules. A low index (weak uncertainty avoidance) indicates more flexibility to face changes, more tolerance to uncertainty. We included this variable because, as previously mentioned, the uncertainty generated by Covid-19 was very high and difficult to manage. Building on the results of studies such as Amiram et al. (2018), which evidences that the forecasts are less accurate when the uncertainty is high, we expect that in cultures with strong uncertainty avoidance (high index) the forecasts deviations will be higher. So, we expect the sign of the coefficients α_{11} and β_{11} to be positive.

Finally, *Stringency* variable is included to consider the possible influence of the actions taken by the governments to curb the spread of the pandemic on analysts and on the forecasts′ deviations. We use the Stringency Index provided by Oxford COVID-19 Government Response Tracker (OxCGRT) dataset, a composite measure of nine metrics: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls.

The index takes a value between 0 and 100 and we take the logarithm. A higher score indicates a stricter action. It's important to note that this index simply records the strictness of government policies. It does not measure or imply the appropriateness or effectiveness of a country's response. Government anti-Covid policies became stricter as the pandemic became more difficult to control and generated more health and economic uncertainty, so it is to be expected that the higher the index, the higher the forecast error (positive sign of the α_{12} and β_{12} coefficients). We use the *Stringency* index on two dates: January 1, year *t*, when the dependent variable is $\left| D_{12,i,t} \right|$, and September 30, year *t*, when the dependent variable is $\left| D_{3,i,t} \right|$.

In order to consider not only the effect of the pandemic itself, but also the effect it may have had on the influence of other variables on the prediction errors, we include as explanatory variables the products of the *Crisis* variable by each of the other firm variables (*Analysts, PoL, Liq, Indebt, ROE)*. Thus, if, for example in equation (2), the *PoL* variable is significant with negative α_3 and the *Crisis x PoL* variable is also significant with negative α_{14}, we would interpret that when the firm is profitable the forecasts deviation 12 months in advance is smaller (α_3 <0), but that this effect is even more pronounced in the context of a pandemic crisis (α_3+ α_{14}). The interpretation would be the same for deviation 3 months advance if in equation (3) coefficients β_3 and β_{14} were negative.

We also include the product of *Crisis* by *Uncertainty*, since we believe that the way uncertainty is managed can have a different effect on the analysts' forecasts accuracy in such acute crisis situations. Products of *Crisis* by the rest of variables are not included because these variables show the same value for all firms in a period and they are highly linked to crisis or not crisis period.

Table 3 presents the descriptive statistics and frequencies of the variables. To avoid outliers introducing bias into the results, we winsorized the variables at 5%. The correlations between variables are shown in Appendix 2.

Table 3. Descriptive statistics and frequencies for the variables analyzed

	Min.	Max.	Mean	Standard dev.
$\lvert D_{12} \rvert$	0.000	1.833	0.344	0.336
$\lvert D_3 \rvert$	0.000	1.645	0.316	0.323
Analysts	1.000	55.000	14.130	7.192
Liq	0.353	4.356	1.598	0.790
Indebt	0.094	14.124	0.847	1.400
ROE	-1.388	0.508	0.112	0.110
VarGDP	0.001	0.113	0.037	0.028
Inflation	-0.003	0.083	0.016	0.019
MarketReturn	-0.143	0.288	0.111	0.108
MarketCapit	0.002	0.576	0.089	0.123
Uncertainty	1.462	1.964	1.795	0.187
Stringency12	0.000	1.916	0.639	0.849
Stringency3	0.000	1.832	1.133	0.807
Dichotomous variables (frequencies)				
	Percentage	*Cumulative percentage*		
Crisis				
0	66.67	66.67		
1	33.33	100.00		
PoL				
0	11.50	11.50		
1	88.50	100.00		

As expected, the mean deviation of forecasts made 12 months before the year-end is higher than when forecasts are issued only 3 months in advance. Companies in the sample have on average adequate liquidity, return on equity of 11.00% and use more equity than borrowed funds to finance themselves. Earnings are positive in the 88.50% of the cases, only 11.50% are losses. The average number of analysts covering the companies in the sample is 14. In terms of economic stability, the average year-on-year change (in absolute values) in GDP over the period analyzed was 3.70%. Although, it is worth mentioning that in 2019 GDP experienced an average increase of 0.57%, in 2020 it suffered an average decrease of 6.00% and in 2021 the average change was positive, at 4.00%. The average inflation rate was 1.60%. Related to the stock markets, the stock market index return was 11.10%. The uncertainty avoidance index ranges from 29 (1.462 in logarithm), in the case of Hong Kong, to 92 (1.964 in logarithm), in the case of Japan. Finally, the average stringency index is higher three months before year-end than twelve months before.

