THE ROLE OF SENTIMENT AND STOCK CHARACTERISTICS IN THE TRANSLATION OF ANALYSTS' FORECASTS INTO RECOMMENDATIONS

Pilar Corredor, Elena Ferrer and Rafael Santamaria
Public University of Navarre
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Abstract
This paper analyses the role of investor sentiment in the translation of analysts' forecasts into recommendations taking into account the sensitivity of stocks to this variable. The study analyses the non-financial firms listed on the London Stock Exchange from 1994 to 2010 using an European and a global sentiment indexes. The results show that, although analysts do translate their earnings forecast valuations into recommendations, the effectiveness of this process is reduced by investor sentiment only in highly sentiment-sensitive stocks. The fact that stocks of this type attract less analyst attention suggests the degree of analyst coverage as a potential conditioner of the observable average results in a particular market. While not totally eliminating this observed effect, the Market Abuse Directive regulation does contribute to reduce the skew between analysts' earnings forecasts and their recommendations. Finally, analysis of this effect reveals that this kind of skew enables investment strategies yielding positive risk-adjusted returns in highly sentiment-sensitive stocks, during periods of high market sentiment.

Keywords: Investor Sentiment, financial analyst, analysts coverage, recommendation, earning forecast, translational effectiveness.

JEL: G02, G15, G24, M41

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1-INTRODUCTION

Analyst credibility is one of the most controversial and widely discussed topics among researchers, market agents, and regulators (Lee, 2012). Any friction in the process by which analysts translate their forecasts into recommendations reduces the utility of the recommendations for investors (Ertimur et al., 2007). For this reason, recent studies have focused on furthering the understanding of the translation process by addressing issues such as the identification of valuation models (constructed from EPS forecast data) related to trading recommendations and what information analysts use (Bradshaw, 2004), the influence of conflict of interests on that process (Ertimur et al., 2007; Barniv et al., 2009 or Chen and Chen, 2009), and the detection of other determinants of the relationship such as insider trading, institutional ownership, trading commissions and investor sentiment (Ke and Yu, 2009).

Investor sentiment has also been identified as a key variable in explaining analyst behaviour, insofar as it reflects general optimism or pessimism about a stock (Baker et al., 2012) or the investor's opinion (usually emotionally driven) regarding future cash flows and investment risk (Chang et al., 2012). High or low market sentiment will affect the market and all its agents, analysts included. Previous research has highlighted analysts' inability to disassociate themselves from latent market optimism, which has been found to affect forecasting and recommendation processes separately (Qian, 2009; Bagnoli et al., 2009; Hribar and McInnis, 2012; and Corredor et al., 2013a and 2014). The effect has also been shown to vary across stock types, as a function of the vulnerability to sentiment of stocks that are hard to value or difficult to arbitrage (HVDA stocks) (see Baker and Wurgler 2006, among others).

In this context, this paper contributes in various ways to the literature. First, we analyze the role of stock characteristics in modulating the effect of investor sentiment on translational effectiveness. Given that sentiment will not necessarily influence analysts' earning forecasts to the same degree as their trading recommendations, because of the characteristic differences between them[1], in ex-post verifiability and the quantitative nature of forecasts versus the qualitative nature of recommendations, it is reasonable to suppose

[1] Because stock recommendations are discrete, while earnings forecasts are continuous, Francis and Soffer (1997) indicate that, even if stock recommendations efficiently incorporate analysts' earnings forecasts, earnings forecasts should be incrementally informative relative to stock recommendations as a predictor of future stock returns. Ke and Yu (2009) assert that analysts have greater incentives to bias recommendations than earnings forecasts, for two reasons: recommendations represent a more comprehensive and direct view of a firm's value and earnings forecasts can be easily checked against realized earnings, while biases in recommendations are much harder to detect due to the absence of an appropriate benchmark.

that sentiment will play some explanatory role in the translation of analysts' forecasts into recommendations and that it will vary across stock types.

Second, due to the very nature of the type of stocks followed by analysts, any study containing analyst information is subject to sample bias, which may skew the results. In fact, analysts concentrate their attention on a certain type of firm, while practically ignoring others, such as young firms, low cap firms, those attracting little media attention, those not listed in selective indexes, etc.[2] Thus, any sample that using analyst coverage data will under-represent such firms, and thus omit HVDA stocks, which are precisely the ones on which behavioural biases, such as those driven by investor sentiment, tend to have the strongest impact (see Baker and Wurgler, 2006, 2007 or Kumar, 2009). This sort of sample bias could be particularly pernicious in the case that concerns us, since it will reduce the sentiment effect in the chosen stock sample, with the result that we would observe a much lower impact on translational effectiveness than we might in a non-biased sample of the market.

We test this hypothesis on the UK stock market, because it is an example of the Anglo Saxon financial system within Europe, and is therefore comparable to the US stock market (the traditional setting for research into stock market issues) but it has a lower degree of analyst coverage, in terms both of the level of analyst activity and the number of stocks followed. It is a fact that European financial markets are subject to less analyst coverage than the US market, as noted by Jegadeesh and Kim (2006), who found levels of around 90% for US firms and no higher than 25% for European firms during the period 1993-2002. In particular, according to data collected by Jegadeesh and Kim (2006, Table I) the number of US firms with at least two active recommendations in the IBES database is 5.86 times greater than the number of British firms. We complete the analysis by testing various subsamples of stocks with different degrees of sensitivity to investor sentiment in order to strengthen the robustness of our findings.

If our hypothesis is correct, our results should qualify the findings obtained by Ke and Yu (2009) for the US market, by showing that sentiment does not necessarily affect translational effectiveness in the case of all stocks, but is concentrated basically in stocks whose characteristics make them more vulnerable to investor sentiment. Since analyst coverage is widespread in the US market, assets of this kind have greater weight in the overall sample, thus accounting for the compatibility of our findings with those of Ke and Yu (2009).

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[2] Bhushan (1989) examines the key determinants of the number of analysts following a particular firm. The main factor is size, with large firms attracting the highest levels of analyst coverage. Marston (1997) also points to this as a key variable in the analyst coverage of UK quoted companies.

Third, while several papers examine the use of valuation models by UK investment analysts (see Barker, 1999a and b, Imam et al. 2008, and Demirakos et al., 2010), they do not consider translational effectiveness. Thus, in addition to the reasons already given, study of the UK market enables the extraction of empirical evidence to add to that coming from the US market and serve as reference against which to draw conclusions regarding the impact of investor sentiment on translational effectiveness in developed European markets, where analyst coverage is always less widespread than in the US market.

Fourth, while there exists previous research on potential variation in translational effectiveness as a result of regulatory measures to control analyst behaviour, our paper also takes stock characteristics and sentitivity to sentiment into account.

Finally, as far as we are aware, no previous studies have attempted to analyze the economic importance of observed biases in the translation of analysts' forecasts into recommendations. We approach this task by constructing several strategies based on the level of investor sentiment and stock characteristics. This analysis enables us to determine whether the discrepancies between earnings forecasts and recommendations is large enough to enable a potentially profitable trading strategy. This exercise highlights the importance of understanding the components of analysts' reports in order to eliminate some of the observed biases.

The paper is organised as follows. Section 2 describes the theoretical framework and the testable hypotheses. Section 3 presents the database and the variable definitions. Section 4 describes the empirical analysis and presents its results regarding the effect of sentiment on transational effectiveness. Section 5 presents several robustness tests and section 6 summarises the main conclusions

2-THEORETICAL FRAMEWORK AND TESTABLE HYPOTHESES

2.1-THEORETICAL FRAMEWORK

Previous research has focused on the US market in trying to explain the relationship between analysts' earnings forecasts and their final recommendations. Schipper (1991) argues that analysts use earnings forecasts to obtain intrinsic stock value estimates on which to base their recommendations. A more recent, deeper analysis of the valuation models on which earnings forecasts are based (Bradshaw, 2004) reveals that analysts' recommendations do not fully reflect their stock value estimates. In the same vein, attempts to identify the variables behind translational effectiveness cite the conflict of interests to which analysts are subject (Ertimur et al., 2007), and US regulatory measures to reduce the influence of analysts' ties with investment banks and brokerage houses. Chen and Chen (2009) show that regulatory change led to a closer correspondence between analysts' recommendations and their stock value estimates by reducing conflicts of interests. Barniv et al. (2009) conclude that, although the regulation has modified analyst behaviour, other factors could still potentially influence the nature of their trading recommendations. Ke and Yu (2009) attribute to other determinants, such as insider trading, institutional ownership, trading commissions and investor sentiment, just as much influence as to conflicts of interests. Simon and Curtis (2011) link translational effectiveness with analyst accuracy, having noticed that the observations made by Bradshaw (2004) occur in less accurate analysts.

