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Abstract

Target prices are an estimation of the future value of a company's stock price. Although there is a general consensus about the importance of firm's fundamentals when forecasting, there are also other determinants. This article sheds light on the effects of uncertainty, financial stress and volatility on target price estimations. To do so, different indicators are elaborated for the eight main Spanish financial entities from 1999 to 2020. They show that, on average, analysts have an optimistic bias in their valuations, and tend to react with a delay to stock movements. The different measures of uncertainty, financial stress and volatility affect their estimations a) fostering the optimistic bias, b) reducing the speed and c) willingness of the adjustment to share price movements, and d) make them trust less on stock prices as indicators of banks' fundamentals. This effects are reinforced by the aggregation method of the composite target price (in particular the role of the older individual contributions). Both factors work in tandem: as the more uncertain the economic and financial environment is, the less likely aggregate target prices would move according to stock prices, because older individual contributions will slow the adjustment process. A simple change in the aggregation method reduces its impact on the indicators, without substantially altering their conclusions.

Keywords: target price, analyst forecast, financial analyst, analyst bias, uncertainty.

JEL classification: G14, G17, G41.

Resumen

Los precios objetivo son una estimación del valor futuro de la cotización de una empresa. Aunque hay un consenso general sobre la importancia de los fundamentales de las empresas a la hora de hacer previsiones, existen también otros determinantes. Este documento explica los efectos de la incertidumbre, el estrés financiero y la volatilidad sobre las estimaciones del precio objetivo. Para ello, se elaboran varios indicadores para las ocho principales entidades financieras españolas desde 1999 hasta 2020. Estos muestran que, en promedio, los analistas tienen un sesgo optimista en sus valoraciones y tienden a reaccionar con retardo a los movimientos de las acciones. Las diferentes medidas de incertidumbre, estrés financiero y volatilidad afectan a sus estimaciones: a) fomentando el sesgo optimista; b) reduciendo la velocidad y c) la voluntad de ajuste a los movimientos del precio de las acciones, y d) haciendo que confíen menos en estos últimos como indicadores de los fundamentales de los bancos. Estos efectos se ven reforzados por el método de agregación del precio objetivo compuesto (en concreto, por el papel de antigüedad de las contribuciones individuales). Ambos factores actúan en tándem: cuanto más incierto sea el entorno económico y financiero, menos probable será que los precios objetivos agregados se muevan en función de las cotizaciones bursátiles, ya que las contribuciones individuales más antiguas ralentizarán el proceso de ajuste. Un simple cambio en el método de agregación reduce su impacto en los indicadores, sin alterar sustancialmente sus conclusiones.

Palabras clave: precio objetivo, estimaciones de analistas, analista financiero, sesgos de analistas, incertidumbre.

Códigos JEL: G14, G17, G41.

1. Introduction

Financial analysts fulfill an important role to investors providing market information, preparing reports and making forecast about the companies they follow. Regarding the latter, one of the main products they prepare are the so-called target prices. A target price is the forecast of the expected level of a company's share price over a given time horizon, usually twelve months. Investors can find them in two forms: as individual analyst's estimates, or as an aggregate or consensus target price. The latter is calculated as an average of various contributions that share the same forecast horizon, but are reported over a varying time period.

Target prices offer multiple advantages for investors. One is their accessibility, which helps them reach a wider audience. This is due to two factors: first, they are relatively easy to find. Some of the most common sources are the main market data providers (i.e., Thomson Reuters-Refinitiv, Bloomberg), reports from investment banks, and a multitude of financial information websites, which, in many cases, provide them at no cost (Palley et al., 2019). Secondly, target prices are straightforward to interpret and understand, even for a less sophisticated investor (Brav and Lehavy, 2003).

In comparison with other estimates, like buy-sell recommendations and earnings forecasts, target prices provide a more concise and explicit assessment about the future value of a company by an analyst (Brav and Lehavy, 2003; Li et al., 2021). In addition, they are revised more often than stock recommendations. Another key point is that, while earnings forecasts often focus on the short-term or cover limited periods (e.g., a fiscal quarter), and stock recommendations offer a discrete valuation (i.e., buy, sell, hold), target prices are continuous and cover a longer time period (Bradshaw et al., 2013). Asquit et al. (2005) find that they contain higher information value than other estimates, and Gleason et al. (2013, p. 12) consider them "more granular, more verifiable, and more comparable across analysts" than the buy-sell recommendations.

They also have some advantages to analysts themselves. There is evidence which find that target prices have a greater impact on stock prices than either earnings forecasts or recommendations, and these reactions are immediate, substantial and permanent (Brav and Lehavy, 2003; Asquit et al., 2005). This implies that market participants consider them more credible and relevant than other estimations (Bradshaw et al., 2013), which turns to be an important incentive for analysts to provide target prices. They also allow experts to be more flexible and express their refined views about the investment potential of a company (Asquit et al., 2005).

The articles mentioned above belong to a growing corpus of literature which focus on target prices. There has been a relatively limited research on them, compared with the studies about earnings forecast and stock recommendations (Bradshaw, 2011; Ho et al., 2018). In addition to the common analysis of their precision level and the determinants of the optimistic bias that analysts consistently exhibit, a relevant stream of works is centered around the determinants of target price formation. There is a general consensus about the importance of firm's fundamentals (such as accounting ratios, balance sheets, income statements, earnings per share, or potential growth), but some authors have theorized about other kind of determinants. Clarkson et al. (2013) and Ho et al. (2018) analyze the importance of the non-fundamental factors, like the past behavior of the stocks and psychological biases. Conflicts of interests and analyst's biases has been the focus of a big number of studies on earnings forecasts, buy-sell recommendations, and also target prices.

Among these non-fundamental factors, the general economic and financial situation is one of the potential elements which could influence analyst's estimations. Companies operate in specific sectors, industries and countries, so, it is logical that their performance is affected by this environment. The observation of markets and business situation could be also used as shortcut to facilitate analyst's work, as it may substitute a more intensive study on the fundamentals. There are various analyses that measure their effect on share's prices, earnings forecasts, and recommendations (Baker and Wurgler, 2007; Bagnoli et al., 2009; Ke and You, 2009; Hribar and McInnis, 2012). For target prices, there are also studies focused on this type of non-fundamental factors, like Clarkson et al. (2013) and Ho et al. (2018), while others partially consider this question (Bonini et al., 2010; Bradshaw et al., 2013).

This paper sheds light on the effects of the general economic and financial situation on target prices, considering specifically how uncertainty, financial stress and volatility affects analyst's estimations. Obviously, the exercise of forecasting already implies the notion of uncertainty, because by definition it is the speculation of what will happen in an unknown future. Therefore, if the general degree of uncertainty is higher, the difficulty of the task increases. But these factors could also be influential for additional reasons.

First, uncertainty and volatility have an effect on three important judgment heuristics: representativeness, availability, and anchoring. In their influential work, Tversky and Kahneman (1974) define these heuristics and explain why they lead to systematic and common biases. *Representativeness* is the tendency to rely on one quantity, item, or fact that is thought to be highly representative or resembles another element of interest. Thus, in periods of economic and/or financial uncertainty, current stock prices and movements are not considered representative of their *normal* values, which leads to take them less into account when forecasting future prices. *Availability* refers to the higher reliance on events that can be easily brought to mind, so the familiarity of an occurrence and how recently it took place enhances it. However, uncertain times, by definition, reduces familiarity even if they are currently happening, making analysts less confident about the situation. *Anchoring* happens when individuals make estimates by starting from an initial value, which is then adjusted. Indeed, financial analysts use the last available information of a company to forecast a target price, including their share price. Nevertheless, although volatile and uncertain periods make them less reliable, they tend to anchor their estimates to the values they show on more stable times.

Second, uncertainty, financial stress and volatility affects analysts' forecast dispersion. When the economic and/or financial situation is more variable, it is expected that individual estimates tend to differ more and show more discrepancies. Therefore, there is a reduction of the "herding behavior" and a smaller use of other analyst's reviews as a non-fundamental input in the calculations. Several studies analyzed how the consensus among analysts affect forecast's accuracy (e.g., Clement and Tse, 2005; Huang et al., 2017), some of them using target prices. Moreira et al. (2017) find that if individual estimates are less different their precision level is higher. Palley et al. (2019) focus on the aggregate target price forecast error, which tends to be bigger when dispersion is high. This is due, in their view, to analysts being slower to update their estimates in volatile periods and with deteriorating firm's fundamentals, although it also reflects logical discrepancies among analysts and higher overall uncertainty.

Third, these periods of higher volatility and uncertainty affect the relevance of non-fundamental versus fundamental factors when estimating. Clarkson et al. (2013) points to the higher relevance of the economic and financial situation in context of greater task complexity. Uncertain times can be considered as such, so they would theoretically influence analysts more than in stable periods. Paradoxically, as derived from the previous mention to the judgment heuristics of Tversky and Kahneman (1974), they will turn to rely more on firm's fundamentals when estimating a future price, because they are considered truly representative, familiar, and works as an anchor of the company's actual performance. Both effects, although apparently contradictory, can occur at the same time: when uncertainty is high analysts are indirectly very affected, so they turn their view to fundamental factors.

Fourth, uncertainty and volatility could reduce the speed at which analysts revise and update their forecasts. When the economic and/or financial environment is turbulent and unstable, or when there is a deterioration of firm's fundamentals, analysts may prefer to wait for publishing their estimations until the situation improves. Palley et al. (2019) find that the time between revisions is longer for firms with higher stock price dispersion. Ho et al. (2018) also point out that when there is bad news about a company's situation analysts are slower to reflect them in their estimates, partly because companies are less likely to publish this kind of information (they tend to withhold bad news but release good news promptly).

The potential effects of the aforementioned points are that, in periods of uncertainty and volatility, analysts would differentiate more their target prices from the evolution of stocks. The influence of the past performance of a company's share on the estimation process of different types of estimates (like earnings forecasts, recommendations and target prices) has been well documented in the literature (Heath et al., 1999; Bagnoli et al. 2009; Zuckerman, 2009; Clarkson et al., 2013; Ho et al., 2018). Therefore, it is expected that analysts will rely less on them in unstable times.

In order to evaluate the effects of uncertainty, financial stress and volatility on analyst's estimations, various target price indicators are elaborated to study how they influence i) the optimism/pessimism of the experts about a company's future (i.e., using the Target Price Differential, or TPD); ii) the degree of confidence they have about the use of the stock price as an indicator of the firm's fundamentals (i.e., using the Absolute Target Price Differential, or ATPD); iii) their view on the importance and future impact of share price variations (i.e., using the Trend Differential, or TD); and iv) the speed at which analysts adjust their estimates (i.e., using the LAG indicator).

The analysis is applied to the eight main (listed) Spanish financial institutions from 1999 to 2020, which allows to study the behavior of both stock and target prices over a long time frame, including episodes of economic and financial uncertainty, as well as more stable times. The indicators described above compare the aggregated target prices to stock prices, both obtained from Thomson-Reuters Refinitiv. The use of the aggregate target price instead of individual analysts' estimates responds to three main reasons. First, although there is abundant literature on the latter, the former has been neglected to a certain degree by previous analyses. Second, its use is more widespread among investors because is easier to find and cheaper, frequently even for free (Palley et al., 2019). And third, it benefits from the “wisdom of crowds”, as it represents a balanced view of what analysts think about a given firm and reduces potential individual biases or more extreme observations (Moreira et al., 2017, Palley et al., 2019).