5. RESULTS

Firstly, given that the rest of the paper refers to the absolute value of the deviations, we study the sign of these deviations. The descriptive statistics of forecast deviations by country are shown in Appendix 3.

Table 4 shows that, in the set of companies analyzed, in both 2019 and 2020 the predictions were optimistic with respect to the results obtained by the companies in a greater proportion of them. However, in 2021 this trend changed, with the deviations being mostly negative, i.e. the predicted result was lower than the actual result.

Table 4. Sign of deviations

	D_{12}			D_3		
	2019	**2020**	**2021**	**2019**	**2020**	**2021**
Over-estimation	60.26%	64.03%	31.75%	56.43%	50.00%	37.14%
Under-estimation	39.74%	35.77%	68.25%	43.57%	50.00%	62.86%

Over-estimation: forecast > earnings; Under-estimation: forecast < earnings

In relation to D_{12}, in the year of the pandemic a positive value is observed in a higher proportion of companies than in 2019. However, 3 months before the year-end, when the pandemic had already hit, the predictions were more conservative in relation to the earnings finally achieved, reducing the proportion of positive D_3.

The pessimism in the predictions clearly extended to 2021, where both D_{12} and D_3 showed mostly negative values. The earnings achieved by the companies exceed in most cases the analysts' forecasts, as the latter were probably negatively influenced by the circumstances of the previous year.

The situations described above are shared by most of the countries analyzed (see Appendix 4). In some of them, the effects of the crisis derived from Covid-19 seemed to be detected by analysts as early as D_{12} of 2020, as there was a decrease in the percentage of companies with positive deviations with respect to the previous year. This is the case for Brazil, Spain, the UK and USA. However, in all of them, the adjustment of the forecasts was clearly observed in those made 3 months before the year-end.

On the other hand, in some countries the drag effect caused by the pandemic on analysts' forecasts in 2021 seemed to be recovered in the forecasts 3 months before year-end. Thus, the proportion of positive D_3 values increased in that year with respect to those observed the previous year in countries such as Germany, Canada, Hong Kong, the UK and USA.

However, Hong Kong presents a somewhat different situation. Not only are the deviations mostly negative in all predictions, especially D_3, but there is also a very significant increase of that negative sign in the predictions referring to 2019 and made 3 months before the closing with respect to those of 12 months before. This may be related to the fact that the Covid-19 cases in that geographic area emerged already at the end of that year, and therefore analysts adjusted their predictions downwards in a very significant way.

5.1. Analysis of differences in deviations between the years: 2019, 2020 and 2021.

In this section we examine the existence of statistically significant differences in forecast errors between the three years under study. The analysis is carried out for deviations in analysts' forecasts 12 months before year-end (D_{12}) and 3 months before year-end (D_3).

For the longer period, the results obtained from the non-parametric Friedman test (Table 5) indicate the existence of significant differences in the forecast errors for the years 2019, 2020 and 2021. In other words, we can confirm that, for the set of companies in the sample, the forecasts accuracy varied depending on the year under study.

Table 5. Friedman's test results for D_{12} and D_3

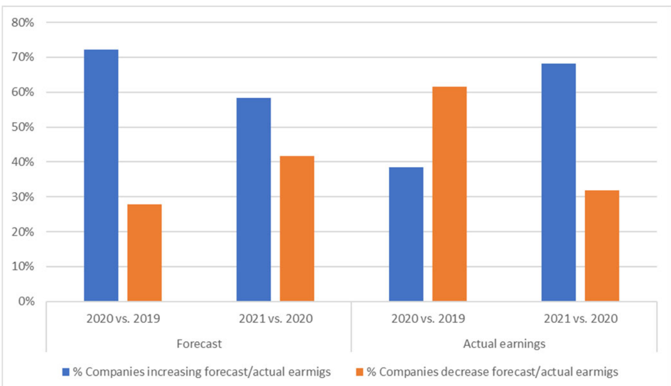
	D_{12}	D_3
Statistics		
Chi-square	65.085	48.160
Asymptotic sig.	0.000	0.000
Mean ranks		
2019	1.69	1.73
2020	2.21	2.15
2021	2.10	2.12

The analysis of the mean ranks in Table 5 shows that in the year in which Covid-19 was launched, the discrepancies between predictions and reality were substantially larger than in 2019. Already in the later year, 2021, although the deviations are still higher than in 2019, they are reduced compared to 2020.