The effect of optimism on translational effectiveness has been given scant attention when compared to the amount it has received in separate studies of analyst forecasts and analyst recommendations, respectively. However, given that one source of optimism is linked to cognitive bias[3], it is worth studying the potential effect of latent investor sentiment on analyst behaviour. Investor sentiment, as a measure of optimism/pessimism about stocks in general, strikes us as an obvious factor to consider in a study of translational effectiveness[4]. Indeed, from the research linking cognitive bias and optimism among analysts, investor sentiment emerges as a possible explanatory factor for the latent optimism in analysts' forecasts and recommendations, and, thereby, in the translation from one to the other[5].

Research on the impact of investor sentiment on trading recommendations has shown that, in a market with latent optimism, analysts' recommendations tend to be more positive (Bagnoli et al., 2009 and Corredor et al., 2013a). Bagnoli et al. (2009), present evidence of the tendency of anlysts to issue more optimistic recommendations following a period of high investor sentiment. They also report lower future returns to stocks recommended by more sentiment-prone analysts. Corredor et al. (2013a) demonstrate the link between positive sentiment and optimistic recommendations, with evidence showing that joint consideration of the type of recommendation, investor sentiment, and stock characteristics yields higher risk-adjusted returns than yielded by the conventional strategies investigated so far (see Womack, 1996; Barber et al. 2001 and 2003; and Balboa et al. 2008 and 2009, among others).

In the research on earnings forecasts, Qian (2009) illustrates the relationship between optimism bias and sentiment, having observed higher optimism during periods of high market sentiment. Hribar and McInnis (2012) and Corredor et al. (2014) observe the same relationship and present similar findings.

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[3] Explanations for observed analyst optimism point to three main factors: economic incentives, cognitive bias, and negative skewness in earnings.

[4] The personal optimism of the individual analyst is another obvious candidate variable for analysis. This paper analyses only the general level of investor optimism/pessimism, measured as investor sentiment. As the literature has shown, investor sentiment influences the level of optimism/pessimism in analysts, but it is only one component of individual optimism and is therefore only an approximation that could be completed with data enabling the incorporation of the idiosyncratic component in individual analyst optimism.

[5]As shown by Corredor et al (2014), analyst optimism is both strategically and cognitively driven. It must also be noted that individual optimism is linked in part to overall market optimism, which we aim to approximate with investor sentiment.

It is worth noting, however, that, forecasts and recommendations will not necessarily be equally sensitive to biases, and investor sentiment could therefore affect each to a different degree. In fact, due to their qualitative nature and the difficulty of their ex-post verification, recommendations are more sensitive than earnings forecasts to cognitive bias. These characteristic differences could, therefore, play a role in the translation of forecasts into recommendations.

In this vein, the only two studies of the effect of investor sentiment, as a possible explanatory variable for translational effectiveness focus on the US market. Chen and Chen (2009) rule out market movements as a possible cause of skewness in the relationship between analysts' recommendations and their valuation model while Ke and Yu (2009) note that investor sentiment reduces translational effectiveness.

This paper tries to complete this topic by studying the role of investor sentiment[6] on translational effectiveness taking into account the role of stock characteristics and, in this vein, potential sample bias due to the number of stocks followed by analysts in a particular market.

2.2.-TESTABLE HYPOTHESES

The behavioral finance literature delves deeper into the effect of investor sentiment on trading decisions. Sentiment, conceptualised as the propensity to speculate, affects the relative demand for stocks that are vulnerable to speculation, whose valuations are subjective and difficult to determine, and whose contemporaneous returns are higher than is justifiable. When sentiment is taken to be optimism or pessimism about stocks in general, the effect of changes in sentiment will be uniform, while arbitrage constraints will vary across stocks. In fact, the literature has shown that arbitrage is particularly costly and risky with certain stock types. These two channels appear to affect the same type of stocks, or, to put it another way, the most speculative stocks are also the hardest to arbitrage and this stock profile will therefore be more sensitive to investor sentiment.

In this line, we further the analysis of the effect of sentiment on translational effectiveness by focusing on the, so far, unstudied UK stock market, taking into account a key factor for exploring the investor sentiment effect, namely, stock characteristics (Lemmon and Portniaguina, 2006; Baker and Wurgler, 2006, 2007; and Baker et al., 2012). Among the set of stock characteristics used to proxy for hard-to-value assets, volatility has been used for

[6] It is important to note that our analysis is centred on the role of investor sentiment, as a proxy for latent market optimism, in translational effectiveness. Several papers have demonstrated the impact of investor sentiment on individual optimism, the analysis of which is not our current interest and can be better approached using more suitable variables (see Mokoaleli-Mokoteli et al., 2009). Unfortunately, we do not have this information. However, among our robustness checks, we briefly explore this issue by incorporating a variable to capture differential analyst optimism, by measuring individual forecasts against the analyst consensus.

its potential to yield clearer results regarding the effect of sentiment on future stock returns (see Baker and Wurgler, 2006, Joseph et al., 2011 and Corredor et al., 2013b), analysts' forecast errors (Hribar and McInnis, 2012; Corredor et al., 2014) and analysts' recommendations (see Corredor et al. 2013a).

The role of stock characteristics in explaining the impact of sentiment on analyst forecasts and recommendations and thereby on translational effectiveness, suggests the following null hypothesis:

H1: *Translational effectiveness is not independent of stock type, and is lower in sentiment-sensitive stocks*.

It has already been noted, furthermore, that analysts concentrate their activity on a particular type of firm, while practically ignoring those with certain characteristics associated with potentially difficult asset valuation and arbitrage. This means that, as the number of firms under analyst coverage grows, so does the number of sentiment-sensitive firms among them and, thereby, the number of candidates for inclusion in the study sample. Thus, if null hypothesis H1 is confirmed, the results obtained for the stocks of one market, overall, will be influenced by the level of analyst coverage, which conditions the typology of the firm sample. This leads to the following null hypothesis:

H2: *A higher level of translational effectiveness will be observed in samples with lower analyst coverage.*

Several studies have shown that analyst optimism is both strategically and cognitively motivated (see, among others, Qian, 2009, Ertimur et al., 2011, Karamanou, 2011, Hribar and McInnis, 2012 or Corredor et al., 2014). While it is unclear whether regulatory measures influence cognitively-driven optimism, it is reasonable to suppose that they will have a noticeable impact on strategically-driven optimism. There is in fact existing evidence of the impact of regulatory changes on analyst behaviour (Dubois et al. 2013). Assuming that regulations have a separate impact on analyst forecasts, distinct from their impact on analyst recommendations, the issue this paper aims to explore is whether they significantly alter the impact of investor sentiment on translational effectiveness.

For this reason, we examine the persistence of the reported relationships after the adoption of the Market Abuse Directive (MAD), by testing the following null hypothesis:

H3:*The adoption of the MAD has not significantly affected the impact of sentiment on translational effectiveness*

In this case, we expect to be able to reject the null hypothesis by finding that the adoption of the MAD has reduced the impact of investor sentiment on translational effectiveness.

3-SAMPLE DESCRIPTION AND VARIABLE DEFINITIONS

Our analysis covers all non-financial firms listed on the London Stock Exchange from 1994 to 2010. According to the World Stock Exchange Federation (2011), the London SE Group is Europe's largest in capitalization terms. This makes it a particularly attractive research setting, given that, as far as we are aware, all the existing research on translational effectiveness has focused on the US market. There are similarities between the two markets, since they both belong to the Anglo Saxon system, which is characterised by low ownership concentration, which, in turn, is associated with higher stock liquidity, more widely-dispersed ownership and control, and a high level of creditor protection (La Porta et al. 1998). As far as investor type is concerned, the majority of institutional investors are mutual funds and pension funds, while private individual investors tend towards more individualistic behaviour, display a low degree of herd behaviour, and show high uncertainty and ambiguity tolerance (Hofstede, 2001). Nevertheless, there is a marked difference between these two markets in terms of analyst coverage. Jegadeesh and Kim (2006) report that, over the period 1993-2002, 90% of the US market received analyst coverage, versus only 67% of the UK market. The almost complete parallel between these two markets is broken only by the degree of analyst coverage[7]. This contrast enables evaluation of the role of analyst coverage in translational effectiveness by checking the consistency of reported findings for the US market with those obtained for the UK market. If translational effectiveness is related to stock characteristics, lower analyst coverage will introduce sample bias because it is precisely this type of assets that attract less analyst attention. Indeed, if we compare the subsample for which for which analyst data exist with the UK firm sample as a whole over the period of analysis, the average size of the firms in the subsample is 532% greater than for the sample as a whole, whereas their volatility and BTM values are 27% and 37% smaller, respectively. Even more striking results emerge when the subsample is reduced by incorporating control variables: the average size of the subsample is 644% greater and the volatility and BTM values are 37% and 42% smaller.

[7] This study could have focused on other European markets with a lower percentage of analyst coverage but other key differences (such as belonging to the continental system or mixed systems) would make any conclusions more difficult to interpret.