To study how economical and/or financial uncertainty influence analyst’s forecasts, it is necessary to measure this concept. There is a general agreement among economists about the negative impact of uncertainty in economic activity (Baker et al., 2016), but being a non-directly observable element, the empirical strategies to proxy it has been numerous. This is due to some extent to the variety of dimensions in which there may be present, like the future trajectory of a sector or country, political and social developments, regulatory and policy changes, or trends in the financial markets. In order to consider this diversity, this article uses three different indicators calculated for Spain: the Economic Policy Uncertainty index (EPU), the Composite Indicator of Systemic Stress (or CISS), and the Ibex 35 implied volatility index (Vibex). The EPU, based on the initial work of Baker et al. (2016) and refined by Ghirelli et al. (2019) for Spain, employs text-based analysis on newspaper’s articles, and allows to measure the uncertainty related to the general economic and political situation. The CISS, created by Holló et al. (2012) for the euro area countries, captures “the current state of instability, i.e. the current level of frictions, stresses and strains (or the absence thereof) in the financial system” (pag. 4). Finally, the Vibex is elaborated by Bolsas y Mercados Españoles (BME), and focus specifically on the financial volatility of the Spanish stock market, where the main Spanish banks which would be analyzed participated.

Using the four target price indicators mentioned above for Spanish banks shows that, on average, analysts have an optimistic bias in their valuations, and tend to react with a delay to stock movements. When analyzing the impact of the three measures of uncertainty on analyst’s estimations, results show that periods of economic instability, financial stress and volatility i) foster the optimistic bias; ii) reduce the speed and iii) willingness of the adjustment to share price movements (i.e., experts believe to a greater extent that price variations will only have temporary effects on their level at the end of the forecast horizon); and iv) make them trust less on stock prices as indicators of banks' fundamentals.

This effects are reinforced by the aggregation method of the composite target price. In addition to considering its advantages, it is important to notice how it can influence its relationship with the uncertainty measures. When adding individual estimations, there are various possibilities to do so: from a simple average to a weighted-one based on the frequency of the contributions, the analyst's precision record, or the antiquity of their forecasts. In the case of Thomson-Reuters Refinitiv, it is a simple average of individual contributions over a given period of time. Thus, older ones will delay the adjustment of the aggregate target price to the evolution of the stock. In order to consider its impact on the behavior of the indicators mentioned before, it is necessary to control for this factor with a variable which counts the number of days between the oldest individual contribution for a given day and the aggregate's publication date. Results show that the longer this time period, the higher the optimistic bias, the perception of stocks' undervaluation, and the delay on the speed the composite adjust to share price movements. A simple modification on the aggregation method (limiting the oldest contributions) reduces its impact on the target price indicators, without altering their relationship with the different uncertainty and volatility measures.

This results can be useful to interpret how the general economic and financial situation affects target price estimations and analyst's biases. When there is an elevated degree of uncertainty, investors should be aware about what it implies for expert's financial reports and forecasts, and act consequently. Obviously market participants already know that trying to predict the future in unstable periods is more difficult and consider these projections in a different light. But knowing the specific size and impact of this variables could help investors to be more conscious about them.

The main contributions of this paper are the following. First, it adds empirical evidence to the literature focused on target prices, which is smaller than the one related to other types of analyst' estimates (specially earnings forecasts and buy-sell recommendations). It also employs the aggregate or consensus target price instead of individual estimations, which have been used in a much larger number of papers. As Palley et al. (2019, p. 1) puts it: "Despite their prevalence and potential influence on investor behavior, consensus target prices have received relatively little attention in the existing literature".

The second contribution is the novel use of variables which measure the economic and financial uncertainty in the literature about target prices. No previous work has been found employing them, and they can shed light on the topic on how the general economic environment can affect analyst's estimations. While there are articles who focus on this type of non-fundamental factors, they use measures which only grasp the financial markets situation, like the sentiment index of Baker and Wurgler (2007) or the behavior of the stock market (Bonini et al., 2010; Bradshaw et al., 2013; Clarkson et al., 2013; Ho et al., 2018). The use of variables which measure the economic policy uncertainty and the financial system as a whole cover a more general view of the economic situation.

Third, this article measures the impact of uncertainty not in the target price precision or the implied return of a portfolio based on them. The majority of the literature analyses how different factors (like firm or country characteristics, conflicts of interest, psychological biases, or the performance of the stock market) affect one or the other indicator. Instead, this work focus purely on how experts estimate: if they are more or less optimistic (not in comparison with the actual stock price at the end of the forecast horizon, but in the moment they publish the target price), if they consider share's price as a good indicator of the actual value of a company, and if the evolution of such price must be actually consider or it is transitory. This kind of analysis has an additional advantage: it can be performed at the same time the target prices are released, without having to wait until the end of the forecast horizon.

Fourth, the performed analysis considers the role of the aggregation method of the composite target price. Other papers which use the consensus focus on the dispersion among analysts and how it influences the precision level of the estimates (Moreira et al., 2017; Palley et al., 2019). This is the first know work which controls for the fact that the aggregate target price is a moving average, and thus older individual contributions delay the adjustments to stock price movements. It also contributes showing an alternative composite target price, that allows to reduce or eliminate the influence of the aggregation method without substantially altering the main empirical results.

Fifth, it focuses on Spanish banks, where most of the existing analytical articles use data of Anglo-Saxon countries or aggregates of developed nations (notable exceptions are Bonini et al., 2010, who study target prices of Italian companies, or Moreira et al., 2017, whose analysis is carried out for Latin American countries). No previous work has been found focusing on Spain or on specific sectors such as banking. An additional advantage of conducting an analysis with a small number of companies is that it allows to observe possible differentiated behavior among them.

The rest of the paper is organized as follows: Section 2 reviews the literature that focus on the role of the non-fundamental factors in target price' formation. Section 3 explains both the target price and uncertainty indicators that will be used during the analysis. Section 4 describes the behavior of this indicators for the Spanish banks during the period considered in this work. Section 5 provides empirical evidence about the relationship of target prices and uncertainty, employing an econometric analysis. In Section 6 the role of the aggregation method is further discussed. Finally, Section 7 concludes.

2. Literature review

Historically there has been a relatively limited research on target prices compared with the studies about earnings forecasts (Bradshaw, 2011; Ho et al., 2018), but in the last decade their numbers are increasing (see Palley et al., 2019, for an updated literature review). Perhaps the most common approach is the analysis of their precision, i.e. if they meet the stock price at the end of the forecast horizon (Bilinski et al., 2013; Bradshaw et al., 2013; Palley et al., 2019, among many others). Several factors play a role, like firm-specific characteristics (e.g., their size or growth trajectory), aspects of country culture (such as their legal system or accounting information dissemination regulations), and attributes of the analysts themselves (e.g., years of experience, reputation, number of companies they evaluate) (Bilinski et al., 2013). One of the main findings of this studies is the optimistic bias analysts tend to show, so a number of papers tried to determine its drivers (Cowen et al., 2006; Bradshaw et al., 2012; Bradshaw et al., 2019).

Another relevant stream of works focused on the determinants of target price formation (i.e., how they are computed). Considering that they are based on an estimated company's evolution, there is a general consensus about the importance of firm's fundamentals such as accounting ratios, balance sheets, income statements, earnings per share (EPS) or potential growth (Bradshaw, 2002; Gleason et al., 2013). As Brav and Lehavy (2003, p. 1935) put it: "Because target prices are forward looking, we argue that […] they ought to be linked to the underlying fundamental value of the firm". This view is founded by the efficient markets hypothesis by Fama (1965, 1970), where share prices reflect all the relevant information available to investors, so the analysis of fundamentals should provide enough data to estimate the future value of a stock with some certainty. Da et al. (2016) points to one of the main difficulties of these studies: the lack of knowledge about the valuation model used by analysts. It is not directly observable, so in their work they assume a common one which uses both earnings forecasts and price-to-earnings ratio predictions. Their relative importance depends on firm's characteristics like stability or growth potential.

However, some authors have theorized about other kind of determinants. Clarkson et al. (2013), in their reference article, distinguish between fundamental factors (those already mentioned) and non-fundamental factors, such as the past behavior of the stocks and market sentiment. Their importance, in their opinion, lies in the role of psychological biases at the moment of estimation (e.g., the greater weight of more recent financial events versus past developments). After all, a target price forecast "is not intended to be an accurate estimate of the fundamental value. […] if analysts are not convinced that the stock price will reflect the fundamental value over the short term because of exogenous factors, they are likely to adjust the forecast appropriately in light of the identified non-fundamental factors" (Clarkson et al., 2013, p. 33). Ho et al. (2018) are also of the opinion that, when revising their forecast, analysts employ various types of inputs in their underlying valuation models, so they do not only use basic accounting data (such as expected earnings, cash flows or dividends), but rely on other factors like recent market and stock behavior, as well as other analysts' reviews to make assumptions about a company's future growth.

The effects of conflicts of interests and psychological biases on analyst's estimates have been the focus of several studies on earnings forecasts, buy-sell recommendations, and also target prices. Bradshaw (2011) provided a rigorous analysis about conflicts of interest, offering a list of their sources in descending order based on the emphasis given to them in prior literature: investment banking fees, currying favor with management, trade generation, institutional investor relationships, research for hire, and analyst's own behavioral biases (see Section 5 of its paper for more detail). There is also evidence that links conflicts of interest to analyst' optimism in earnings forecasts (Ke and You, 2006), buy-sell recommendations (Arand and Kerl, 2012; Cowen et al., 2006), and target prices (Bradshaw et al., 2012), because experts issue more favorable estimates seeking to maintain a good relationship with the company's management to generate new business opportunities or enhance their personal careers. Mehran and Stultz (2007) gives some ideas to mitigate the adverse impact of conflicts of interest, like stronger competition, the presence of institutional investors, and legal and regulatory actions. Other non-fundamental factors have been also considered, like analyst's nationalities (Bae et al., 2008), characteristics of the institutional investors (Bilinski et al., 2015; Brown et al., 2015), the firm's momentum (based on its current growth and share's trading volume and price) (Jegadeesh et al., 2004), the herding behavior (Jegadeesh and Kim, 2010; Moreira et al., 2017), and analyst's overconfidence (Zuckerman, 2009).

Among the non-fundamental factors, the general economic and financial situation is one of the potential elements which could influence analyst's estimations. This is not a surprise, considering that is impossible to isolate a company's analysis from the performance of its sector, market, or country of domicile. When forecasting, analysts use all kind of inputs, and the overall market sentiment could be one of them. When there is optimism/pessimism among investors it has the potential to be translated to financial analysts, which tend to bias their estimates voluntarily or unwittingly. Various authors have related the market sentiment index calculated by Baker and Wurgler (2007) to share's prices, earnings forecasts and stock recommendations. For example, Hribar and McInnis (2012) show how it influences short-term earnings estimates, making analysts more (less) optimistic the higher (lower) the sentiment indicator is. Bagnoli et al. (2009) and Ke and Yu (2009) find that the buy-sell recommendations are also correlated with this index, which may be caused in their view to the use of this indicator as a shortcut used to facilitate analyst's work, as the observation of investor sentiment may substitute for a more intensive analysis of the fundamentals.