These results indicate that the surprise outbreak of the pandemic in 2020 had a clear effect on the level of accuracy of analysts' forecasts. Recall that the first case of Covid-19 appears to have been documented in China in December 2019. At that time, nor in the first months of 2020 did anyone foresee that this virus would reach pandemic levels. Analysts did not incorporate this information and the effect that this problem was going to have on the economy in general and on companies' earnings in particular into their predictions at the beginning of 2020.

Indeed, as can be seen in Graphic 1, analysts increased their earnings forecasts for 2020 compared to the forecasts for 2019 in 72.08% of the companies in the sample. On the other hand, the earnings reached by these companies in 2020 were mostly reduced (in 61.54% of cases) compared to earnings in 2019. This optimistic behavior of analysts in their forecasts at the beginning of 2020 and the significant decrease in corporate earnings in that year as consequence of the pandemic, largely explain the significant increase observed in the forecast deviations.

Graphic 1. % of companies increasing/decreasing forecast and actual earnings for D_{12}



In 2021, with better information, analysts refined their predictions, although, the error was higher than two years earlier. The volatility that the pandemic incorporated into economic magnitudes and business operations undoubtedly justifies this fact.

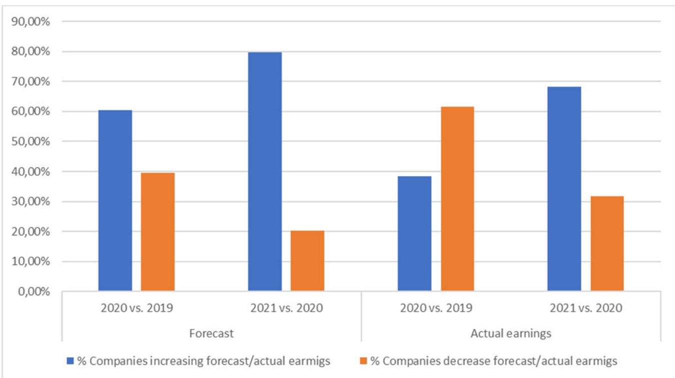
In this respect, Graphic 1 shows again that only for the 58.26% of the companies in the sample the analysts' forecasts were higher in 2021 than in 2020. We can also see that the corporate earnings increased in 68.16% of the cases. Thus, the lower optimism of analysts and the increase in corporate earnings meant that the confluence between the two was greater in 2021 than in 2020.

If we refer the analysis to the forecasts 3 months before the year-end, the results obtained also show significant differences between the deviations observed in three financial years (Table 5).

The evolution of these deviations is similar to that discussed above. There is a notable increase in the forecast error in 2020, softening somewhat in 2021, while without falling to the levels of 2019. Although, the virus was already widespread worldwide at the time of the prediction, its effects on the results were not sufficiently adjusted in the analysts' forecasts.

This is evident in Graphic 2, where we can see that analysts increased their forecasts in 2020 compared to those in 2019 in 60.39% of the cases, while, on the contrary, earnings decreased in 61.54% of the companies.

Graphic 2. % of companies increasing/decreasing forecast and actual earnings for D_3



Finally, it is interesting to compare the behavior of the forecasts at both time horizons based on the mean ranks obtained from the Friedman test. As we have already indicated, in both D_{12} and D_3 the forecast error increased significantly in 2020, and then was decreasing in the following year. However, the increase observed in the pandemic year is substantially larger in D_{12} than in D_3.

We can explain this by the knowledge that existed at both points in time regarding the problem we were facing. In D_3, analysts were already aware of the magnitude of the pandemic and discounted, although not fully, but the effect it could have been observed in companies' earnings. This may account for the larger deviation observed in D_{12} relative to D_3 and the change of it respect to 2019. A comparison of the results in Graphic 1 and 2 shows this fact. The earnings forecasts increased in most cases in D_{12} and in D_3, but in D_3 less markedly (72.08% of cases compared to 60.39%), while actual earnings decreased in most cases. This downward adjustment of forecasts continued in the 12-month forecasts made in 2021; however, the 3-month forecasts predicted more positive performance (79.69% of the forecasts were more optimistic), as was the case (68.16% of the companies increased their earnings).