3.1-Analyst recommendations and earnings forecasts

The variables relating to analysts' releases are drawn from the Factset[8] database. The reason for this choice of database is that it provides fuller coverage in Europe than the I/B/E/S (Balboa, et al. 2008). Our analysis uses individual-level analyst recommendation data, together with one-year-ahead (*FY1*) and two-year-ahead (*FY2*) individual-level analysts' EPS forecasts. These earnings forecast data are used to construct the residual income valuation model. Constraints are imposed on the full sample in order to ensure data quality. One is to remove from the sample any forecasts issued less than 90 days prior to firms' profit announcements[9]. Another, which echoes the procedure used by Ke and Yu (2009), is that each analyst must issue the stock recommendation and one-year-ahead and two-year-ahead earnings forecasts on the same day. After applying these constraints, we have 40,835 observations involving 264 stocks, 1,979 analysts, and 255 brokerage houses over the period January 1994 to December 2010[10].

3.2- Investor sentiment

Our first sentiment proxy is based on recent research published by Baker et al. (2012) and Chang et al. (2012), among others, in which global sentiment indices are constructed from local sentiment indices. There is an indisputable need for a global sentiment index, because our sample analysts and their brokerage houses all operate in a global setting. Local indexes are not appropriate because they do not capture the full impact of investor sentiment[11] (see Baker et al., 2012, Chang et al., 2012 or Corredor et al., 2013b). In fact, in recent papers analyzing the effect of sentiment on stock returns, the tendency is to construct global sentiment indexes incorporating proxies for local sentiment. Baker et al. (2012) construct investor sentiment indexes for six major stock markets and combine them into a global one. Chang, et al. (2012) use the first main component of US, UK, French and German sentiment as a measure of global investor sentiment.

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[8] As well as the major international firms that regularly send their recommendations to I/B/E/S, contributors to this database include some domestic analysts, which results in wider coverage in European countries. Nevertheless, like other forecast databases, FactSet is affected by potential survivorship bias, and also selection bias, because it collects recommendations and forecasts from brokerage houses that collaborate on a voluntary basis. Correction of these two biases is not possible.

[9] These observations are omitted because of their proximity to the release of profit announcements and the consequent reduction in the risk of bias in forecasting errors.

[10] The number of observations in the benchmark model is reduced to 27,733 due to unavailability of the necessary data with which to construct the residual income valuation model, since we could not obtain Factset book-value-per-share and dividend-payout-ratio data for all the observations. Due to the construction of the control variables, in particular stock characteristics and analyst accuracy, the sample consists of 23,020 observations.

[11] The results of the analyses restricted to a UK index show that it does not play a significant role in explaining the behaviour of financial analysts covering UK firms.

Given that the country that concerns us is European, this study also includes an overall European composite indicator, which may avoid potential overestimation of the global sentiment index in the regression model.

In line with Baker and Wurgler (2006), we use the composite sentiment index to compute the European sentiment proxy (*SentEU*). This index captures the commonality between investor sentiment in four of the largest European stock markets in capitalization terms: Germany (*SentGE*), France (*SentFR*), Spain (*SentSP*) and the UK (*SentUK*). These local proxies are obtained by means of 3 individual sentiment indicators: turnover, the volatility premium and the consumer confidence index[12]. From these three variables, we derive a sentiment index for each country using the same mechanism as Baker and Wurgler (2006).

Given the possibility that each of the sentiment indicators considered may have both a sentiment component and a common economic cycle component, they are first orthogonalised to a series of a macro-economic variables in order to control for possible economic cycle effects[13]. They are then grouped into the first factor obtained using principal component analysis. Once obtained, the four local factors are included in the construction of the European sentiment index. The index scores for this Sent EU are as follows[14]:

$$SentEU_t = 0.32 * SentFR_t + 0.43 * SentGE_t + 0.34 * SentSP_t + 0.27 * SentUK_t \quad (1)$$

The same principal component analysis approach is used to create a Global sentiment (*SentGlobal*) that takes the form of a composite index which captures the commonality of the *SentUS* and *SentEU* indices[15]. For our US sentiment proxy (*SentUS*), we use the composite sentiment index created by Baker and Wurgler (2006, 2007)[16].

This first factor explains 81.15% of the variance, with the following scores:

$$SentGlobal_t = 0.55 * SentUS_t + 0.55 * SentEU_t \quad (2)$$

The *SentUS* and *SentEU* indices show positive correlation at a significant level (0.65). The correlation of each of these indices with *SentGlobal* is 0.908.

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[12] The reason for the choice of these measures is their relationship with the level of BW sentiment, together with data availability. Constructional details of the turnover index can be found in Baker and Stein (2004), and Jones (2002), and those of the volatility premium, in Baker et al. (2012). The consumer confidence index, which is available from the European Commission website, has been used in numerous studies, such as Brown and Cliff (2005), Lemmon and Portniaguina (2006), and Schmeling (2009) among others.

[13] Following Baker and Wurgler (2006), and Schmeling (2009), the macroeconomic variables considered are the industrial output index, durable and non-durable goods consumption, and the unemployment rate.

[14] The first principal component explains 51.87% of the total variance. The results show that the four composite country-specific indicators enter with the expected sign, since they have a positive influence on the SentEU composite index (the weights obtained for each country are 0.32 for France, 0.43 for GE and 0.34 and 0.27 for SP and UK respectively).

[15] Japanese market sentiment and other Asian market data are excluded because of data limitations.

[16] This index can be found at Wurgler's website: http://www,stern.nyu.edu/~jwurgler

3.3- The valuation model

Our analysis requires us to estimate an intrinsic value for a stock (*V*) reflecting analyst earnings forecast information. In line with the model proposed by Frankel and Lee (1998), we construct a proxy for the intrinsic value of a stock fulfilling this requirement[17]. The model in question, which is based on that of Ohlson (1995), incorporates all the information contained in the analysts' earnings forecasts and takes the following form:

$$V = B_t + \frac{(FROE_t - r_e)}{(1+r_e)} B_t + \frac{(FROE_{t+1} - r_e)}{(1+r_e)^2} B_{t+1} + \frac{(FROE_{t+2} - r_e)}{(1+r_e)^2 r_e} B_{t+2} \quad (3)$$

where $FROE_t$ is the forecast return on equity for year t, B_t is the book value of common shareholders' equity at year t, and r_e is the annualised cost of equity estimated using the procedure described by Fama and French (1997). This model assumes that the residual income forecast in t+2 continues in perpetuity.

Frankel and Lee (1998) estimate $FROE_t$, $FROE_{t+1}$ and $FROE_{t+2}$ using a one-year-ahead EPS forecast (*FY1*) and a two-year-ahead EPS forecast (*FY2*) and estimates of the book value (B_t and B_{t+1}). The notation is as follows:

$$FROE_t = FY1/[(B_{t-1} + B_{t-2})/2] \quad (4)$$

$$FROE_{t+1} = FY2/[(B_t + B_{t+1})/2] \quad (5)$$

$$FROE_{t+2} = [FY2(1+LTG)]/[(B_{t+1} + B_t)/2] \quad (6)$$

$$B_t = B_{t-1}[1 + FROE_t(1-k)] \quad (7)$$

$$B_{t+1} = B_t[1 + FROE_{t+1}(1-k)] \quad (8)$$

$$B_{t+2} = B_{t+1}[1 + FROE_{t+2}(1-k)] \quad (9)$$

where k is the dividend payout ratio in year t-1. Due to the unavailability of long-term earnings forecast data, *LTG* is calculated as the growth rate implied from the one-year-ahead and two-year-ahead earnings forecasts. The analyst data required for the estimation of the valuation model are obtained from Factset. The stock prices required for the estimation of the cost of equity are drawn from the Datastream Thomson Financial database. Following Ke and Yu (2009), we discard all observations that have $FROE_t$ or k of more than 100% and a negative book value.

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[17] This model is also used in Ali et al (2003), Bradshaw (2004), Chen and Chen (2009) and Ke and Yu (2009). These last authors argue in favour of using this measure rather than a heuristic valuation model, such as the price-earnings-to-growth (PEG) model, since the purpose in hand requires, not an analyst's estimation of the stock´s intrinsic value, but a stock´s intrinsic value reflecting analyst earnings forecast information.

The V estimate is scaled by the price[18] P in order to obtain the V/P ratio which provides a proxy for the attractiveness of a given stock according to analyst reports.