There are prior studies which specifically consider the impact of the economic and financial situation on target prices. Clarkson et al. (2013), analyzing the role of non-fundamental factors, use the 52-week maximum stock price and the recent market sentiment as such. The use of these variables is supported by previous works which links anchors like this to investment decisions (following the ideas of Tversky and Kahneman, 1974) and other types of analyst's forecasts. Analysts may employ them consciously or not, a distinction that is not considered, but they are expected to play a role in the forecast' formation process. The assumption is that a higher degree of reliance on them when estimating is likely to lead to larger target price errors. Their results show that higher values of the 52-week maximum (relative to the current share price) and more positive market sentiment are correlated with higher target price forecasts and thus larger optimistic bias and estimating errors. Ho et al. (2018) test various hypothesis about the association between target price revisions and recent market and excess stock returns. As previously mentioned, these are considered inputs used by analysts when estimating. They find a strong and positive correlation between these revisions and the market behavior, so increasing returns will lead to higher target prices.

Other papers do not focus on this question, but partially consider it including variables related to the overall financial market performance in their studies about target price precision. Bonini et al. (2010) use the market momentum (the returns of the Italian stock index in the six months before the target price issuance date) as a proxy of the relative growth of the financial market. They expect a negative effect of this variable on analyst's accuracy because they would overestimate their predictions in an upward market, a result that their regressions actually show. This conclusion is similar to the one of Clarkson et al. (2013), but other works find the opposite. For example, Bilinski et al. (2013, p. 833) find that estimation errors were higher during the period of the Global Financial Crisis (GFC) due to "higher forecasting uncertainty and unexpectedly poor stock return performance". Bradshaw et al. (2013) use the market return (measured during the time horizon of the target price forecast) as one of the explanatory variables of the target price accuracy. Their results show that analysts are less ex-post optimistic in rising markets, which implies forecasting errors are smaller in up rather than down markets.

In conclusion, there is evidence that analyst not only focus on the future of the companies they analyze when calculation the target price (using their fundamentals as the main input), but also look at the past performance of the firm's shares as well as the recent evolution of different financial market indicators. The explicit or implicit use of this non-fundamental factors is related to behavioral and psychological biases, like the higher relevance of recent events versus past ones, the reliance on established anchors, their use as shortcuts to facilitate the analyst's task, or how the overall sentiment directly affects their over optimism/pessimism.

3. Target price and uncertainty indicators

3.1. Target price indicators

In order to evaluate the effects of uncertainty, financial stress and volatility on analyst's estimations, various indicators are elaborated based on the comparison between the target price (*TP*) and the market stock price (*P*). From a "classical" point of view, as already mentioned, both should be very similar since in theory the stock price contains all the information available to investors (Fama, 1965, 1970), which would make the target price redundant. However, this does not happen, pointing out the existence of market efficiency failures.

To analyze the divergences between the two prices and observe the direction in which they differ the Target Price Differential (*TPD*) is calculated, as the difference between the aggregate target price and the stock price, divided by the latter. To avoid endogeneity issues, the calculation is made using the *TP* released on day *t* and the closing *P* on day *t*-1. That is:

$$TPD_t = \frac{TP_t - P_{t-1}}{P_{t-1}}$$

A *TPD* greater than zero implies the analysts' believe that the share price at the end of the forecast horizon will be higher than the current one (i.e., the stock is undervalued with respect to the company's fundamentals, and the analysts are optimistic about its future). On the contrary, if *TPD* is negative, they assume that the share price will be lower than the one in day *t* (i.e., the stock is overvalued, and the analysts are pessimistic).

To analyze how large or small is this differential, regardless of the sign, the Absolute Target Price Differential (*ATPD*) is computed:

$$ATPD_t = \left|\frac{TP_t - P_{t-1}}{P_{t-1}}\right|$$

In this case, if the spread is large (small), it means that the under/overvaluation of the stock price relative to the company's fundamentals is also big (small), implying that analysts would be less (more) confident about the value of the stock as an indicator of the firm's fundamentals or future situation.

Besides the comparison between both prices at the same moment in time, it is possible to study their evolution during a specific period and analyze how different they are. When there is a variation in a company's stock price analysts can choose whether to reflect this movement in their forecast or not. In order to see these variations (considering a monthly basis[1]), the stock Price Trend (*PT*) and the Target Price Trend (*TPT*) are computed:

$$PT_t = \frac{P_t - P_{t-30}}{P_{t-30}}$$

$$TPT_t = \frac{TP_t - TP_{t-30}}{TP_{t-30}}$$

If the signs of both indicators are equal (e.g., if an increase in the share price is accompanied by an increase in the target price), analysts believe that the stock price movement will have a permanent impact on its future level, and will adjust their forecast accordingly. If they differ (e.g., an increase in the share price and a decrease of the target price), analysts consider that recent stock price movements will only have a one-off effect, and will not affect their future level.

The spread between the two trends also helps to know how much the stock price movements are believed to be significant or not in their future level. The Trend Differential (*TD*) is computed as[2]:

$$TD_t = |TPT_t - PT_t|$$

Its interpretation is similar to what was already mentioned: low values of *TD* indicate that analysts consider stock price movements as relevant factors for their future level (i.e., they will have permanent effects). High values mean the opposite: recent share price movements are not relevant for their future, and won't have long-term effects.

Finally, it is possible to know how fast or slow analysts are adjusting their estimations. When they see changes in the stock price of a company which in their opinion will have permanent effects, they could modify their forecasts accordingly. There may be a time gap between the share price change and the target price adjustment, so, in order to measure it, the LAG indicator, defined as the number of weeks the target price has to be delayed to minimize the Absolute Target Price Differential ($ATPD$)[3], is computed:

$$LAG_t = number\ of\ delayed\ weeks\ to\ minimize\ the\ ATPD$$

[1] The use of the monthly basis is based on the previously mentioned bias which states that people tend to favor recent events to historical ones. It also follows the example of Clarkson et al. (2013), who introduces recent market sentiment as an explanatory variable for their target price prediction error indicator, also measured one month before the target price announcement date. Quarterly and yearly variations have also been used in the econometric models of this work, obtaining similar results to those showed below.
[2] The use of the absolute value relies on the assumption that knowing which trend is bigger is not as relevant as knowing how much they differ, and it does not have an obvious interpretation.
[3] The number of delayed weeks is limited to sixteen.

When *LAG* is high, the adjustment is slow, which can be due to voluntary reasons (e.g., analysts do not consider that the effect of the share price change would be immediate) or involuntary (e.g., due to forecast errors or related with the aggregation method of the composite target price, as explained before). In case *LAG* is low, then the adjustment will be fast.

In summary, the comparison between the stock price and the aggregate target price at the moment the latter is published allows to study i) the optimism/pessimism of the experts about a company's future thanks to the *TPD*; ii) the degree of confidence they have about the use of the stock price as an indicator of the firm's fundamentals with *ATPD*; iii) their view on the importance and future impact of share price variations with the *TD* indicator; and iv) the speed at which analysts adjust their estimates with *LAG*.

3.2. Economic and financial uncertainty indicators

Considering the complexity and multi-dimensionality of the economic and financial environment, it is necessary to clarify which type of uncertainty is going to be measured. As mentioned in the introduction, this paper employs three different indicators: one to grasp the uncertainty related to the general economic and political situation (*EPU*); another one focused on the instability and stress of the financial system as a whole (*CISS*); and one specific for the volatility of the stock market (*Vibex*). They allow to analyze how diverse definitions of uncertainty can have distinct influences in the target price formation process. All of these indexes are computed for Spain and consider only Spanish characteristics[4].

The Economic Policy Uncertainty Index, or *EPU*, was first develop by Baker et al. (2016) for the United States and eleven other countries, including all G10 economies. It aims to capture the concerns about future actions of economic and monetary policy and their potential effects. This indicator is based on newspapers coverage frequency, using a text-based analysis to count the number of articles in leading media which contain specific words (e.g., "economic", "uncertain", "congress", "Federal Reserve", for the U.S.). Thus, higher values of the index mean a larger degree of uncertainty. Due to the limited newspaper coverage, there was room to an improvement for the index built for countries

[4] These are not the only measures of uncertainty built for Spain. For example, the European Central Bank calculates the Country-Level Index of Financial Stress (CLIFS) and the Composite Indicator of Sovereign Stress (SovCISS); other public entities like the Comisión Nacional del Mercado de Valores (CNMV) also build the Financial Market Stress Indicator (FMSI). All them are based on the original CISS proposed by Holló et al. (2012), so they do not differentiate enough and refer to the same dimension of the economic environment.

other than U.S. Ghirelli et al. (2019) refined it for Spain, by i) expanding the newspapers coverage; ii) using a richer set of keywords; and iii) covering a longer sample period. Chart 1 (upper graph) shows its evolution. It remained relatively stable until 2007, when the news regarding the GFC and its posterior effects where reflected in an increase which reached its peak in 2012, with the Spanish financial aid. After that, it tended to decrease, but the trend changed in October 2017 around the Catalan crisis, and hit a new maximum in the wake of the coronavirus pandemic in the first quarter of 2020.

The Composite Indicator of Systemic Stress (*CISS*) is provided by the European Central Bank (ECB) for the euro area countries and United States, United Kingdom and China[5]. It is based on the work by Holló et al. (2012) to measure the contemporaneous instability in the financial system, so it can be understood as an index of systemic risk. It aggregates 15 variables, grouped in five categories (financial intermediaries sector, money markets, equity markets, bond markets and foreign exchange markets)[6]. Its methodology puts more weight on episodes in which stress spreads in several market segments at the same time, so when it shows high values it means that financial stress is more systemic. The middle graph in Chart 1 exhibit its behavior during the considered period. Not surprisingly, the *CISS* increased at the beginning of the GFC and reached a historical maximum in 2009, although its values during the following years were also high. From 2014 to 2020, it remained low (with the exception of the years 2015-2016, related to the financial turbulences at the end of 2015 and the Brexit referendum), but it soared upward again in 2020 with the coronavirus crisis.

The *Vibex* is a measure of the volatility of the main Spanish stock market index (Ibex 35). Proposed by González-Pérez and Novales (2011), and offered by Bolsas y Mercados Españoles (BME), reflects the evolution of the implied volatility quoted on the options on the Mercado Oficial de Opciones y Futuros Financieros (MEFF), with a constant 30-day time horizon. Its evolution can be seen in the lower graph of Chart 1. Data starts on 2007, but has enough time-span to capture the two main uncertain episodes of the period considered on this paper: the GFC and the coronavirus pandemic. It follows a pattern similar to that of the CISS, reaching two peaks in 2008 and 2020, and showing also relatively high values during the euro area sovereign debt crisis during the years 2010-2013, and near the Brexit referendum in 2016.