This downward adjustment in forecasts made 3 months before the end of 2020 is consistent with the results obtained by Hao *et al.* (2022), as they confirmed the negative impact of Covid-19 on the forecasts. However, they are contrary to those obtained by other studies in relation to other previous crises, see studies of Ackert and Hunter (1995), Loh and Mian (2003), Zhang (2006), Basu, Markov and Shivakumar (2010), Hann, Ogneva and Sapriza (2012) and Hugon, Kumar and Lin (2016). They all found that analysts tend to underreact to bad news. One possible explanation is that the unprecedented and unexpected effects of the pandemic at all levels generated an extreme shock among analysts compared to other crises, inducing analysts to overreact in a pessimistic manner.

5.2. Analysis of differences in deviations across countries

In order to analyze whether the behavior of the deviations across countries is homogeneous or not over the years under study, we performed the non-parametric Kruskal-Wallis test.

The results obtained for both D_{12} and D_3 (Table 6) show that there are significant differences in the prediction errors between the eight countries analyzed in all years. These differences cannot be attributed to the outbreak of the pandemic, given that they already exist in 2019 and continue in the following years.

Table 6. Kruskal-Wallis test results for D_{12} and D_3.

	D_{12}			D_3		
Statistics	**2019**	**2020**	**2021**	**2019**	**2020**	**2021**
Chi-square	51.544	38.093	31.355	42.449	26.962	78.228
Asymptotic sig.	0.000	0.000	0.000	0.000	0.001	0.000
Ranks						
$D_{m\ Brazil}$	325.88	265.24	349.68	328.54	297.42	426.89
$D_{m\ Canada}$	298.16	275.21	286.49	296.48	251.96	218.84
$D_{m\ France}$	287.74	326.69	265.67	303.81	291.56	230.78
$D_{m\ Germany}$	241.88	280.68	232.61	231.34	295.70	206.50
$D_{m\ Hong\ Kong}$	280.32	248.76	316.82	247.63	238.09	267.66
$D_{m\ Japan}$	228.96	217.06	254.63	254.17	264.23	275.47
$D_{m\ Spain}$	296.42	293.78	351.34	255.26	316.61	285.39
$D_{m\ UK}$	414.43	375.37	283.04	411.71	381.16	317.60
$D_{m\ US}$	198.24	222.44	267.87	187.76	205.54	198.90

The mean ranks in Table 6 show that no ordering of countries according to the magnitude of the deviations persists over time. Nor is there a pattern of behavior that could be associated with the Covid-19 effect (prediction errors are also heterogeneous in 2019 and 2021).

5.3. Variables explaining deviations in analysts' forecasts

To examine which variables do explain the forecasts' deviations and to what extent the crisis triggered by Covid-19 influences them, we run the multivariate linear regression for the two selected time scales (equations 2 and 3).

The results referring to the forecasts' error 12 months (D_{12}) and 3 months (D_3) before the year-end can be seen in Table 7.

In relation to the impact of the pandemic on the **prediction error 12 months before the year-end**, the main variable is *Crisis*, which is significant, with a positive coefficient (α_1= 1.153). The deviation is therefore larger in 2020 than before and after the pandemic. Analysts' forecasts prior to the global expansion of Covid-19 did not take into account the expected effect of Covid-19 on companies' earnings. As a result, prediction errors were higher. This is consistent with the univariate tests results. Moreover, the value of α_1 is higher than the other coefficients, which indicates that *Crisis* is the variable with the most weight in explaining the prediction error.

Table 7. Regression results for D_{12} (equation 2) and D_3 (equation 3)

$$\left|D_{12,i,t}\right| = \alpha_0 + \alpha_1\, Crisis_t + \alpha_2\, Analysts_{it} + \alpha_3\, PoL_{it} + \alpha_4\, Liq_{it-1} + \alpha_5\, Indebt_{it-1} + \alpha_6\, ROE_{it-1} + \alpha_7\, VarGDP_{ct} + \alpha_8\, Inflation_{ct} + \alpha_9\, MarketReturn_{ct} + \alpha_{10}\, MarketCapit_{ct} + \alpha_{11}\, Uncertainty_c + \alpha_{12}\, Stringency_{12,c,t} + \alpha_{13\text{-}18}\, Crisis_t \, x\, X + e_{it} \qquad (2)$$

$$\left|D_{3,i,t}\right| = \beta_0 + \beta_1\, Crisis_t + \beta_2\, Analysts_{it} + \beta_3\, PoL_{it} + \beta_4\, Liq_{it-1} + \beta_5\, Indebt_{it-1} + \beta_6\, ROE_{it-1} + \beta_7\, VarGDP_{ct} + \beta_8\, Inflation_{ct} + \beta_9\, MarketReturn_{ct} + \beta_{10}\, MarketCapit_{ct} + \beta_{11}\, Uncertainty_c + \beta_{12}\, Stringency_{3,c,t} + \beta_{13\text{-}18}\, Crisis_t \, x\, X + e_{it} \qquad (3)$$

X = Analysts, PoL, Liq, Indebt, ROE, Uncertainty.