3.4- Control variables

Analysts' recommendations are positively associated with investment banking business and pressures from brokerage houses. Several studies (Hodgkinson, 2001; Ljungvist et al., 2006; Ertimur et al., 2007; Ke and Yu, 2009; Chen and Chen, 2009; and Lee, 2012, among others) have shown that analysts' reports are influenced by conflicts of interest. Following Ertimur et al (2007), we construct a proxy for conflicts of interest by sorting analysts into two groups based on their level of participation in new IPOs[19]. The variable is defined as a dummy variable (*ConfInt*) that takes a value of 1 for analysts employed by a firm that has participated in any new IPO in the main UK stock market for at least 8 years and 0 otherwise[20]

In line with Ke and Yu (2009), and with a view to mitigating potential V/P measurement errors, we include two additional control variables: the book-to-market (*BTM*) ratio as a measure of value relevance, and analyst accuracy (*ACC*) as a measure of each analyst's forecasting quality relative to the rest of the sample. *BTM* is calculated as the ratio of book value to market value at the end of the fiscal year prior to the year the recommendation is made. *ACC* is is obtained by comparing the analyst's absolute forecast error to the absolute forecast error of the consensus forecast for the same stock[21] (see Clement, 1999).

$$ACC_{i,j,t} = \left(\frac{Abs(FE_{i,j,t}) - Abs(FEConsensus_{it})}{Abs(FEConsensus_{it})} \right) \tag{10}$$

Where $FE_{i,j,t}$ is the absolute forecast error for analyst j's forecast for firm i in year t and $Abs(FEConsensus_{it})$ is the absolute consensus forecast error for firm i in year t . $FE_{i,j,t}$ ($FEConsensus_{it}$) is calculated as the actual reported earnings of firm i in fiscal year t minus

[18] Due to the fact that analysts may filter their recommendations 1 day prior to the date of release (Ke and Yu, 2009), we use the price at two days prior to the release date. Irvine et al. (2007) even found that analysts filter information to benefit their clients up to 5 days prior to the date of release. The results scaled by the price 5 days before are practically the same.

[19] Ertimur et al., (2007) construct a measure that groups analysts into 3 groups according to their employability in brokerage houses engaged in investment banking activities and according to the reputation of the brokerage houses. Due to unavailability of data, we are able to form only 2 groups based on a single variable.

[20] The data were obtained from the London Stock Exchange. We lack more precise information with which to create a conflict-of-interest measure. In consequence, we use this variable strictly for control purposes, without any presumption as to its usefulness for further analysis.

[21] This variable refers to the accuracy of the analyst's previous forecast. To avoid significantly reducing the number of observations (by 43%), however, we use current instead of lagged forecast accuracy. It is important to note that the current and lagged variables yield similar results. Since this variable was intended for control purposes only, we opted for the compromise solution. To remove outliers, mainly due to denominators close to 0, the data are winsorised at the 5 and 95% percentile.

the (*EPS*) earnings forecast for firm i, issued on date t for that fiscal year, by the individual analyst j (by analyst consensus) scaled by the analyst's absolute earnings forecast (by analyst consensus).

$$FE_{i,j,t} = \left(\frac{ActualEPS_{i,t} - EPS_{i,j,t}}{Abs\left(EPS_{i,j,t}\right)} \right) \tag{11}$$

Experience is another variable considered to influence analysts' reports (Clement, 1999; Mikhail et al., 1997, 1999; Ertimur et al., 2007 or Shon and Young, 2011 among others). In line with Clement (1999), we consider analysts' general experience (*GenExp*) calculated as the number of years (including the year of report date t) that analyst j has been issuing firm earnings forecasts, minus the mean number of years the analysts have been issuing earnings forecasts for any firm. As a second experience proxy, we consider firm experience (*EspExp*) taking the number of years (including the year of report date t) that analyst j has followed stock i minus the mean number of years for which earnings forecasts exist for stock i.

We consider the effect of firm size (MV) as another potential control variable for the determination of buy and sell recommendations which is practically industry standard in analyst studies (Mokoaleli-Mokoteli et al., 2009, Ertimur et al., 2011 and Loh and Stulz, 2011). Firm size is measured using the market capitalization of equity at the end of the year preceding the recommendation date.

We enlarge our set of control variables by including analyst coverage per stock. Analyst following (AF) represents the number of analysts following the firm j and is perceived to be essential for the correct valuation of the firm by the market (Mokoaleli-Mokoteli et al., 2009). Finally, we include the variable SIGMA to reflect the volatility of the stock measured as the twelve months' standard deviation[22].

4-EMPIRICAL ANALYSIS AND RESULTS

4.1-Methodology

Our empirical analysis focuses on the relationship between recommendations and earnings forecasts and how this is influenced by investor sentiment. The following is our benchmark model:

$$\begin{aligned} \mathrm{Prob}\left(REC_{ijt}\right) &= \beta_1 SENT_{t-1} + \beta_2 \left(\frac{V}{P}\right)_{ijt} + \beta_3 SENT_{t-1} \left(\frac{V}{P}\right)_{ijt} + \beta_4 ConfInt_{ijt} + \beta_5 GenExp_{ijt} + \beta_6 EspExp_{ijt} + \\ &\beta_7 BTM_{it} + \beta_8 ACC_{ijt-1} + \beta_9 MV_{it} + \beta_{10} AF_{it} + \beta_{11} SIGMA_{it} + \varepsilon_{ijt} \end{aligned} \tag{12}$$

The dependent variable REC_{ijt} is analyst j's recommendation for stock i on recommendation date t. Factset ranks the recommendations received by brokerage houses on a 5-point scale. In line with Bradshaw (2004), Jegadeesh et al., (2004) or Ljungqvist et al.,

[22] We are grateful to the referees for suggesting the inclusion of these control variables.

(2006), we code the recommendation as 1=sell; 2=underweight; 3=hold; 4=overweight; 5=buy. This coding allows for a more intuitive interpretation, whereby a positive recommendation suggests a buy rating signalled by a higher *V/P* ratio. As a robustness test, we also used a 3-point scaling code, since overweight and buy can be interpreted as meaning that the stock will outperform the benchmark over the next 6-12 months and can therefore be combined, while sell and underweightd mean the same thing and can also be combined[23]

REC_{ijt} is a discrete variable representing the preferences or opinions of investors who follow analysts' recommendations for a given stock. When calculated in the manner described above, this variable may be implicitly ranked by its utility and thus has an ordinal nature. This suggests Ordered Probit analysis as the best method to estimate our model[24]. The standard errors are clustered by stock and adjusted for heteroskedasticity and serial autocorrelation. Year dummies are also included to control for time effects.

The regressors for the model are investor sentiment, the intrinsic value estimate of the stock on which the recommendation is made and their interaction (which captures translational effectiveness) and a series of control variables. *SENT* is latent market sentiment in the end of the year previous to the recommendation date[25]. As already mentioned in the theoretical framework, Bagnoli et al. (2009) and Corredor et al. (2014) show that high market sentiment leads analysts to issue more favorable recommendations. In this line, we expect *SENT* to have a positive and significant sign.

$(V/P)_{ijt}$ is the estimated value of stock i on report date t using the earnings forecasts issued by analyst j for stock i, and scaling by the market price. If a stock valuation based on analysts' earnings forecasts explains the trade recommendations, we should observe buy(sell) recommendations for stocks with a higher(lower) *V/P* ratio; that is, we can expect the *V/P* variable to have a positive and significant coefficient.

The $SENT_{t-1}*(V/P)_{ijt}$ variable captures the moderating effect of sentiment on the effectiveness of valuation models to generate investment recommendations. If we accept that the role played by sentiment in analysts' reports leads them to make more favorable recommendations, we can expect the interaction $SENT_{t-1}*(V/P)_{ijt}$ to have a negative and significant coefficient, insofar as sentiment reduces translational effectiveness.

The model also includes the control variables described in section 3.4 (*ConfInt, GenExp, EspExp, BTM, ACC,MV*, *AF* and *SIGMA*).

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[23] Ho and Harris (1998) indicate that the five-level rating is used only to "sugar coat" bad news and therefore has no useful technical meaning. Accordingly, we code the recommendation as 1=sell and underweight, 2=hold and 3=overweight and buy.

[24] Ke and Yu (2009) use OLS to estimate their model, noting the results to be similar to those obtained by means of ordered Probit estimation. Given our model specification, we consider that the ordered Probit method provides the more accurate estimation.

[25] Although the sentiment index is a monthly index, for the purposes of this paper investor sentiment is measured in December of the year prior to issue of the forecasts and recommendations (see Baker and Wurgler, 2006, 2007).

Table I Panel A shows the descriptive statistics of the model variables. Consistent with analysts' tendency towards optimism, their recommendations tend, on average, to be overweighted (3.599). In fact, the 75th percentile are buy recommendations and the median recommendation is overweighted[26]. Both the mean and median stock *V/P* ratios are higher than 1, which is consistent with a higher percentage of favorable recommendations. Despite a high degree of variability, both sentiment indexes are positive on average. 70.30% of analysts are subject to conflict of interests, have 3.762 years' overall experience, and 2.243 years' specific experience. The number of analysts following a firm reach, on average, to 15 and mean volatility is 9.90%. Panel B shows the correlation matrix of the independent variables. The coefficients obtained are significant[27] although the correlation between the variables is low in overall terms.

4.2-Results

4.2.1- Translation of analysts' forecasts into recommendations. Full sample

The results of the estimation of equation (12) for the full stock sample are given in Table II. They include the results for the basic model (1) without any control variables, and for the extended model (2) with all the control variables. In both cases, 5- and 3-point scale, estimates and results using both sentiment proxies are shown (SentGlobal and SentEU).