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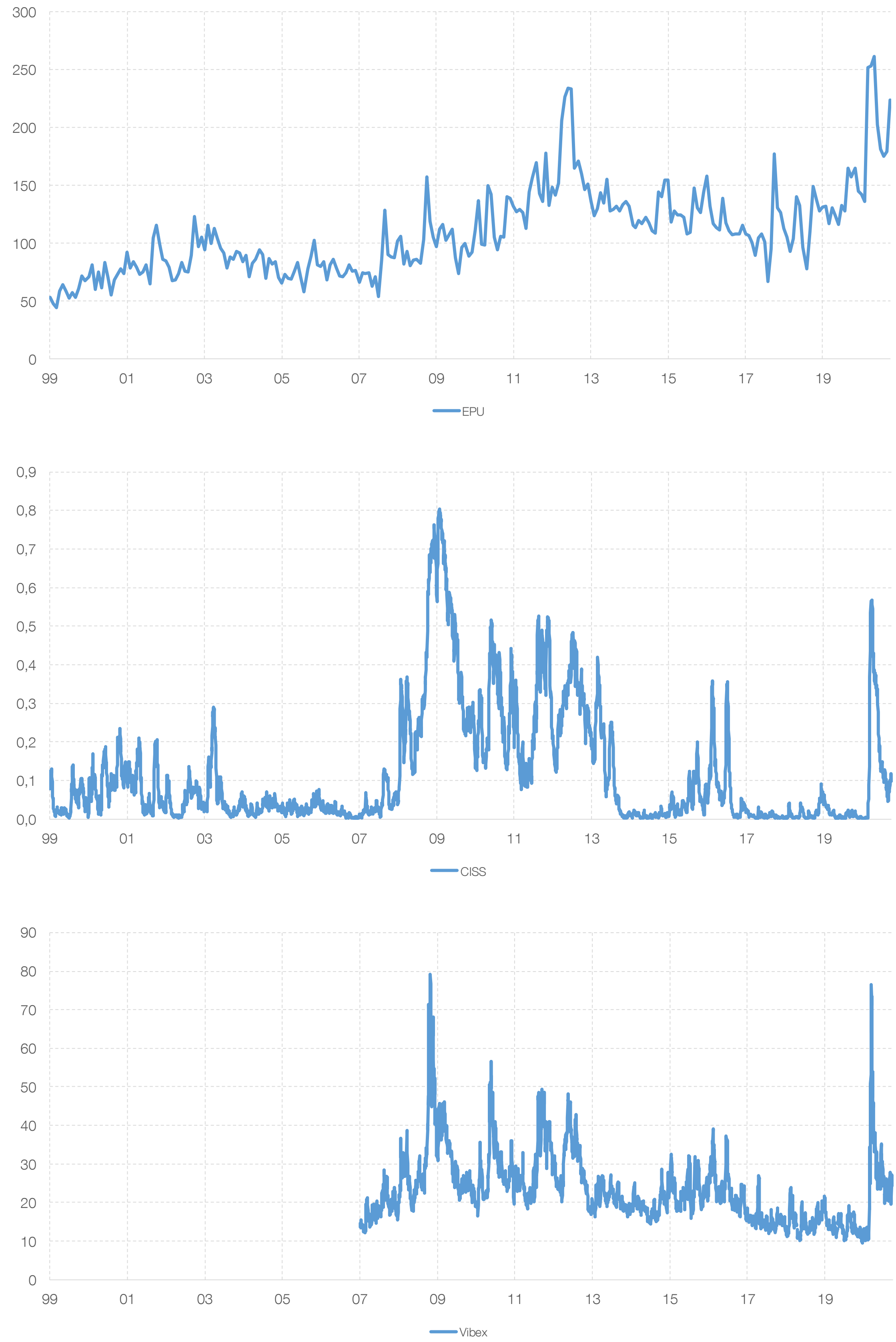
[5] The data used for Spain is the New CISS, which employs a revised weighting scheme for the raw indicators, and it is calculated on a daily basis.
[6] There are five sub-indices focus on each of the categories, but they are not available for Spain.

Chart 1: Uncertainty indicators for Spain



Sources: Policy Uncertainty for the EPU, ECB for the CISS, and Bloomberg for the Vibex.

4. Behavior of target prices of Spanish banks

Chart 2 shows the evolution of the stock price and the aggregate target price of the eight largest Spanish banks during the considered period. The starting date is January 1999 (or the initial trading day if it is posterior), which allows to analyze the behavior of both series over a long period of time, including episodes of both financial stability and uncertainty. Data on prices are obtained from Thomson-Reuters Refinitiv, which computes the aggregate target price as the statistical average of all analyst's estimates who shares the same time horizon (i.e., both new forecasts and revisions), regardless of when they were made. It is published on a daily basis. Some days have been manually removed, when the number of individual contributors was smaller than ten[7].

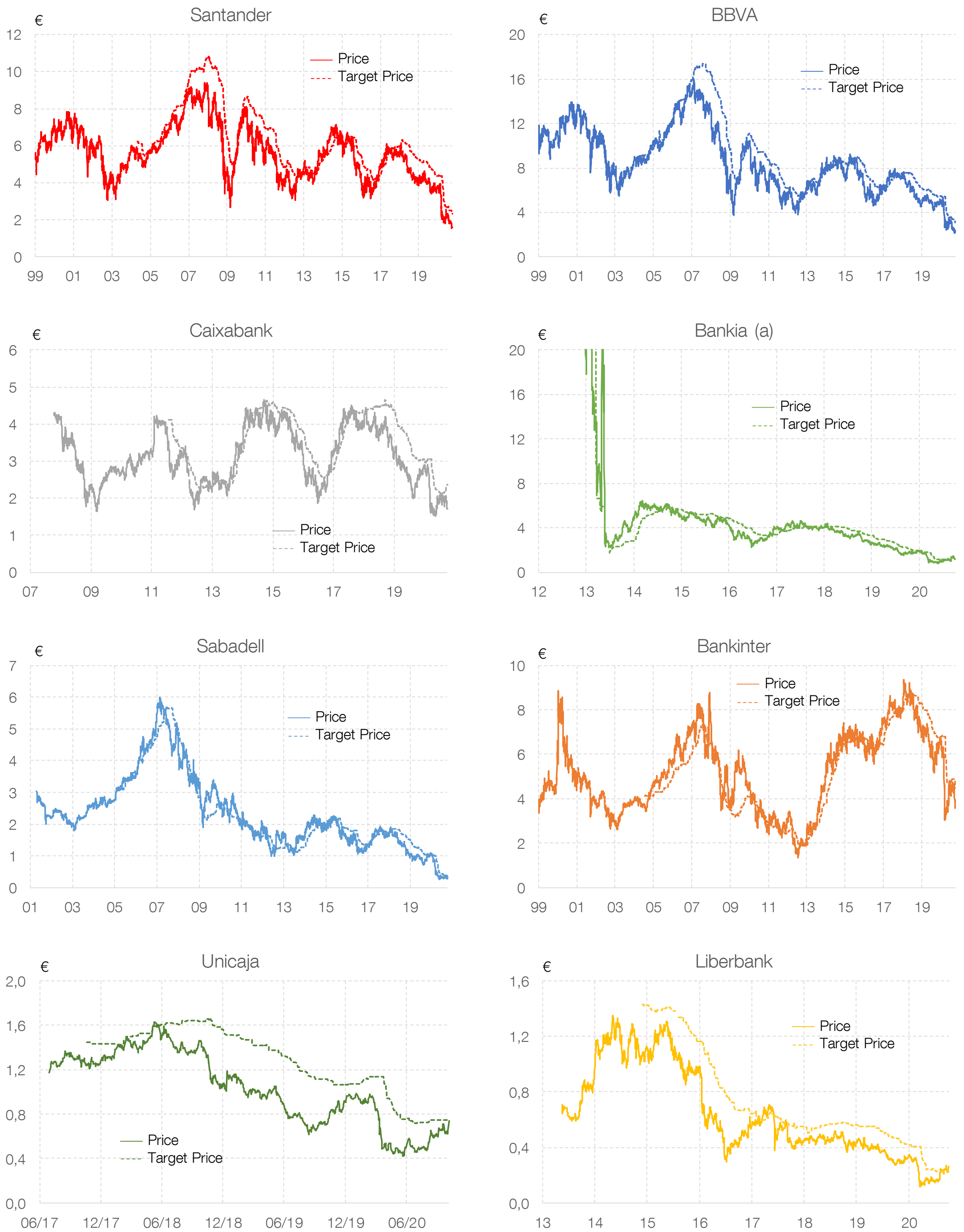
It can be seen that, in general, the target price has moved closely to the evolution of the share. The correlation between both prices shows, perhaps unsurprisingly, a high value: 92% for the average of the eight entities (table 1, left column). Analysts are therefore influenced to a large extent by the past performance of the stocks when calculating their estimates.

More interesting is the fact that the discrepancies between the two series show some patterns: i) target prices tend to be, on average, higher than the stock prices, ii) there is a time gap between the movements of the share prices and the estimates, and iii) these are more pronounced in prolonged periods of share price's decrease. In fact, this observed optimism and lag tend to disappear when prices maintain a growing path for a long period of time. This points out to the existence of two different behavior regimes: one for the periods when stock prices have a continuous upward trend, and another for time intervals when they tend to decline.

A detailed examination of the indicators outlined in the previous section would confirm this patterns. Table 1 contains their average for the whole time period and each of the eight banks. First, the mean of the Target Price Differential (TPD) is greater than zero in almost all cases (the exception is Bankinter) and show a common value of 0,15 (second column), meaning that target prices are 15% higher than stock prices. In general, analysts consider that the stocks are undervalued with respect to their future value, and are optimistic about their growth. This confirms the result obtained in the literature that target prices tend to be biased upwards. However, given that we are working with an aggregate, this bias may also be related to its aggregation method.

[7] The average number of analyst's contributions per day is twenty-two.

Chart 2: Stock price and aggregate target price evolution



Source: Thomson Reuters-Refinitiv.

(a) The vertical axis is truncated at lower values to better show the recent evolution, as the initial share price (around 180€) distorts its graphical representation.

The absolute difference between both prices, computed with the *ATPD* (Table 1, third column), shows an average of 0,2 for the eight entities, meaning that the aggregate target price is 20% away from the share price. This indicator is easier to interpret looking

Table 1. Indicator averages

	Correlation	TPD	ATPD	TD	LAG
Santander	0,90	0,15	0,17	0,06	8,85
BBVA	0,93	0,15	0,16	0,06	9,25
Caixabank	0,85	0,12	0,15	0,07	8,91
Bankia	0,98	0,06	0,18	0,10	10,45
Sabadell	0,97	0,05	0,14	0,08	8,78
Bankinter	0,92	-0,03	0,12	0,07	9,70
Unicaja	0,88	0,33	0,33	0,08	9,45
Liberbank	0,95	0,35	0,35	0,10	11,21
AVERAGE	0,92	0,15	0,20	0,08	9,57

Source: own elaboration based on Thomson Reuters-Refinitiv data.