	***D*$_{12}$ (equation 2)**			***D*$_3$ (equation 3)**		
	Standardised coefficients	**t-statistic**	**Significance**	**Standardised coefficients**	**t-statistic**	**Significance**
Crisis	α_1 1.153	1.956	**0.051**	β_1 0.119	0.218	0.828
Analysts	α_2 -0.032	-0.777	0.437	β_2 -0.033	-0.800	0.424
PoL	α_3 -0.191	-5.154	**0.000**	β_3 -0.347	-8.920	**0.000**
Liq	α_4 -0.009	-0.212	0.832	β_4 -0.032	-0.724	0.470
Indebt	α_5 0.047	1.041	0.298	β_5 -0.022	-0.506	0.613
ROE	α_6 -0.113	-3.084	**0.002**	β_6 -0.082	-2.222	**0.027**
VarGDP	α_7 0.132	2.360	**0.019**	β_7 0.033	0.578	0.563
Inflation	α_8 0.100	1.598	0.110	β_8 0.004	0.069	0.945
MarketReturn	α_9 -0.106	-2.374	**0.018**	β_9 -0.064	-1.387	0.166
MarketCapit	α_{10} -0.071	-1.374	0.170	β_{10} -0.077	-1.556	0.120
Uncertainty	α_{11} -0.114	-2.242	**0.025**	β_{11} -0.164	-3.242	**0.001**
Stringency$_{12}$	α_{12} -0.067	-1.467	0.143	β_{12} 0.018	0.417	0.676
*Crisis*Analysts*	α_{13} -0.003	-0.039	0.969	β_{13} -0.058	-0.772	0.440
*Crisis*PoL*	α_{14} -0.708	-7.409	**0.000**	β_{14} -0.341	-3.908	**0.000**
*Crisis*Liq*	α_{15} 0.029	0.324	0.746	β_{15} 0.053	0.612	0.540
*Crisis*Indebt*	α_{16} 0.092	0.686	0.493	β_{16} 0.152	1.171	0.242
*Crisis*ROE*	α_{17} 0.027	0.512	0.609	β_{17} -0.069	-1.360	0.174
*Crisis*Uncertainty*	α_{18} -0.515	-0.982	0.326	β_{18} 0.213	0.437	0.676
	F=25.224 Sig. 0.000 Adjusted R-Squared =0.326 N=1,838			F=27.433 Sig. 0.000 Adjusted R-Squared =0.340 N=1,905		

The *PoL* variable is also significant, showing a lower prediction error in companies with positive earnings (α_3= -0.191). The prediction of negative earnings appears to be more difficult. Moreover, this complexity is significantly increased by the effect of the pandemic. In pandemic period, the difference between deviations for firms with positive earnings and for loss-making firms are greater (α_{14}= -0.708 and α_3+ α_{14}= -0.899). Analysts adjust their forecasts better when the company reach positive earnings. It is unquestionable that Covid-19 significantly reduced corporate earnings, in some cases pushing companies into unexpected losses. This was difficult for analysts to anticipate and to capture in their forecasts.

Similarly, higher return on equity makes the forecasts more accurate (α_6= -0.113). In other words, a better economic situation has a positive effect on the accuracy of forecasts. The outbreak of the pandemic did not significantly modify this evidence (α_{17} is not significant).

The degree of instability of the country's economy (*VarGDP*) and the return on the stock market index in which the firms are listed (*MarketReturn*) are also significant. In more unstable economies companies' earnings are more difficult to forecast by analysts, so the forecast errors are higher (α_7= 0.132). By contrast, the relation between *MarketReturn* and forecast error is negative (α_9= -0.106), meaning that analysts´ forecasts are more accurate in more profitable stock markets.

Finally, *Uncertainty* variable is also significant and negatively related with forecast error (α_{11}= -0.114). It means that in countries where uncertainty avoidance is greater the forecasts are more accurate, contrary to expectations. This discrepancy could be due to the fact that in environments with high uncertainty avoidance, analysts are more cautious, evaluating a wider range of factors for their predictions, which can lead to more accurate forecasts. Covid-19 did not significantly affect to the relation between Uncertainty and analysts´ forecasts error (*Crisis x Uncertainty* is not significant).