It is interesting to note that investor sentiment is positive and clearly significant in all the above-mentioned estimations, showing that latent optimism among investors increases analyst optimism in average terms, as indicated by the higher value of analyst recommendations.

The data reveal that the *V/P* ratio is positively associated with recommendations, indicating that analysts use residual income valuation models to generate trading recommendations. Stock value estimates above their prices lead to more positive recommendations, given the positive and significant association that exists between earnings forecasts and recommendations.

The coefficient of the interaction variable, *SENT*V/P*, which captures the impact of sentiment on translational effectiveness, is negative but lacks significance, suggesting that investor sentiment influences translational effectiveness in general terms but is not moderated by the value of the stock. These results contrast with those of Ke and Yu (2009) who do report a moderating effect of sentiment on translational effectiveness. The sample bias due to lower analyst coverage (in terms of numbers of stocks) in the UK market with

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[26] In the case of the 3-point scale, due to the recoding of the overweight recommendation as = 3, the 75th percentile are buy recommendations and the median recommendation is buy (2.381)

[27]Except for BTM with Esp Exp, ACC with BTM and SIGMA with ACC

respect to the US market leading to under-representation of HVDA stocks[28], which could affect the findings for the full sample. We will return to this issue later when we discuss the analysis of this specific stock type.

Observation of the control variables shows that they all lack significance except accuracy and analyst coverage, which are negative and significant at the 10% level. Finally, it is interesting to note that basically the same findings emerge whether we use the European or the global sentiment index, and whether we use the basic model or the extended model including the control variables[29]. The findings hold for both the 3- and the 5-point coding scale, which is a strong indication of their robustness.

4.2.2- Translation of analysts' forecasts into recommendations. Stock characteristics.

As shown in the theoretical framework, the effect of investor sentiment is greater in HVDA stocks. This section focuses on observing whether the effect of investor sentiment on translational effectiveness varies with stock characteristics. As argued previously, this study uses volatility to characterise the sensitivity of stocks to investor sentiment. Starting with the complete model (2) (equation 12), we add new variables indicating whether stocks are sentiment sensitive.

$$\begin{aligned}\text{Prob}\left(REC_{ijt}\right) &= \beta_1 SENT_{t-1} + \beta_2 DQ_{HVDA,t} * SENT_{t-1} + \beta_3 DQ_{SEC,t} * SENT_{t-1} + \beta_4 \left(\frac{V}{P}\right)_{ijt} + \beta_5 SENT_{t-1}\left(\frac{V}{P}\right)_{ijt} + \\ &\beta_6 DQ_{HVDA,t} * SENT_{t-1}\left(\frac{V}{P}\right)_{ijt} + \beta_7 DQ_{SEC,t} * SENT_{t-1}\left(\frac{V}{P}\right)_{ijt} + \beta_8 Z_{ijt} + \varepsilon_{ijt}\end{aligned} \quad (13)$$

where Z captures the set of control variables (*ConfInt*, *GenExp*, *EspExp*, *BTM, ACC, MV, AF and SIGMA).* The model now includes two dummy variables for stock characteristics and their interaction with sentiment and translation. DQ_{HVDA} is a dummy variable that takes a value of 1 for stocks in the top quintile in terms of difficulty of valuation and arbitrage, proxied by volatility (5th volatility quintile), and 0 otherwise. DQ_{SEC} captures the effect of the stocks in the bottom quintile, that is, it takes a value of 1 for the least hard to value (1st volatility quintile) stocks and 0 otherwise. The joint estimation of the two quintiles enables a direct comparison to reveal potential differences between them. To construct these variables, the stocks are sorted annually into quintiles based on their past volatility. As in the previous

[28] Note that analyst coverage is higher in larger stocks, stock size being inversely associated with difficulty of valuation.

[29] For the control variable, conflict of interest, 3 approximations, in addition to those mentioned in section 3.4, were taken and the results hold for all of them. The first is a dummy variable that takes a value of 1 for brokerage houses that have participated both in IPOs and non-IPOs in the principal market and AIM. The second takes a value of 1 when they have participated in the main market, both in IPOs and non-IPOs; and, in the third, the dummy variable is defined as shown in section 3.4 but, instead of 8 years, it considers the average number of years participation in IPOs in the main market. The conclusions are similar. These results are available from the authors upon request.

case, the ordered nature of the dependent variable suggests estimation by means of an Ordered Probit model. The standard errors are clustered by stock and adjusted for heteroskedasticity and serial autocorrelation. Time effect dummies are also included.

The results of the estimation of equation (13) are given in Table III[30], where the data show a similar effect of sentiment on recommendations as found in equation (12), that is, positive and significant. In addition, the differential between the sentiment effect in the top and bottom quintiles clearly shows that the stocks in the fifth volatility quintile, that is, the most sentiment-sensitive, are more likely to receive positive recommendations during periods of investor optimism.

The coefficient of the value-to-price ratio (*V/P*) is positive and significant, as in the previous estimation, suggesting that analysts use forecasting data to generate their recommendations. The coefficient of overall translational effectiveness as a function of market sentiment lacks significance. Nevertheless, after sorting the stocks into quintiles based on their volatility, the results prove revealing. HVDA stocks, as captured by the variable DQ_{HVDA}, have a higher probability of showing lower translational effectiveness when investor sentiment is high, since the $DQ_{HVDA,t}*SENT*(V/P)_{ijt}$ coefficient is negative and significant. In less sentiment-sensitive stocks, the value of the $DQ_{SEC,t}*SENT*(V/P)_{ijt}$ coefficient is positive, albeit not significant. Joint interpretation of the effect of this variable in more sentiment-sensitive stocks (negative coefficient) and less sentiment-sensitive stocks (positive coefficient) might explain the lack of an observed effect in the analysis of the non-sorted sample[31]. These results enable us to confirm hypothesis H1, which predicted that the sentiment effect is not independent of asset type and that translational effectiveness is lower in sentiment-sensitive stocks. This tells us not only that forecast and recommendation releases are individually influenced by a moderating variable relating to their sensitivity to market sentiment, but that there also exists another effect emanating from the process by which forecasts are translated into recommendations. The different nature of the two variables (the first being numerical and continuous, the other being qualitative) and differences in their ex-post verifiability might help to explain this additional effect.

The difference between sentiment-sensitive and other stocks in terms of the effects on the translation of forecasts into recommendations suggests the possibility that the overall

[30] Estimations were also performed using other stock characteristics linked with difficulty of valuation and arbitrage, such as size, the BTM ratio and dividend payout, but the results were less clear than in the described estimation using volatility. The analysis is in line with Corredor et al., 2013b and 2014, who also use volatility to explore analyst performance considering it to be the best criterion for detecting sensitivity to market sentiment. The results are available from the authors upon request.

[31] Given the demonstrated fact that market sentiment affects analysts' recommendations and earnings forecasts separately, the *V/P* ratio may capture part of that effect. In order to strengthen the robustness of our results, we repeat the analysis using an orthogonalised value of the *V/P* ratio net of sentiment. This yields similar results to those obtained previously.

findings for a given market may be conditioned by the level of analyst coverage in terms of the number of stocks followed by any analyst, since, as already noted, there exists a proven bias towards stocks with characteristics that would exclude them from the subset of sentiment-sensitive stocks. This also lays open the possibility of the findings for the US market obtained by Ke and Yu (2009) being compatible with ours for the UK market. Lower analyst coverage in the UK removes a large portion of sentiment-sensitive stocks from the sample, thereby making it difficult for our overall finding to coincide with the US case where such stocks attract analyst coverage and are therefore much more widely represented in the sample.

To explore this possibility, we performed two complementary analyses that would enable us more effectively to test the second hypothesis in this paper, H2, which states that greater translational effectiveness is observed in samples with lower analyst coverage. We begin the first of these analyses by estimating model (2) using the subset of stocks forming the fifth sentiment-sensitive quintile[32]. We then add to the initial sample by incorporating stocks from the fourth and third quintiles. If the hypothesis is confirmed, the effect of the reduction in translational effectiveness should be clearly observed in the first sample and gradually weaken as less sentiment-sensitive stocks are added. The second analysis is performed using the stocks from the fifth quintile into which we incorporate a number stocks equal to a whole quintile but drawn randomly from the first to the fourth quintiles. We expect the result to be similar, but the weakening of the effect more striking than in the previous analysis, given that the added stocks do not belong to a specific quintile.

The results obtained from these two analyses (see Table IV) support the tested hypothesis. In the first analysis, the observed impact on translational effectiveness becomes weaker as less sentiment-sensitive stocks are added. In fact, when the stocks from the third quintile (Panel C) are incorporated, the effect loses significance at conventional levels. The results of the second analysis (Panel D) are also very revealing, since the incorporation of the random quintile eliminates the effect of investor sentiment on translational effectiveness. Again, it is important to note that the obtained results are clearly robust to the use of both the European and the global sentiment index, and both the 3- and the 5-point recommendation scale.