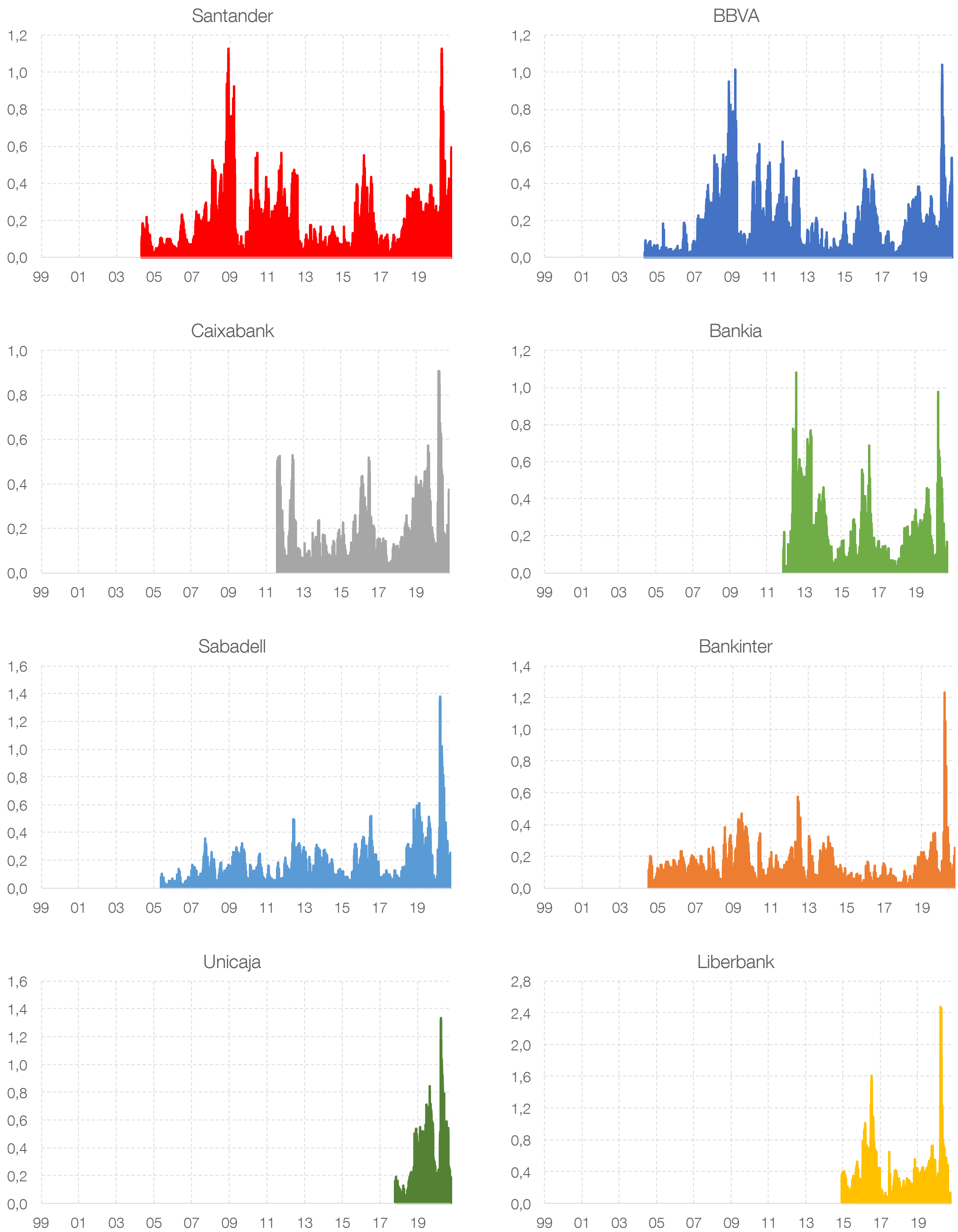
Indicators: TPD (Target Price Differential), ATPD (Absolute Target Price Differential), TD (Trend Differential), LAG (lag indicator).

at its time evolution, as appears in Chart 3. Two periods clearly stand out, showing higher and above-average values: the start of the GFC in 2008-2009, and the beginning of the Covid-19 crisis. In some cases, the *ATPD* is higher than one, meaning that the target price was at least twice higher/lower than the share price. Also high (albeit smaller) increases are observed at other times, like the financial turbulences of the years 2011-2012 and in 2016, related to the financial distress at the beginning of the year and the Brexit referendum afterwards. The message obtained with this indicator points to the main idea of this work: that the under/overvaluation of the stock price considered by analysts is higher in periods of crisis and volatility than in stable times. In other words, they are more confident about the value of shares as an indicator of the company's fundamentals in the latter.

A similar pattern can be found studying the Trend Differential indicator (*TD*). As shown in Table 1 (fourth column), the average for the main Spanish banks is 0,08, which indicates a gap between the trends of both prices of an 8%[8]. But looking at the evolution of this indicator (Chart 4), it is possible to see that values above this number are observed in many periods, being more prominent on times of financial turmoil like the GFC, the years of the sovereign debt crisis in Europe (2011-2013), and the beginning of the pandemic of Covid-19 in 2020. The data corroborate that, on average, analysts tend to

[8] Looking at the monthly trends of both prices (measured by the *PT* and *TPT* indicators), on average, they showed different signs 43% of the time. This indicates that for more than half of the period analysts thought that the monthly variation of the stock price would have permanent effects in the long term, although the percentage of time where they consider it would be a one-off event is not negligible at all.

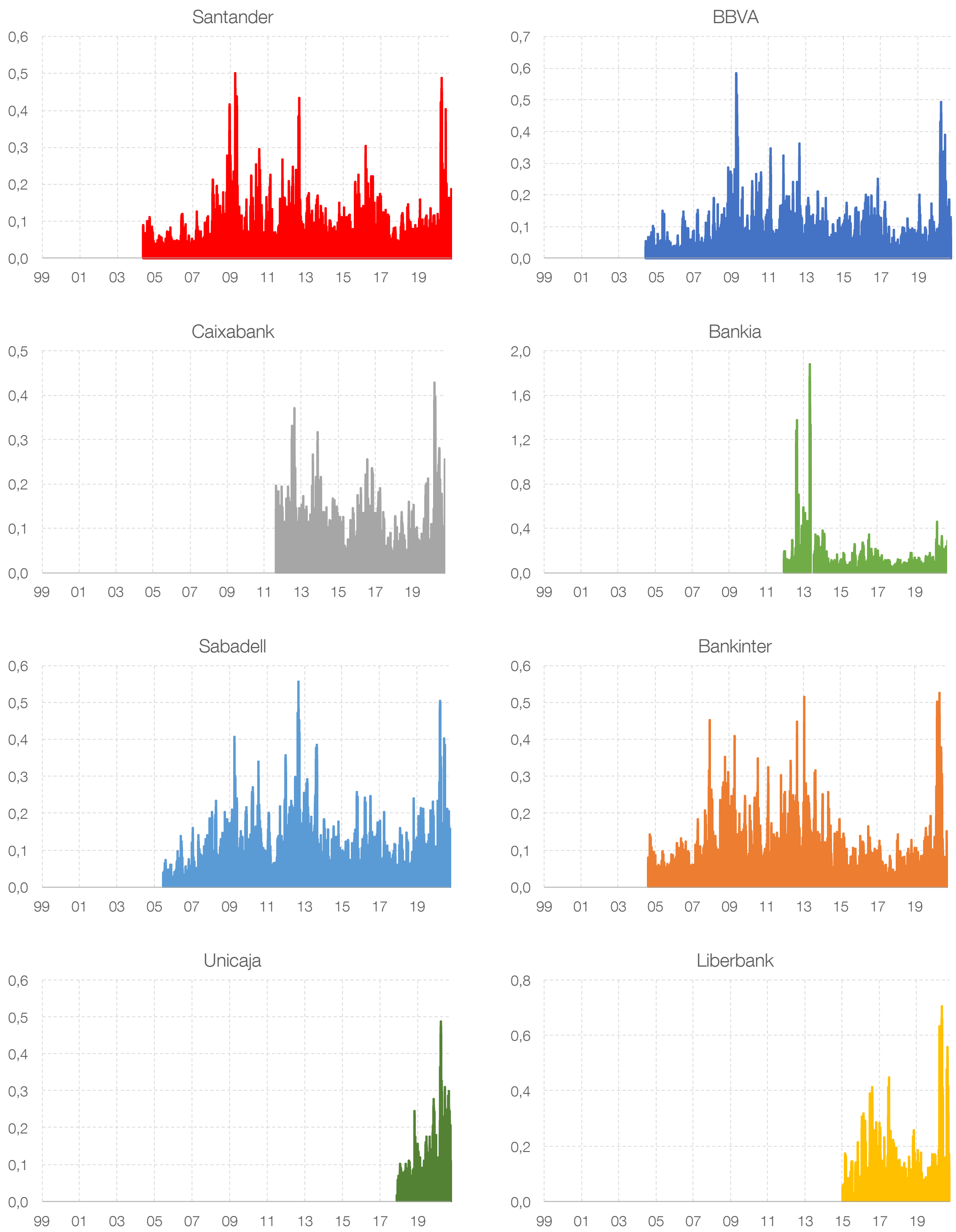
Chart 3: Absolute Target Price Differential (ATPD) evolution



Source: own elaboration based on Thomson Reuters-Refinitiv data.

modify more their target price forecasts accordingly to the direction in which the stock prices move in more stable periods (i.e., they think that their movements will have permanent effects), while in times of crisis they believe that what happens to the share prices will be temporary and therefore adjust less their estimations.

Chart 4: Trend Differential (TD) evolution

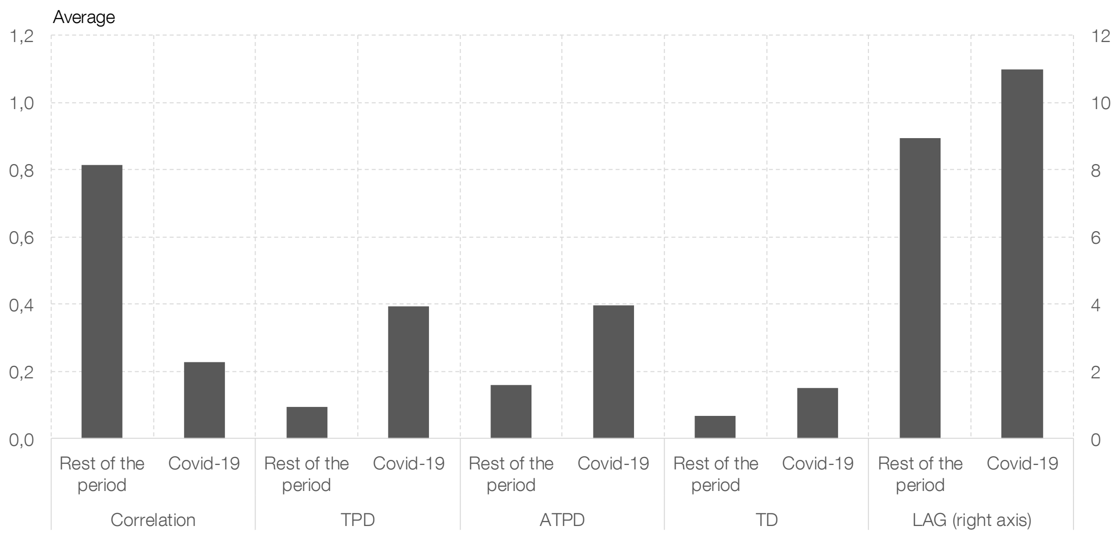


Source: own elaboration based on Thomson Reuters-Refinitiv data.

The observed gap between the movements of the stock prices and the aggregate target prices are analyzed using the *LAG* indicator. Table 1 (right column) shows the number of weeks that the latter has to be delayed to minimize its difference with the share prices. On average the delay is above nine weeks (approximately two months) for the group of banks, without significant differences between them. As with the optimistic bias, the aggregation method of the composite target price partly explains this lag.

To better understand the combined information provided by the indicators, it is useful to analyze what happens in a given period in more detail. The recent Covid-19 crisis serves as a good example, as it helps to observe how analysts reacted to an exogenous shock such as a pandemic[9]. During the first months of the crisis, correlation between both prices showed exceptionally low values, indicating that analysts tended to focus less on the past movements of the shares and more on the company's fundamentals when estimating (Chart 5). This also implied that they were slower to adjust their forecasts downwards (reflected in a higher *LAG* than in previous periods), and when they did so, it was to a lesser degree than the actual share price declines (which causes higher *TD* values). This is also reflected in the exceptional records of both *TPD* and *ATPD*, which means a greater optimism than in past periods (not with respect to previous years' target prices, but in comparison with contemporaneous quotations), and a stronger belief on the shares' undervaluation.