If we transfer this analysis to the **forecasts made 3 months before earnings release**, the *Crisis* variable is no longer significant. By the end of 2020, the pandemic had already been declared and analysts were able to adjust their predictions, at least in part, to the effects of the new situation on business performance. Prediction errors therefore did not vary significantly by Covid-19.

As in D_{12}, the economic position of the company is relevant. The sign of the earnings (*PoL*) has a significant impact on the deviations, also in the same direction (β_3= -0.347). The impact of this variable on the prediction error is also significantly affected by Covid-19 (β_{14}=-0.341), indicating that analysts make less error in profit forecasting than in loss forecasting and that this is more accentuated during the Covid-19 crisis (β_3+ β_{14}= -0.688) also when forecasts are made three months before year-end.

Similarly, when return on equity is lower the earnings are more difficult to predict and forecasts are less accurate (β_6= -0.082). The pandemic did not significantly modify this evidence (β_{17} is not significant).

The effect of uncertainty avoidance on forecasts made 3 months in advance is also significant. As in D_{12}, where uncertainty avoidance is greater the forecasts errors are lower (β_{11}=-0.164) and this relation was not modified by the crisis due to Covid-19.

6. CONCLUSIONS

The aim of the study is to determine the impact of Covid-19 on the adequacy of analysts' forecasts to actual companies' earnings and to know to what extent other variables (company, macroeconomic and country variables) affect the prediction error and evaluated whether the pandemic modified this effect.

In the countries analyzed, forecast errors were higher in 2020 than in 2019 and 2021. This situation arose primarily because analysts' forecasts did not adequately capture the significant decline in companies' earnings in the year of the pandemic.

We have also observed that the increase in the prediction error in forecasts made 12 months before the year-end was significantly higher than that arising from predictions made 3 months in advance. Evidently, analysts at the end of 2020 already knew, although not in full, the magnitude of the crisis and discounted this information in their predictions. At the beginning of that year, nothing foresaw that the health crisis would reach pandemic levels and, therefore, the impact would have on the global economy.

In terms of the sign of the forecast errors, we found that in both 2019 and 2020, forecasts were substantially optimistic. This reaffirms the previous interpretation, in the sense that in the year of the pandemic, analysts were unable to anticipate the real impact that the pandemic was going to have. However, in the year after Covid-19, in 2021, this situation was clearly reversed, with analysts predicting earnings that were mostly lower than those actually achieved.

The above conclusions can be extended to each of the nine countries in our sample. However, this does not mean that the performance of the analysts has been the same in each of them. We have shown that there were significant differences in the prediction errors among the nine countries in the sample, and that these were observed in the three exercises under study. This leads us to conclusion that these divergences across countries cannot be attributable to the drastic changes generated by the pandemic.

Regarding the influence of the variables analyzed on the prediction error, the analysis carried out reaffirms that the pandemic significantly increased this error in the forecasts made 12 months before year-end. However, the effect is no longer significant in forecasts made 3 months in advance, when analysts and society in general, were already aware of the crisis caused by the pandemic.

In addition to this evidence, we found that analysts' forecasts were more accurate when the companies' earnings are positive or when the return on equity of the company is higher. Likewise, in countries where the uncertainty avoidance is greater the forecasts are more accurate probably due to the analysts are more cautious in their forecasts, especially in times of crisis.

The impact of some of these variables was significantly altered in the year of the pandemic. Thus, in 2020, the forecast errors were even larger for loss-making firms than for profit-making ones. It is due to the effect of the crisis on the impact of the earnings´ sign on analysts´ forecasts.

Our study contributes to the literature by providing new evidence on how the Covid-19 crisis affected the accuracy of analysts' forecasts in a global environment of nine countries from different geographical areas, with different levels of economic stability and different cultures. The findings have important implications for the usefulness of analysts' forecasts. These forecasts must be interpreted taking into account the environment in which they are made, given that their accuracy and, therefore, their usefulness are affected in crisis situations due to the fact that earnings are more volatile and more difficult to predict. Moreover, we should not forget that the economic situation of each company, the characteristics of the stock markets and the way in which uncertainty is managed also affect the forecasts accuracy.

The study has some limitations derived from the existence of other variables that may affect the forecast accuracy and that have not been considered. Also, the impact of Covid 19 did not manifest at the same time or homogeneously in all countries, which may also affect the results. Finally, the peculiarities of the nine countries and markets included in the sample must be taken into account in order to generalize the conclusions obtained.