These results lead us to conclude that our findings could be misleading because the incorporation of analyst information leads to the under-representation of a certain type of firm within the sample as a whole, which results in a biased sample. In our analysis, stock

[32] It is important to note that, due to the sample bias generated by lower analyst coverage, not even the sentiment-sensitive stock quintile truly captures this type of stock, since the firms that best fit this subsample will probably be ignored by analysts, leaving us unable to incorporate forecasts or recommendations on these firms into the analysis.

valuation and arbitrage problems, as a sentiment-linked stock characteristic, emerge as a key explanatory factor in the analysis of translational effectiveness, but might be being overlooked in Ke and Yu (2009) whose results appear to suggest that translational effectiveness is the same for all market stocks.

Nevertheless, as already noted, we cannot rule out the compatibility of the above results with those presented by Ke and Yu (2009), due to the aforementioned unavoidable sample bias in the UK subsample analysis.

In summary, the results show that, when releasing their trade recommendations, analysts are influenced by the level of investor sentiment present in the market. However, the reduction of the translational effectiveness does not affect all stocks to a significant degree, its significance being limited to more sentiment-sensitive stocks.

4.2.3- Translation of analysts' forecasts into recommendations. Influence of the Market Abuse Directive.

The literature has shown evidence of the impact of regulatory changes on analyst behaviour (Dubois et al. 2013). Taking into account the potential regulatory impact on the strategic component of analyst behaviour, and the characteristic differences between forecasts and recommendations, the issue remaining for empirical analysis is whether regulatory measures have a significant impact on the translation of analysts' forecasts into recommendations.

In 2003, the EU passed the Market Abuse Directive[33], aimed at preventing managers from releasing selective information and at uniform treatment of conflicts of interest among analysts in the EU member countries. Since then, all EU members have applied these standards in their respective countries, the UK having implemented this directive in July 2005. The US had adopted a similar initiative in 2003.

To test the impact of this directive on the impact of sentiment on translational effectiveness, we estimate equation (14). The dummy variable labelled *PostMAD* takes a value of 1 for the period following the implementation of the directive, and 0 for the period prior to its implementation, plus its interaction with the remaining variables[34]. The model takes the following form:

[33] Directive 2003/125

[34] PostMAD is interacted only with the control variable ConfInt, which is the one that might be influenced by the Market Abuse Directive. The estimation is carried out jointly for both periods for the sake of efficiency and to facilitate direct testing of the PostMAD variable.

$$\begin{aligned}\text{Prob}(REC_{ijt}) = {} & \beta_1 SENT_{t-1} + \beta_2 SENT_{t-1} * PostMAD + \beta_3 DQ_{HVDA,t} * SENT_{t-1} + \beta_4 DQ_{HVDA,t} * SENT_{t-1} * PostMAD + \\ & \beta_5 DQ_{SEC,t} * SENT_{t-1} + \beta_6 DQ_{SEC,t} * SENT_{t-1} * PostMAD + \beta_7 \left(\frac{V}{P}\right)_{ijt} + \beta_8 \left(\frac{V}{P}\right)_{ijt} * PostMAD + \beta_9 SENT_{t-1} * \left(\frac{V}{P}\right)_{ijt} + \\ & \beta_{10} SENT_{t-1} * \left(\frac{V}{P}\right)_{ijt} * PostMAD + \beta_{11} DQ_{HVDA,t} * SENT_{t-1} \left(\frac{V}{P}\right)_{ijt} + \beta_{12} DQ_{HVDA,t} * SENT_{t-1} \left(\frac{V}{P}\right)_{ijt} * PostMAD + \\ & \beta_{13} DQ_{SEC,t} * SENT_{t-1} \left(\frac{V}{P}\right)_{ijt} + \beta_{14} DQ_{SEC,t} * SENT_{t-1} \left(\frac{V}{P}\right)_{ijt} * PostMAD + \beta_{15} Z_{ijt} + \varepsilon_{ijt}\end{aligned} \tag{14}$$

The results of the estimation are shown in Table V. The data for the variables considered in equation 14 display the same behaviour as observed in the previous estimations. The coefficients for stock value and investor sentiment are positive and significant, and the sentiment effect on HVDA stocks is greater and modulated by stock V/P, which is negative and significant. The inclusion of the dummy variable to identify the post-directive period yields some interesting results. With the introduction of the directive, the global sentiment effect diminishes significantly, which vouches for the effectiveness of the directive, since it has mitigated, albeit not completely eradicated, the impact of a factor which is external to the firm's asset value. However, introduction of the directive does not appear to affect the relationships observed in more sentiment-sensitive stocks, since the dummy variables relating to the effect of sentiment on the top quintile during the *PostMAD* period are not significant. Furthermore, the variables relating to translational effectiveness ($\left(\frac{V}{P}\right)_{ijt} * PostMAD$ and $DQ_{HVDA,t} * SENT_{t-1} \left(\frac{V}{P}\right)_{ijt} * PostMAD$) are also non-significant at conventional levels, thus preventing us from formally rejecting null hypothesis H3.

Nevertheless, overall, these results reveal a reduction in the impact of sentiment following the implementation of the directive. The degree of reduction is not the same in all stocks, however, since the more volatile stocks still differ from the rest of the sample. The explanation is compatible with that presented for the results of Corredor et al (2014), where it is shown that there are two distinct aspects to analysts' forecast errors: strategic behaviour and cognitive bias, each with individual significance. The directive has clearly reduced the incentive to issue deliberately skewed recommendations (strategic behaviour), but, as might be expected, it has had no significant effect on the unconscious error (cognitive bias). Given that this last effect is more prevalent in hard-to-value stocks, it is easy to explain why they are much less affected by the directive.

4.2.3- Investment strategies

The effect of investor sentiment on the translation of earnings forecasts, linked with the V/P ratio, enables the implementation of strategies designed to trade on this anomaly. In order to analyse the importance of the role of sentiment and the value of the V/P ratio in this anomaly, every month t we design several strategies. The first is the benchmark strategy, in which we use all stocks that have been the object of an analyst forecast during month t. We take a buy position if the value of the $(V/P)_t$ ratio is greater than unity, and a sell position if it is less than unity. For each stock, the return for the holding period from month t to month t+12 is then computed. Finally, returns are aggregated in equal-weighted portfolios.

If the effect is exclusively due to the value of this ratio, this strategy should yield a significant positive return. The results presented in the previous sections indicate, however, that the said anomaly occurs at times of high investor sentiment, particularly affecting the subset of more sentiment-sensitive stocks. We therefore implement 3 further strategies: "5Q", "5QHS", and "N5QHS", aimed at testing for variation in the impact of skewness in the translation of forecasts into recommendations at different levels of investor sentiment and for different stock characteristics. The first strategy is identical to the benchmark strategy, except that it is implemented only on the stocks contained in the fifth volatility quintile[35] and is based primarily on stock characteristic. The second and third strategies are implemented exclusively in periods of high investor sentiment (defined as those in which investor sentiment in year t is above the median recorded for December of the year t-1). The second "5QHS" differs from "5Q" only in that it is implemented in periods of high investor sentiment. Note that, in this case, volatility serves as a proxy to identify more sentiment-sensitive stocks. The third strategy "N5QHS" is again identical to "5QHS", except that it is implemented using all stocks except those belonging to 5Q. Using this last strategy, we aim to analyze the impact of investor sentiment on non sentiment-sensitive stocks.

If, as this paper has shown, high investor sentiment is the reason for the reduction in translational effectiveness in highly sentiment-sensitive stocks, we should find that the "5QHS" strategy yields a positive value. The "N5QHS" strategy could have a positive value, albeit clearly lower than that yielded by "5QHS". Finally, the "5Q", which captures the effect of the stock characteristic, will yield the average return to highly volatile stocks weighted by their exposure to periods of high and low investor sentiment. This value will therefore be slightly higher than that of the benchmark strategy.

Finally, the expected result for the benchmark strategy will be close to 0, since it disregards the variables that influence translational effectiveness (the level of investor sentiment and the sentiment sensitivity of the stocks).

Given that, when sorting by V/P values greater and less than unity, we are likely to come up against values very close to unity, we repeat the three strategies described above,

[35] Every month t, stocks are sorted into volatility quintiles irrespective of whether they have received an earnings forecast for that month.

using the following sorting criteria: a) V/P<0.95 and V/P>1.05; and b) V/P<0.90 and V/P>1.10.