Chart 5: Indicator averages in the Covid-19 crisis (a)



Source: own elaboration based on Thomson Reuters-Refinitiv data.

Indicators: TPD (Target Price Differential), ATPD (Absolute Target Price Differential), TD (Trend Differential), LAG (lag indicator).

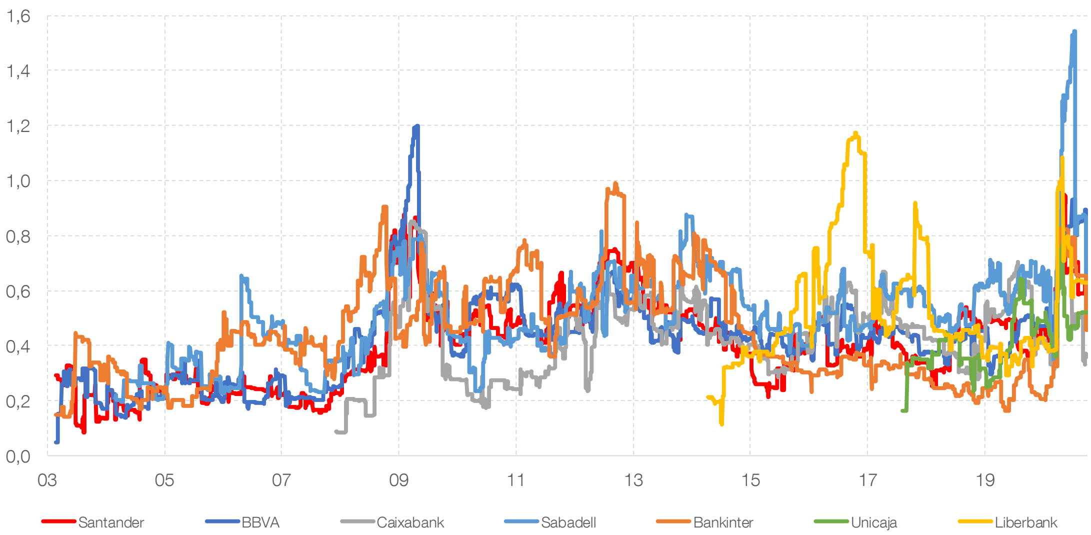
(a) Covid-19 crisis: from March 1st, 2020 to October 5th, 2020.

Finally, one way to check the impact of uncertainty and financial distress on the dispersion of analyst's contributions is reflected on Chart 6. It shows the range of the

[9] The last data in this article correspond to October 5th, 2020.

individual target price estimates (or difference between the highest and the lowest ones) for the Spanish banks considered in this study. In general, dispersion increases are observed at the beginning of the GFC and also in the first months of the Covid-19 pandemic. The most stable periods (2003-2008, and between both crisis) show smaller range sizes[10]. As expected, periods with higher uncertainty and volatility cause more dispersion on individual predictions.

Chart 6. Range of analysts' estimates (a) (b)



Source: own elaboration based on Thomson Reuters-Refinitiv data.

(a) Difference between the 95th percentile and the 5th percentile of the individual estimates, divided by the aggregate target price.

(b) Excluding Bankia, since the range size at the beginning of its quotation distorts its graphical representation.

In conclusion, the joint analysis of stock prices and the aggregate target prices of Spanish banks shows that, on average analysts have an optimistic bias in their valuations, and tend to react with a delay to stock movements. Furthermore, periods of economic instability, financial stress and volatility affects their estimations i) fostering the optimistic bias; ii) reducing the speed and iii) willingness of the adjustment to share price movements, and iv) make them trust less on stock prices as indicators of banks' fundamentals.

[10] With occasional exceptions such as Bankinter at the end of 2012 or Liberbank at the end of 2016, which may respond to idiosyncratic reasons of each entity.

5. Empirical analysis

5.1. Model specification

To empirically evaluate how uncertainty, financial stress and volatility affect analyst's target price estimations, an econometric analysis will be carried out. The base models which will be used are the following, based on the one employed by Bilinski et al. (2013) to study the determinants of target price errors:

$$TPD_{it} = \beta_0+\beta_1 X_t + \beta_2 lnPERIOD_{it} + \beta_3 EPS\_D_{it} + \beta_4 lnCAP_{it} + \varepsilon_{it} \quad (1)$$

$$ATPD_{it} = \beta_0+\beta_1 X_t + \beta_2 lnPERIOD_{it} + \beta_3 EPS\_AD_{it} + \beta_4 lnCAP_{it} + \varepsilon_{it} \quad (2)$$

$$TD_{it} = \beta_0+\beta_1 X_t + \beta_2 lnPERIOD + \beta_3 EPS\_TD_{it} + \beta_4 lnCAP_{it} + \varepsilon_{it} \quad (3)$$

$$lnLAG_{it} = \beta_0+\beta_1 X_t + \beta_2 lnPERIOD_{it} + \beta_3 lnEPS\_LAG_{it} + \beta_4 lnCAP_{it} + \varepsilon_{it} \quad (4)$$

The dependent variables are the indicators used in this article: the Target Price Differential (TPD_{it}), the Absolute Target Price Differential ($ATPD_{it}$), the Trend Differential (TD_{it}), and the LAG indicator (LAG_{it}). The X_t denotes the main explanatory variables, i.e. the monthly evolution of each of the three uncertainty indicators for Spain: the Economic Policy Uncertainty index (EPU_t), the Composite Indicator of Systemic Stress ($CISS_t$), and the volatility index of the Ibex 35 ($VIBEX_t$).

The variable ($PERIOD_{it}$) measures the number of days between the oldest individual contribution to the aggregate target price for a given day and its publication date, to control for the effect of the aggregation method. It is an important variable, because as mentioned in the introduction, it plays a role in the behaviors of the indicators showed in the previous section. The aggregate target price is computed as a simple average of various analysts' contributions over a given period of time[11]. It is, therefore, a moving average, which uses *t-n* estimates to calculate the aggregate released on day *t*. This implies that when an analyst changes its valuation, the older contributions will delay the adjustment of the aggregate. The longer the time period over which individual contributions are allowed to be included (i.e., the further back in time the oldest contribution is made), the longer the lag in the adjustment.

[11] For example, in the case of Thomson Reuters-Refinitiv, whose data are used in this paper, there is no limit on the date of the contributions. In the aggregate built by Bloomberg the limit is three months.

In theory, this delay should have a similar impact regardless of the evolution of shares. Thus, both in periods of stability and volatility the aggregate target price would suffer a lag in its adjustment to the former. However, as observed in Chart 2, this is not the case: when stock prices decline over a long period of time the delay is more apparent than when prices tend to rise. This is consistent with the optimistic bias continuously observed in the literature. Additionally, given that in stable times analysts tend to differ less in their estimates, it is to be expected that older forecasts would be relatively more similar to recent ones, which should reduce the adjustment time.

To control the role of the company's fundamentals in the analyst's estimation process, four indicators are built for the differences between the Earnings Per Share (EPS) and its estimations, in the same vein as the target price ones: their differential or EPS_D_{it}, their absolute differential or EPS_AD_{it}, their trends differential or EPS_TD_{it}, and their adjustment speed or EPS_LAG_{it}. To proxy for the individual characteristics of each bank it is used their market capitalization (CAP_{it}). Finally, the error term is denoted as ε_{it}.

The estimations are performed by OLS panel data regressions with fixed effects, previously eliminating the most extreme observations of each entity (those outside the range of the 1-99th percentiles). The analysis is conducted for the eight main Spanish banks (*i*) during the period 01-Jan-1999 to 05-Oct-2020 (*t*). Target price data (both the aggregates and the individual contributions), stock prices, *EPS* and market capitalization are obtained from Thomson-Reuters Refinitiv. The *EPU* and *CISS* data are publicly available in the webpages of the Economic Policy Uncertainty index (which hosts the revised version of Ghirelli et al., 2019) and the Statistical Data Warehouse of the ECB, respectively[12]. The implied volatility ($Vibex$) and the EPS estimates are from Bloomberg. The Appendix offers the definition of the variables, their descriptive statistics and the correlations among them.

5.2. Econometric results

Table 2 shows the results of the models (1) - (4), where the dependent variables appear in the upper row, and the coefficients of the explanatory variables and their significance levels in the rows below. There is one column per combination of target price indicator-uncertainty index. In general, they show that the uncertainty and financial volatility measures have a positive and significant effect on the four target price indicators. As

[12] EPU for Spain (https://www.policyuncertainty.com/spain_GPU.html), CISS data (https://sdw.ecb.europa.eu/browseExplanation.do?node=9689686).

expected, if they increase, analysts tend to be more optimistic about the banks' future situation (i.e., not in comparison to previous years, but with respect to current stock prices), are less confident about the value of share prices as indicators of banks' fundamentals (i.e., their undervaluation is higher), believe that price movements will only have temporary effects, and slow the speed at which they adjust their estimates.

Looking at the size and significance of the coefficients, the clearest effect of the uncertainty and volatility measures is on the *TPD* (model 1) and *ATPD* (model 2) indicators. Regarding the first one, a one-point increase in the *EPU* or *VIBEX* (i.e., implying they double in a month) causes a rise of 17% and 15% respectively on this differential. In the case of the *CISS*, the effect is much smaller: the *TPD* will only growth about 2%. The impact on the *ATPD* is similar, albeit smaller: an increase of one-point in the *EPU* or *VIBEX* indices produces a 10% rise on this indicator. Again, the size of the coefficient in the estimation which uses the *CISS* is smaller (above 1%). Significance levels are particularly strong for this two differentials: all three uncertainty variables show *p*-values below 0.1%, except in the specific case with the *ATPD* and *VIBEX*, which is below 1%.

In the case of the TD, the size of the impact is smaller, and differs more between the three uncertainty measures (model 3). If the *CISS* or the *VIBEX* doubles in a month, the trends will differ a 0.5% and 3% more, respectively. The *EPU* index does not seem to affect this indicator. The significance levels of the previous two coefficients are not weak though (*p*-value below 0.1%). The results on the *LAG* indicator (model 4) are the most puzzling ones: both the *EPU* and the *CISS* indicators have an impact, but their size is very different (i.e., a one-point increase causes the adjustment speed of the aggregate to slow a 41% and 3%, respectively) and their level of significance is small compared with the other target price indicators. The *VIBEX* does not show any effect on the speed at which analysts adjust their estimates.

Regarding the different impact of the *CISS* measure, compared with the ones of the *EPU* and *VIBEX*, may be due to the fact that it is the uncertainty indicator with the most extreme variations. On average for the period considered in this analysis, the *CISS* has a monthly percentage change of 90% (i.e., it almost doubles each thirty days). In the case of the *EPU* the average is 2%, and 4% for the *VIBEX*. This difference still remains even after removing the most extreme observations to estimate the regressions. Thus, increases of the same size of this index cause a much smaller impact on target price indicators because they are more common. The higher volatility of the CISS is thought to be related with its construction method and not with the economic dimension it measures (the financial system as a whole), so the smaller size of its coefficients it is less important for this study than the fact that it actually has an effect on target price estimates.