From the study carried out and its limitations, we derive some potential areas for future research. It may be interesting to study the impact of other variables alternative to those used in the forecast accuracy or to extend the sample to other countries and markets. Also, given the peculiarities of the crisis caused by the pandemic, the impact of Covid 19 could be compared with that of other previous financial crises.

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Appendix 1: Sample characterization by country

millions of euros		Min.	Max.	Mean	Standard dev.
Brazil	Assets 2021	847	2000797	155278	390729
	Earnings 2021	-7222	121228	7541	20470
	Equity 2021	-21054	387329	31415	66593
Canada	Assets 2021	2892	1726407	179089	383031
	Earnings 2021	1188	15781	2660	3220
	Equity 2021	-134	99818	20776	22160
France	Assets 2021	8244	2625819	237671	567100
	Earnings 2021	-1020	24692	3980	5219
	Equity 2021	3157	108679	27071	25469
Germany	Assets 2021	8244	1316077	147194	272596
	Earnings 2021	222	14843	3156	3563
	Equity 2021	896	130010	24735	26616
Hong Kong	Assets 2021	21069	35074621	2643391	6911646
	Earnings 2021	-28426	338731	39223	68677
	Equity 2021	6923	3038038	368272	588752
Japan	Assets 2021	75208	358421843	10365103	38632630
	Earnings 2021	-577900	4957716	116698	395705
	Equity 2021	39477	23404547	1496290	2516656
Spain	Assets 2021	341	1566272	114783	294959
	Earnings 2021	-2933	12677	1549	2960
	Equity 2021	178	86930	11969	17955
United Kingdom	Assets 2021	105	21761983	105807	296585
	Earnings 2021	-2933	15349	1546	2910
	Equity 2021	-4662	146507	12850	23296
USA	Assets 2021	34819	3743567	305455	698371
	Earnings 2021	-4202	94680	16065	20062
	Equity 2021	-14999	294127	54817	60862

Appendix 2: Correlations

	absD12	absD3	Analysts	PoL	Liq	Indebt	ROE	Crisis	VarGDP	Volatility	Market Return	Market Capit	Uncertainty	Inflation	Stringency 12	Stringency 3
absD12	1															
absD3	0.683	1														
Analysts	-0.032	-0.105	1													
PoL	-0.417	-0.448	0.055	1												
Liq	-0.082	-0.072	-0.058	0.086	1											
Indebt	-0.022	-0.043	0.146	0.045	-0.225	1										
ROE	-0.143	-0.171	0.147	0.218	-0.008	0.027	1									
Crisis	0.176	0.124	-0.016	-0.094	-0.031	-0.003	0.040	1								
VarGDP	0.261	0.177	0.231	-0.076	-0.081	0.111	0.002	0.572	1							
Volatility	0.255	0.214	0.048	-0.110	-0.041	0.013	-0.012	0.915	0.821	1						
MarketReturn	-0.267	-0.247	0.031	0.125	0.039	-0.019	0.014	-0.479	-0.505	-0.805	1					
MarketCapit	0.047	-0.043	0.419	0.034	-0.149	0.149	0.316	-0.026	0.162	0.000	0.007	1				
Uncertainty	-0.093	0.010	-0.314	-0.044	0.116	-0.292	-0.163	0.000	-0.38	0.058	0.266	-0.642	1			
Inflation	0.086	0.121	-0.036	0.042	-0.028	0.014	0.104	-0.323	-0.001	-0.428	0.247	0.589	-0.16	1		
Stringency12	0.011	0.034	0.112	0.031	0.024	0.076	-0.139	-0.437	0.216	-0.336	0.024	-0.011	-0.104	0.311	1	
Stringency3	0.181	0.157	0.058	-0.068	-0.008	0.012	-0.109	0.479	0.509	0.589	-0.526	-0.010	-0.038	0.025	0.546	1