As already noted, the monthly portfolios are constructed exclusively from stocks for which an analyst has issued a one-year-ahead earnings forecast[36]. This means that there will be some months for which there are no stocks with which to form the buy/sell portfolio. In the event of this occurring, we ensure the possibility of a self-financed strategy, by assuming that investment or borrowing are possible at the risk-free rate for that month[37]. The descriptive statistics and the test results for the null hypothesis of 0 returns[38] to the strategy are shown in Table VI. As can be seen, the return to the benchmark strategy is close to 0 (0.05% monthly). Those of strategies "5Q" and "5QHS", however, are somewhat higher (0.37% and 0.88%), although, strictly speaking, neither is significant at conventional levels. The mean monthly return to strategy "N5QHS" is negative (-0.09%), but again not different from zero. Different results emerge when we exclude stocks with earnings forecasts with V/P ratios within the intervals of 0.95-1.05, or 0.90-1.10. In both cases, the return to strategy "5QHS" ("5QHSa" and "5QHSb", respectively) are positive and significant at the 10% level, with higher than 1% mean monthly returns. Neither of the two remaining strategies, "5Q" and "N5QHS", yields a return significantly different from zero at the conventional levels, in either case a or b. It is also important to emphasise the role of stock characteristics, as shown by the returns to strategies "5QHS" and "N5QHS" in each case (a and b), which are significantly different, revealing that, at times of high investor sentiment, the reduction in translational effectiveness is greater in highly sentiment-sensitive stocks.

The above results do not take into account the potential risk exposure associated with the proposed strategies. The fact that we are working with self-financed strategies (based on buy and sell portfolios) requires us to test whether they have significant exposure to the classic risk factors. To do this, we regress the mean monthly returns to each of the 9 proposed strategies, and to the benchmark strategy, on a constant and the monthly risk factors in the classic Fama French (1993) model.

$$R^{i}_{(V/P)>K_2,t,t+l} - R^{i}_{(V/P)<K_1,t,t+l} = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + u_t \tag{15}$$

[36] As well as the 90-day constraint between earnings forecast and end of fiscal year, which forces the exclusion of November and December data, there are occasions when there are no forecasts for any of the stocks in the strategy portfolio.

[37] In the event of it being impossible to construct either portfolio, as can occur when, for instance, portfolio construction takes places during a period of high or low investor sentiment, we assume non-implementation of the strategy instead of assuming a null return strategy, since the latter could lead to bias in the calculation of mean strategy returns.

[38] The t statistic incorporates the White (1980) correction.

where $R^{i}_{(V/P)>K_2,t,t+l} - R^{i}_{(V/P)<K_1,t,t+l}$ is the return to the self-financed portfolio. $R^{i}_{(V/P)>K_2,t,t+l}$ is the equally-weighted return of the sample stocks i (i= full sample, 5Q, 5QHS and N5QHS) that have an analyst's earnings forecast during that month, and a V/P ratio > K_2 (K_2=1, 1.05 and 1.10). For every stock considered, we consider average monthly return to be the mean monthly return for the holding period t to t+m (in the case in hand, m= 12 months). $R^{i}_{(V/P)<K_1,t,t+l}$ is the same for stocks with a *V/P* ratio <K_1 (K_1=1, 0.95 and 0.90). *RMRF*, *SMB* and *HML* are the Fama-French risk factors[39], and α is the risk-adjusted return to the strategy.

The results of the above estimation are given in Table VII, where it can be seen that strategy "5QHS" yields positive risk-adjusted returns, which are significant at the 10% level in all three cases considered ("5QHS", "5QHSa" and"5QHSb"). All the remaining strategies, except "5Qa" (probably due to the high returns obtained during periods of high investor sentiment), fail to yield risk-adjusted returns different from zero. In fact, since the risk exposure of self-financed strategies is quite low, there is hardly any difference between the risk-adjusted and raw returns.

These results show that, during periods of high investor sentiment, and in more sentiment-sensitive stocks, the distorsion in the translation from forecast into recommendations is great enough to enable the implementation of strategies yielding positive risk-adjusted returns, which is not the case for the sample as a whole or for the subset of sentiment-sensitive stocks if the strategy is implemented regardless of the level of market sentiment.

These results further the findings of other authors who have found the value of analysts' recommendations to differ across stock types and levels of market sentiment (see Corredor et al., 2013a).

5-ROBUSTNESS CHECKS

5.1. –Changes in variables

The analysis described in the preceding sections examines the variables by levels. An alternative approach is to look at changes in analysts' forecasts in relation to changes in stock recommendations[40]. Following Mokoaleli-Mokoteli et al. (2009), changes in recommendations are classified into a dummy variable, which takes a value of 1 for all changes resulting in an overweight or buy rating and 0 for those resulting in an underweight

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[39] As a proxy for RM, we take the FTSE100 index return. To obtain a homogeneous risk-free interest rate for the whole period, our reference is the Maastricht Criterion Bond Yield (MCBY), published by EUROSTAT and based on the return rate for the ten-year bond secondary market.

[40] We are grateful to the referees for suggesting this alternative approach.

or sell rating. To enlarge our sample, we also record a value of 1 for reiterations of overweight or buy ratings and 0 for reiterations of underweight or sell ratings. It is interesting to note that this classification results in differences between the 5- 3-point scales used in the analysis, because, in the case of the 5-point scale, we do not include upgrades (from1 to 2) or downgrades (from 5 to 4) in by which the recommendation remains positive or negative, respectively. In line with the cited authors, we also exclude changes and reiterations involving hold ratings.

The logit estimates of the full model are given in Table VIII, where it can be seen that, while the majority still hold, the reduction in translational effectiveness observed in the sentiment-sensitive stocks is not significant. The immediate reaction might be to think that the two analyses yield different results. This could be a hasty conclusion, however, bearing in mind the problems raised by this alternative in the case in hand due to the analyst coverage bias in our study sample. In particular, analysis of the changes requires data from two consecutive time points. Failure to find data at either time point prevents estimation of the variable for the the firm in question and thereby its removal from the sample. In light of the lower coverage associated with sentiment-sensitive stocks, there is a greater probability of losing data from that quintile than from any other[41], which means that this analysis requires dropping from the sample an even greater proportion of sentiment-sensitive stocks, among which the aforementioned significant effect was found. This motivates us to maintain the findings obtained using variables in levels.

5.2. – Endogeneity

Contemporaneous measures of investor sentiment, analyst recommendations and earnings forecasts are, of course, prone to endogeneity bias, a problem that is greatly reduced in the above-described analysis by the fact that investor sentiment is measured in December of the year prior to issue of the forecasts and recommendations. Also, as noted by Bagnoli et al (2014) endogeneity concerns are mitigated in our setting because, while investor sentiment will probably have a significant impact on analyst recommendations, an analyst issuing recommendations for individual firms is *a priori* unlikely to influence collective investor optimism about the entire market.

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[41] The percentage of available observations in the model with variables in changes is clearly lower than in the model with variables in levels: 48.3% from the first quintile and only 35.7% from the last quintile, indicating a 26.1% relative loss of observations in the latter. Nor can it be ruled out that the bulk of this percentage is made up of more sentiment-sensitive stocks.

Another potential concern is endogeneity between forecasts (captured byV/P) and recommendations. This is less easy to deal with. One possibility is to estimate the full model in two stages, as follows:

We first estimate the following model:

$$V/P_{i,j,t} = \beta_0 + \beta_1 V/P_{i,j,t-1} + \beta_2 SENT_{t-2} + u_t \tag{16}$$

which yields estimates of $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$ and, given the lagged values of V/P and SENT, it is possible to obtain the predicted V/P $(\hat{V}/P_{i,j,t})$.

The full model is then estimated using, as in the previous cases, Ordered Probit analysis:

$$\begin{aligned}\text{Prob}\left(REC_{ijt}\right) = {} & \beta_1 SENT_{t-1} + \beta_2 DQ_{HVDA,t} * SENT_{t-1} + \beta_3 DQ_{SEC,t} * SENT_{t-1} + \beta_4\left(\frac{\hat{V}}{P}\right)_{ijt} + \beta_5 SENT_{t-1}\left(\frac{\hat{V}}{P}\right)_{ijt} + \\ & \beta_6 DQ_{HVDA,t} * SENT_{t-1}\left(\frac{\hat{V}}{P}\right)_{ijt} + \beta_7 DQ_{SEC,t} * SENT_{t-1}\left(\frac{\hat{V}}{P}\right)_{ijt} + \beta_8 Z_{ijt} + \varepsilon_{ijt}\end{aligned} \tag{17}$$

The results are shown in Table IX, where it can be seen that sentiment has a significant positive impact, which is greater in more sentiment-sensitive stocks. The predicted variable $\hat{V}/P_{i,j,t}$ also has the expected positive sign. Finally, the results again confirm lower translational effectiveness in stocks that are more sentiment sensitive. It should be noted that these results are robust to the use of both sentiment indexes (global and European) and both scales (3-point and 5-point). Thus, there is no reason to think that the results shown in the preceding sections of the paper might be biased by endogenity issues.

5.3. – PostMAD and Economic cycle

The results from the analysis of the influence of the Market Abuse Directive, could be affected by time trend, economic cycle, and other confounding effects[42], although this possibility can probably be ruled out in the first case, due to the inclusion of year effects. The economic cycle, on the other hand, could seriously condition the results. To explore this issue, therefore, we include, as exogenous variables, four macroeconomic variables: the industrial production index (IPI), consumption of durable (CDI) and non-durable goods (NDI) and the rate of unemployment (UR) in order to protect the results from the effect of possible changes in the economic cycle.