Table 2. Econometric results

Variables	(1) TPD			(2) ATPD		
EPU	0.169*** (0.000)			0.107*** (0.000)		
CISS		0.0186*** (0.000)			0.0137*** (0.000)	
VIBEX			0.147*** (0.000)			0.0912** (0.009)
ln PERIOD	0.130*** (0.000)	0.118*** (0.000)	0.132*** (0.000)	0.0827* (0.036)	0.0796* (0.031)	0.0884* (0.025)
EPS_D	0.00969 (0.102)	0.0147* (0.019)	0.0145* (0.018)			
EPS_AD				-0.00308 (0.559)	-0.00729 (0.211)	-0.00684 (0.254)
ln CAP	-0.135* (0.032)	-0.152* (0.016)	-0.142* (0.021)	-0.145** (0.006)	-0.154** (0.006)	-0.147** (0.007)
cons	0.656 (0.203)	0.888 (0.088)	0.728 (0.158)	1.080*** (0.001)	1.187** (0.001)	1.073** (0.002)
R-sq	0.144	0.179	0.166	0.193	0.214	0.192
F	87.15	81.06	61.83	36.11	30.44	4.758
N	1030	19721	18463	1030	19721	18463

p-values in parentheses
* p<0.05, ** p<0.01, *** p<0.001

PERIOD, the variable which controls for the role of the aggregation method of the composite target price, has also a positive and significant effect on the indicators *TPD*, *ATPD* and *LAG*. The further back in time the oldest individual contribution is considered for a given day, the larger will be the optimistic bias and the perception of undervaluation of the stocks that the aggregate would reflect. It does not change the perception of the composite about the possible one-off or permanent effects of stock prices' movements (the coefficients of *TD* are negative but with no significance), but is has an effect on the *LAG* indicator, meaning that, as expected, an increase of this time period slows the adjustment to share price developments.

Table 2 (cont.)

Variables	(3) TD			(4) LAG		
EPU	0.0111 (0.322)			0.412* (0.015)		
CISS		0.00490*** (0.000)			0.0321** (0.002)	
VIBEX			0.0351*** (0.000)			0.168 (0.057)
ln PERIOD	-0.00289 (0.615)	-0.00398 (0.305)	-0.00195 (0.477)	0.627* (0.018)	0.648* (0.017)	0.695* (0.032)
EPS_TD	0.0118 (0.164)	0.00342 (0.221)	0.00243 (0.387)			
ln EPS_LAG				0.169 (0.093)	0.139 (0.100)	0.0751 (0.232)
ln CAP	-0.0605*** (0.000)	-0.0590*** (0.000)	-0.0574*** (0.000)	0.168 (0.460)	0.0689 (0.739)	0.149 (0.374)
cons	0.659*** (0.000)	0.651*** (0.000)	0.626*** (0.000)	-3.369 (0.071)	-2.483 (0.175)	-3.348* (0.046)
R-sq	0.189	0.141	0.129	0.060	0.045	0.037
F	93.56	68.21	66.52	13.17	12.60	14.35
N	1021	18011	17110	1002	17567	16544

p-values in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Methodology: OLS panel data regressions with fixed effects and robust standard errors. TPD_{it}: Target Price Differential; $ATPD_{it}$: Absolute Target Price Differential; TD_{it}: Trend Differential; LAG_{it}: Lag indicator; EPU_t: Economic Policy Uncertainty index; $CISS_t$: Composite Indicator of Systemic Stress; $VIBEX_t$: Ibex 35 volatility index; $PERIOD_{it}$: contribution period; EPS_D_{it}: EPS Differential; EPS_AD_{it}: EPS Absolute Differential; EPS_TD_{it}: EPS Trend Differential; EPS_LAG_{it}: EPS lag indicator; CAP_{it}: market capitalization, cons: constant. R-sq: R-squared, F: F-statistic for joint significance, N: number of observations.

The bigger impact of *PERIOD*, perhaps unsurprisingly due to the nature of the indicator, is on the *LAG*: a rise of a 1% in the temporal period over individual contributions are allowed to be included produces a decrease on the adjustment speed to stock price's movements of about 60-70%, depending on the specification (model 4). In the case of the other indicators which show statistical significance, the effects of *PERIOD* are smaller: around 13% for the *TPD* (model 1), and 8% for the *ATPD* (model 2). Every specification for each model (changing the uncertainty measure) shows very similar results and significance levels, pointing to the fact that the aggregation method has a homogeneous effect regardless the rest of independent variables.

Control variables (i.e., the indicators constructed for the *EPS* and the banks' market capitalization) show different outcomes. While the former are not significant in almost any model (only the *EPS* differential has a positive and significant effect on the *TPD*, albeit small), the entities' size has a role on three indicators (i.e., *TPD*, *ATPD* and *TD*). Larger banks tend to have smaller differentials: a 1% increase of the market capitalization causes a fall on the *TPD* and *ATPD* of around a 14%, while the *TD* declines a 6% (models 1-3). This relationship has been noticed in previous works, for example Brav and Lehavy (2003) found that the target price/stock price ratio is inversely related to firm size. Moreira et al. (2017) analyze the link between this variable and target price accuracy, showing that the smaller the company size, the greater the error (which could be explained by the better information environment that bigger companies present). Baker and Wurgler (2007) and Clarkson et al. (2013) also consider that small firms are more sensitive to market sentiment and viewed as riskier, which difficult an accurate valuation.

These results confirm the hypothesis of this paper: the existence of periods of financial instability and uncertainty affect how analysts assess the future situation of Spanish banks and their perception of stock movements. The distinct economic and financial dimensions of uncertainty exert an influence on the target price indicators regardless of which one is measured (i.e., the general economic and political situation, the financial system as a whole, and the stock market), with some minor exceptions. Although the *EPU* shows larger coefficients, pointing to its greater effect, this could also be caused by the way this measure is constructed, as was previously discussed.

These effects are reinforced by the aggregation method of the composite target price. Thus, older individual contributions will cause the aggregate to reflect a higher optimistic bias, a bigger perception of stocks' undervaluation, and a longer delay on the speed the composite adjust to share price movements. However, it does not affect the reflected perception whether changes in stock prices will have a one-off or permanent effect on their future level. Both factors also act in tandem, as the more volatile and uncertain the economic and financial environment is, the less likely aggregate target prices would move according to stock prices, because older individual contributions will slow the adjustment process. This partly causes the optimistic bias, as the combined action of both effects will cause higher target prices than share prices over longer periods of time.

Regarding how these results are linked to the existing literature, they must be compared with works which consider the impact of the market performance and investor sentiment on analyst's forecasts, because there is not any known empirical study about the relationship of uncertainty and target prices. In order to do this, it is being assumed that uncertainty and volatile periods are analogous to declines on financial markets performance and investor sentiment. Considering this, the results presented here are in line with those which found an inverse relation between market performance and target price forecast errors, that can be related to the *TPD* and *ATPD* behavior. For instance, Bradshaw et al. (2013) observed that positive returns of the stock market index improve target prices' accuracy, and Bilinski et al. (2013) found that the Global Financial Crisis had a negative impact. The opposite is found on Bonini et al. (2010) and Clarkson et al. (2013), who show that a positive market momentum increases analyst's optimism and thus decreases their accuracy. Similar results appear on the literature about other types of estimates, like earnings forecasts and recommendations (Bagnoli et al., 2009; Hribar and McInnis, 2012). It is important to remark that these studies focus on the comparison between target prices and stock prices at the end of the forecast horizon, which differs to the differentials computed here (accuracy is not considered, and optimism is measured at the publication day of the aggregate target price).

In addition to the impact on the accuracy, the paper of Ho et al. (2018) found that analysts react differently to bad and good news when revising their target prices. If the information about a company is bad, they tend to rely more heavily on firm's fundamentals and are slower reflecting it in their revisions, due to the different disclosure strategies of firms depending on the nature of the information they provide. This is in line with the results obtained here for the *ATPD* and *LAG* indicators, where uncertain and volatile periods cause experts to rely more on fundamentals than on stock performance and to delay their adjustment to it.

6. The role of the aggregation method

Along with uncertainty, financial stress and volatility, an important factor affecting the behavior of the composite target price is its own aggregation method, as established previously. As a moving average, older analyst's estimates slow down the changes on the aggregate. However, unlike the first case, it is possible to make changes to this calculation in order to reduce its influence on the indicators. Considering that the used aggregate for a given day does not limit how old the individual contributions are, it is possible to calculate a new one where there is a time limit. To do so, it is necessary to obtain the dates on when they were made from the original source of data (Thomson-Reuters).

It allows to create an alternative Target Price (*aTP*), where the individual estimates issued or revised more than one month before the aggregate target price publication date are eliminated. It is expected that, using this new price to recalculate the indicators, the importance of the variable which measures the time period between the oldest individual contribution and the publication date of the aggregate (*PERIOD*) decreases or even disappears. The effect of the uncertainty and financial volatility measures on the target price indicators would not be affected by this change, so, the role of *EPU*, *CISS* and *VIBEX* should remain similar to the original specifications.

The following models use the original indicators as dependent variables, but recalculated with the aforementioned alternative Target Price (*aTP*): TPD_aTP_{it}, $ATPD\_aTP_{it}$, TD_aTP_{it} and LAG_aTP_{it}. The variable *PERIOD* has been recalculated accordingly, which in this case it can only be one month at most ($PERIOD\_1M_{it}$)[13]:

$$TPD\_aTP_{it} = \beta_0 + \beta_1 X_t + \beta_2 lnPERIOD\_1M_{it} + \beta_3 EPS\_D_{it} + \beta_4 lnCAP_{it} + \varepsilon_{it} \tag{5}$$

$$ATPD\_aTP_{it} = \beta_0 + \beta_1 X_t + \beta_2 lnPERIOD\_1M_{it} + \beta_3 EPS\_AD_{it} + \beta_4 lnCAP_{it} + \varepsilon_{it} \tag{6}$$

$$TD\_aTP_{it} = \beta_0 + \beta_1 X_t + \beta_2 lnPERIOD\_1M_{it} + \beta_3 EPS\_TD_{it} + \beta_4 lnCAP_{it} + \varepsilon_{it} \tag{7}$$

$$lnLAG\_aTP_{it} = \beta_0 + \beta_1 X_t + \beta_2 lnPERIOD\_1M_{it} + \beta_3 lnEPS\_LAG_{it} + \beta_4 lnCAP_{it} + \varepsilon_{it} \tag{8}$$

Table 3 shows the results of the estimation of models (5) – (8). It can be seen that, in those whose dependent variable is the *TPD*, the *ATPD* and *LAG* (i.e., models 5, 6 and 8), the new *PERIOD* variable is no longer significant (with one exception on the combination *VIBEX-LAG*, which shows an unexpected negative sign). In all this models, the variables which capture the uncertainty and financial market volatility do not modify their behavior: they continue to show approximately the same significance, sign and coefficient sizes as in the original specifications. Control variables (EPS indicators and the market capitalization) also remain in general as in the initial models, without altering the results to a great degree.

The specifications with the Trend Differential (*TD*) (i.e., model 7) offer, however, an unusual result. In this case, the significances of the interest variables are reversed:

[13] The variables using the EPS have not been recalculated by limiting the older individual contributions to their estimates due to data limitations, so they are the same as in the original models.

uncertainty and financial volatility ceases to play a role in the analyst's perception of the future effects of changes in stock prices, while the new variable *PERIOD_1M* becomes significant on two of three estimations (the ones which *CISS* and *VIBEX*), and more surprisingly, with a negative coefficient (i.e., a 1% increase in the temporal period over individual contributions are allowed to be included means a 1.3% and 1.4% smaller differential, respectively).