Appendix 3. Descriptive statistics for D_{12} and D_3 by country

		D_{12}			D_3		
		2019	2020	2021	2019	2020	2021
Brazil	Minimum	-1.231	-1.222	-0.903	-0.987	-0.943	-1.005
	Maximum	0.845	0.727	1.015	0.763	0.551	0.026
	Mean	-0.098	-0.160	-0.176	-0.063	-0.248	-0.683
	Standard deviation	0.490	0.546	0.541	0.426	0.393	0.308
Canada	Minimum	-0.985	-1.322	-0.862	-1.373	-0.826	-0.436
	Maximum	0.870	1.552	0.715	0.578	0.667	1.110
	Mean	-0.027	0.114	-0.166	-0.124	-0.105	0.042
	Standard deviation	0.471	0.702	0.393	0.468	0.386	0.367
France	Minimum	-0.161	-0.980	-0.902	-0.205	-1.262	-1.038
	Maximum	0.847	1.301	0.707	1.007	1.397	0.625
	Mean	0.227	0.392	-0.136	0.207	0.111	-0.021
	Standard deviation	0.304	0.626	0.408	0.318	0.640	0.386
Germany	Minimum	-0.168	-1.290	-0.588	-0.255	-1.400	-0.359
	Maximum	0.744	0.705	0.475	0.870	0.657	0.409
	Mean	0.168	0.156	-0.070	0.143	-0.117	0.063
	Standard deviation	0.248	0.538	0.307	0.281	0.572	0.213
Hong Kong	Minimum	-0.896	-0.971	-0.988	-0.899	-0.963	-0.884
	Maximum	0.726	0.776	0.789	0.398	0.231	0.586
	Mean	-0.098	-0.040	-0.157	-0.148	-0.238	-0.110
	Standard deviation	0.418	0.482	0.499	0.344	0.369	0.408
Japan	Minimum	-0.355	-1.182	-0.708	-0.428	-1.190	-0.985
	Maximum	0.828	1.038	0.678	0.658	0.899	0.622
	Mean	0.090	0.092	-0.135	0.078	0.078	-0.172
	Standard deviation	0.266	0.498	0.339	0.257	0.489	0.381
Spain	Minimum	-1.368	-1.833	-1.540	-1.642	-1.269	-1.519
	Maximum	0.469	0.799	0.180	0.349	1.317	0.129
	Mean	-0.013	-0.291	-0.493	-0.153	-0.182	-0.372
	Standard deviation	0.469	0.870	0.465	0.563	0.626	0.473
United Kingdom	Minimum	-0.886	-1.387	-1.314	-0.952	-1.645	-0.538
	Maximum	0.987	1.614	0.492	0.866	1.154	0.857
	Mean	0.383	0.311	-0.094	0.311	-0.006	0.293
	Standard deviation	0.548	0.918	0.529	0.513	0.874	0.399
USA	Minimum	-0.083	-0.240	-0.669	-0.058	-0.533	-0.169
	Maximum	0.497	1.293	0.783	0.372	0.650	1.018
	Mean	0.115	0.320	-0.040	0.080	0.000	0.144
	Standard deviation	0.166	0.466	0.406	0.124	0.314	0.333

Appendix 4. Sign of deviations by country

		D_{12}			D_3		
		2019	**2020**	**2021**	**2019**	**2020**	**2021**
Brazil	**Positive deviations**	43.75%	38.81%	30.77%	42.65%	28.77%	7.02%
	Negative deviations	56.25%	61.19%	69.23%	57.35%	71.23%	92.98%
Canada	**Positive deviations**	60.71%	63.46%	27.27%	53.57%	33.93%	50.00%
	Negative deviations	39.29%	36.54%	72.73%	46.43%	66.07%	50.00%
France	**Positive deviations**	74.29%	81.48%	34.21%	72.97%	54.29%	51.28%
	Negative deviations	25.71%	18.52%	65.79%	27.03%	45.71%	48.72%
Germany	**Positive deviations**	70.59%	83.87%	50.00%	65.71%	56.76%	57.89%
	Negative deviations	29.41%	16.13%	50.00%	34.29%	43.24%	42.11%
Hong Kong	**Positive deviations**	43.55%	49.15%	40.00%	29.03%	28.13%	40.00%
	Negative deviations	56.45%	50.85%	60.00%	70.97%	71.88%	60.00%
Japan	**Positive deviations**	60.85%	71.00%	27.83%	60.85%	67.68%	29.05%
	Negative deviations	39.15%	29.00%	72.17%	39.15%	32.32%	70.95%
Spain	**Positive deviations**	70.37%	50.00%	16.67%	57.14%	37.50%	21.88%
	Negative deviations	29.63%	50.00%	83.33%	42.86%	59.38%	78.13%
United Kingdom	**Positive deviations**	80.95%	78.95%	41.67%	76.19%	64.00%	84.00%
	Negative deviations	19.05%	21.05%	58.33%	23.81%	36.00%	16.00%
USA	**Positive deviations**	76.00%	70.37%	33.33%	76.00%	50.00%	53.33%
	Negative deviations	24.00%	29.63%	66.67%	24.00%	50.00%	46.67%

Positive deviations: forecast > earnings; Negative deviations: forecast < earnings