Despite this last case, the general conclusion it that with a simple modification of the calculation method it is possible to eliminate its influence on the behavior of the aggregate with respect to share prices. Analysts continue to show a bigger optimistic bias, have a higher perception of stock's undervaluation, and delay their adjustment to stock's movements in periods of increasing uncertainty, financial stress and volatility, regardless of how their contributions are aggregated.

Table 3. Econometric results with the aTP

Variables	(5) TPD_aTP			(6) ATPD_aTP		
EPU	0.177*** (0.000)			0.0975* (0.012)		
CISS		0.0156*** (0.000)			0.0112*** (0.000)	
VIBEX			0.139*** (0.000)			0.0866** (0.007)
ln PERIOD_1M	0.0872 (0.095)	0.0192 (0.334)	0.0223 (0.290)	-0.0130 (0.615)	-0.00715 (0.436)	-0.00807 (0.409)
EPS_D	0.0202*** (0.001)	0.0251** (0.001)	0.0246** (0.001)			
EPS_AD				0.00427 (0.166)	0.00481 (0.331)	0.00514 (0.294)
ln CAP	-0.0190 (0.748)	-0.0490 (0.389)	-0.0415 (0.458)	-0.142*** (0.001)	-0.141*** (0.001)	-0.136** (0.001)
cons	-0.00176 (0.998)	0.494 (0.397)	0.422 (0.461)	1.530*** (0.000)	1.501*** (0.001)	1.460*** (0.001)
R-sq	0.081	0.072	0.070	0.245	0.213	0.201
F	19.67	30.04	95.00	11.46	48.79	12.79
N	1068	20185	18936	1068	20185	18936

p-values in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 3. (cont.)

Variables	(7) TD_aTP			(8) LAG_aTP		
EPU	-0.00865 (0.423)			0.385* (0.047)		
CISS		0.000841 (0.288)			0.0218* (0.041)	
VIBEX			0.0111 (0.145)			0.174 (0.114)
ln PERIOD_1M	-0.0464 (0.059)	-0.0127** (0.007)	-0.0141** (0.003)	0.168 (0.232)	-0.0364 (0.394)	-0.0770* (0.047)
EPS_TD	0.0220 (0.150)	0.0200 (0.061)	0.0198 (0.066)			
ln EPS_LAG				0.0755 (0.395)	0.0738 (0.329)	0.0493 (0.425)
ln CAP	-0.0552*** (0.000)	-0.0520*** (0.000)	-0.0513*** (0.000)	0.139 (0.154)	0.0861 (0.311)	0.121 (0.119)
cons	0.758*** (0.000)	0.623*** (0.000)	0.621*** (0.000)	-0.201 (0.825)	0.945 (0.218)	0.813 (0.256)
R-sq	0.115	0.060	0.060	0.022	0.010	0.008
F	66.57	61.21	36.86	2.594	4.127	19.64
N	1049	18157	17282	988	16566	15626

p-values in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Methodology: OLS panel data regressions with fixed effects and robust standard errors. TPD_aTP_{it}: *Target Price Differential recalculated with the aTP;* $ATPD\_aTP_{it}$: *Absolute Target Price Differential recalculated with the aTP;* TD_aTP_{it}: *Trend Differential recalculated with the aTP;* LAG_aTP_{it}: *Lag indicator recalculated with the aTP;* EPU_t: *Economic Policy Uncertainty index;* $CISS_t$: *Composite Indicator of Systemic Stress;* $VIBEX_t$: *Ibex 35 volatility index;* $PERIOD\_1M_{it}$: *contribution period (max. 1 month);* EPS_D_{it}: *EPS Differential;* EPS_AD_{it}: *EPS Absolute Differential;* EPS_TD_{it}: *EPS Trend Differential;* EPS_LAG_{it}: *EPS lag indicator;* CAP_{it}: *market capitalization, cons: constant. R-sq: R-squared, F: F-statistic for joint significance, N: number of observations.*

7. Conclusions

Target prices are an estimation of the future value of a company's stock price. Although there is a general consensus about the importance of firm's fundamentals when forecasting, there are also other determinants related to conflicts of interest, behavioral and psychological biases, and the general economic and financial situation. This paper wants to shed light about the effects of the latter, considering specifically how uncertainty, financial stress and volatility affects analyst's target price estimations. These could be influential for various reasons: they have an effect on important judgment heuristics (representativeness, availability, and anchoring), impact analysts' forecast dispersion, affect the relevance of non-fundamental versus fundamental factors when estimating, and reduce the speed at which analysts revise and update their forecasts. The potential effects of the aforementioned points are that, in periods of instability, analysts would differentiate more their target prices from the evolution of stocks.

In order to evaluate the effects of uncertainty, financial stress and volatility on analyst's estimations, various target price indicators are elaborated to study how they influence i) the optimism/pessimism of the experts about a company's future (i.e., using the Target Price Differential, or TPD); ii) the degree of confidence they have about the use of the stock price as an indicator of the firm's fundamentals (i.e., using the Absolute Target Price Differential, or ATPD); iii) their view on the importance and future impact of share price variations (i.e., using the Trend Differential, or TD); and iv) the speed at which analysts adjust their estimates (i.e., using the LAG indicator). Due to the diversity of dimensions in which uncertainty may be present, the article uses three different measures: the Economic Policy Uncertainty index (EPU), the Composite Indicator of Systemic Stress (CISS), and the Ibex 35 implied volatility index (Vibex).

The analysis is made for the eight main Spanish financial entities in the period between the years 1999 and 2020. The target price indicators show that, on average, analysts have an optimistic bias in their valuations, and tend to react with a delay to stock movements. When analyzing the impact of the three measures of uncertainty on analyst's estimations, results show that periods of economic instability, financial stress and volatility i) foster the optimistic bias, ii) reduce the speed and iii) willingness of the adjustment to share price movements (experts believe to a greater extent that price variations will only have temporary effects on their level at the end of the forecast horizon), and iv) make them trust less on stock prices as indicators of banks' fundamentals.

This effects are reinforced by the aggregation method of the composite target price. Thus, older individual contributions will cause the aggregate to reflect a higher optimistic bias, a bigger perception of stocks' undervaluation, and a longer delay on the speed the composite adjust to share price movements. Both factors also act in tandem, as the more volatile and uncertain the economic and financial environment is, the less likely aggregate target prices would move according to stock prices, because older individual contributions will slow the adjustment process. A simple modification on the aggregation method (limiting the oldest contributions) reduces its impact on the target price indicators, without altering their relationship with the different uncertainty and volatility measures.

There are numerous ways to extend the analysis performed here. To venture just a few, it would be possible to focus more on individual contributions instead of the aggregate, in order to control in more detail different factors that can affect their estimates and revisions like the analysts' individual characteristics, possible conflicts of interest, or their specific biases. Another possibility is to perform a cointegration analysis of both target and stock prices, to also know how their long-term relationship changes in uncertain periods and what is their adjustment speed in the short-term. Finally, a similar work can be extended to other sectors and companies within Spain, or compare between what happens with Spanish banks and financial entities of similar countries.

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Appendix

Table A.1. Variables definition

Variable	Name	Definition	Data source
TPD	Target Price Differential	Difference between the aggregate target price on day t and the stock price of t-1, divided by the latter	Thomson Reuters-Refinitiv
ATPD	Absolute Target Price Differential	Absolute difference between the aggregate target price on day t and the stock price of t-1, divided by the latter	Thomson Reuters-Refinitiv
TD	Trend Differential	Absolute difference between the monthly variation of the target price and that of the share price	Thomson Reuters-Refinitiv
LAG	Lag indicator	Number of weeks the target price has to be delayed to minimize the ATPD (max. 16 weeks)	Thomson Reuters-Refinitiv
EPU	Economic Policy Uncertainty index for Spain	Monthly variation of the EPU	Policy Uncertainty webpage
CISS	Composite Indicator of Systemic Stress for Spain	Monthly variation of the CISS	European Central Bank
VIBEX	Ibex 35 volatility index (Vibex)	Monthly variation of Vibex	Bloomberg
PERIOD	Contribution period	Number of days between the oldest individual contribution and the publication date of the aggregate target price (90 days moving average)	Thomson Reuters-Refinitiv
EPS_D	EPS Differential	Difference between the estimated EPS on day t and the EPS of t-1, divided by the latter	Thomson Reuters-Refinitiv and Bloomberg
EPS_AD	EPS Absolute Differential	Absolute difference between the estimated EPS on day t and the EPS of t-1, divided by the latter	Thomson Reuters-Refinitiv and Bloomberg
EPS_TD	EPS Trend Differential	Absolute difference between the monthly variation of the estimated EPS and that of the EPS	Thomson Reuters-Refinitiv and Bloomberg
EPS_LAG	EPS lag indicator	Number of weeks the estimated EPS has to be delayed to minimize the EPS_TD (max. 16 weeks)	Thomson Reuters-Refinitiv and Bloomberg
CAP	Market capitalization	Market capitalization in euros	Thomson Reuters-Refinitiv

Table A.2. Descriptive statistics

Variable	Num. obs.	Average	Std. Dev.	Min.	Max.
TPD	23279	0,11	0,22	-0,77	2,48
ATPD	23279	0,17	0,17	0	2,48
TD	23070	0,07	0,08	0	1,89
LAG	22587	9,38	5,98	0	16
EPU (index)	261	108,84	37,42	44,44	261,61
CISS (index)	5531	0,12	0,16	0	0,80
VIBEX (index)	3509	23,32	9,13	9,61	79,24
PERIOD	22219	261,11	55,92	106,38	568,09
EPS_D	20990	-0,10	1,66	-54,55	50,78
EPS_AD	20990	0,26	1,64	0	54,55
EPS_TD	18776	0,11	0,65	0	30,11
EPS_LAG	18475	5,42	5,65	0	16
CAP	29926	25127	26974	225	110390

Table A.3. Correlations

	TPD	ATPD	TD	lnLAG	EPU	CISS	VIBEX
TPD	1						
ATPD	0,82	1					
TD	0,19	0,32	1				
ln LAG	0,27	0,37	0,00	1			
EPU	0,18	0,15	0,06	0,07	1		
CISS	0,24	0,27	0,30	0,04	0,22	1	
VIBEX	0,27	0,28	0,30	0,05	0,40	0,79	1
ln PERIOD	0,15	0,12	0,00	0,16	-0,01	0,02	0,03
EPS_D	0,04	0,03	0,02	0,01	-0,01	0,01	0,00
EPS_AD	0,03	0,06	0,04	-0,02	-0,05	-0,01	-0,02
EPS_TD	-0,03	0,02	0,05	-0,05	-0,05	-0,01	0,01
ln EPS_LAG	0,06	0,01	-0,02	0,10	-0,03	-0,08	-0,05
ln CAP	-0,07	-0,21	-0,19	0,02	-0,03	-0,05	-0,04

	lnPERIOD	EPS_D	EPS_AD	EPS_TD	lnEPS_LAG	CAP
ln PERIOD	1					
EPS_D	-0,02	1				
EPS_AD	-0,05	-0,29	1			
EPS_TD	-0,07	-0,03	0,16	1		
ln EPS_LAG	0,02	-0,07	0,07	0,03	1	
ln CAP	0,05	-0,08	-0,02	-0,06	0,28	1

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