The new results are shown in Table X, and can be seen to be very similar, both with and without the aforementioned economic cycle variables. The only difference worth noting is that no significant sentiment effect can be observed either before or after the MAD when the recommendations are gauged on the 3-point scale. However, a significant effect can still be

[42] We are grateful to the associate editor for mentioning this possibility.

observed in the more sentiment-sensitive quintile. This confirmation of the results obtained using the 5-point recommendation scale (which implies greater detail) and the close similarity of the findings regarding the influence of the MAD enable us to rule out any serious time-trend or economic-cycle effects in the results presented previously.

5.4. – Individual Optimism

Given the evidence in the literature regarding the impact of investor sentiment (as a measure of investors' overall optimism/pessimism about stocks) on analyst forecast and recommendation issuing behaviour, whether driven by strategic motives (see Ertimur et al, 2011 or Karamanou, 2011), cognitive biases (see Qian, 2009 or Hribar and McInnis, 2012) or both (Corredor et al, 2014), this paper has tested to see whether this variable has a significant impact on the translation effectiveness from forecasts into recommendations.

This paper does not, therefore, attempt to study the specific impact of individual analyst optimism on translational effectiveness, since investor sentiment may induce different levels of optimism in individual analysts. Although this issue is well worth investigating, we cannot go very far towards resolving it with the data currently at our disposal. Nevertheless, in order to include a variable relating to optimism in the individual analyst in expression (13), we have replaced the investor sentiment variable with one that captures differential analyst optimism, that is, the individual earnings forecast minus the consensus earnings forecast, orthogonalised to the information in the sentiment variable (OPT^{*}) . We should stress that this variable does not capture the optimism of the analyst, it captures only the optimism differential between the analyst and the consensus left unexplained by overall market optimism.

$$\begin{aligned}\text{Prob}\left(REC_{ijt}\right) = {} & \beta_1 OPT^{*}_{t-1} + \beta_2 DQ_{HVDA,t} * OPT^{*}_{t-1} + \beta_3 DQ_{SEC,t} * OPT^{*}_{t-1} + \beta_4\left(\frac{V}{P}\right)_{ijt} + \beta_5 OPT^{*}_{t-1}\left(\frac{V}{P}\right)_{ijt} + \\ & \beta_6 DQ_{HVDA,t} * OPT^{*}_{t-1}\left(\frac{V}{P}\right)_{ijt} + \beta_7 DQ_{SEC,t} * OPT^{*}_{t-1}\left(\frac{V}{P}\right)_{ijt} + \beta_8 Z_{ijt} + \varepsilon_{ijt}\end{aligned} \tag{18}$$

The results are shown in Table XI. Analysis of the optimism differential reveals that, overall, its effect only appears to upgrade the analyst's recommendation, and that, in contrast to investor sentiment, it does not vary with stock type. Nor does it have any significant impact on translational effectiveness, either on the stock sample as a whole or on more sentiment-sensitive stocks. Finally, it is worth noting that 3- and 5-point scale measurements yield very similar results. We must repeat, however, that we are measuring the effect of differential analyst optimism, and therefore cannot elaborate further on the possible effect of individual analyst optimism on translational effectiveness.

Next, we incorporate the optimism differential variables from expression (18) into the full model described in expression (13). The first thing we notice is that this makes no significant change in the investor sentiment effect, which, again, is greater in stocks that are more sensitive to sentiment. It should be noted that, in the 3-point scale measurement, the inclusion of the optimism differential reduces the explanatory power of investor sentiment to the point of non-significance for the stock sample as a whole, although it remains positive and significant for more sentiment-sensitive stocks. The remaining variables yield similar results as before, leaving our findings for translational effectiveness unaltered; that is, investor sentiment reduces translational effectiveness only in sentiment-sensitive stocks.

Replacement of differential measures with more exact estimates of individual analyst optimism, in line with those used by Mokoaleli-Mokoteli et al. 2009, could help to reveal the magnitude of the potential effect of both individual and overall optimism on analyst forecasts and recommendations, and, of course, on the translation of forecasts into recommendations. This is an interesting question for future research.

6-CONCLUSIONS

This paper analyses the effect of investor sentiment, used as a measure of investors' optimism/pessimism about the stock market as a whole, on the effectiveness with which analysts' earnings forecasts translate into recommendations. The study uses data from the UK stock market because of its worldwide relevance and cultural similarity with the US stock market, which is the usual focus of this type of analysis. This similarity, far from diminishing the research appeal of the UK market, actually heightens it when the interest lies in the level of analyst activity. European financial markets are subject to less analyst coverage than the US market. Lower or no analyst coverage of certain types of firms (young, small, non-dividend paying, non-listed on selective indexes, with low media attention,…) means that they, and thereby HVDA stocks, are under-represented among all quoted firms, thus biasing our study sample. As expected, the results show that investor sentiment has no significant influence in the translation of analysts forecasts into recommendations. Nevertheless, the probability of sentiment-sensitive stocks showing lower translational effectiveness is greater when investor sentiment is high. In our analysis, valuation and arbitrage problems, as sentiment-linked stock characteristics, emerge as a key explanatory factor in the analysis of translational effectiveness.

Thus, although our findings for the UK market and those reported by Ke and Yu (2009) for the US market are different, they are nevertheless perfectly compatible if we take into account the lower relative weight of more sentiment-sensitive stocks in our subsample. We have also been able to show that, when the sample is reduced to sentiment-sensitive stocks, the results are similar to those presented by the cited authors, although the effect gradually fades as other types of stocks are added. This suggests a need to qualify the findings of Ke and Yu (2009) by adding that the effect of investor sentiment on translational effectiveness is not independent of stock characteristics, but clearly stronger in more sentiment-sensitive stocks.

The Market Abuse Directive (MAD), passed in December 2003, has helped to bring analysts' recommendations more into line with their forecasts, as shown by the overall reduction in the sentiment effect. Nevertheless, skews persist in HVDA stocks. It is interesting to note that this directive has had no significant impact on translational effectiveness. Given that optimism is both strategically motivated and cognitively driven (see Corredor et al., 2014), the directive may have had a significant impact on the strategic component, but its impact on the cognitive component is less easy to determine. Note that the cognitive component probably has a greater influence on qualititative variables (recommendations) which are difficult to verify ex-post than on quantitative, verifiable variables (forecasts). The key relevance of this component in HDVA stocks might explain why there is no significant observable effect on translational effectiveness.

Finally, the results for self-financed strategies based on the skew between forecasts and recommendations when related to investor sentiment and stock type, show that, in periods of high investor sentiment and for more sentiment-sensitive stocks, the skew can be great enough to enable positive risk-adjusted returns, which is not the case for the sample as a whole or for the subset of sentiment-sensitive stocks if the strategy is implemented regardless of the level of market sentiment.

All of these findings hold interesting implications for the understanding of analysts' behaviour and performance. Since analysts' recommendations influence investor decision-making, any insight into the process by which they are formulated is potentially useful both to investors and regulators. In the event of these skews being due to strategic behavior on the part of analysts, it is within the power of regulators to reduce their scale and incidence and thereby improve price setting.

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Table I. Descriptive statistics.

Panel A: Descriptive statistics

	Mean	St.dev.	Min	25%	Median	75%	Max
Rec 5-point scale	3.599	1.187	1.000	3.000	4.000	5.000	5.000
Rec 3-point scale	2.381	0.727	1.000	2.000	3.000	3.000	3.000
V/P	1.487	0.792	0.604	0.853	1.284	1.922	3.369
Sent Global	0.027	1.023	-1.546	-0.575	0.182	0.376	2.721
Sent EU	0.037	0.984	-1.635	-0.765	0.217	0.721	1.798
ConfInt	0.703	0.457	0.000	0.000	1.000	1.000	1.000
Gen Exp	3.762	3.038	0.000	1.000	3.000	6.000	15.000
Esp Exp	2.243	2.169	0.000	1.000	2.000	3.000	15.000
BTM	0.504	0.428	0.034	0.234	0.382	0.625	2.500
ACC	0.594	1.676	-0.813	-0.261	0.014	0.603	6.162
MV	3,471.54	9,104.65	2.69	255.51	675.39	2,240.98	118,909.80
AF	15.648	11.853	1.000	8.000	12.000	18.000	53.000
SIGMA	0.099	0.055	0.019	0.063	0.084	0.120	0.469

Panel B: Correlation matrix

	Sent Global	Sent EU	V/P	ConfInt	Gen Exp	Esp Exp	BTM	ACC	MV	AF	SIGMA
Sent Global	1.000										
Sent EU	0.933	1.000									
V/P	-0.247	-0.267	1.000								
ConfInt	-0.044	-0.042	0.042	1.000							
Gen Exp	-0.145	-0.159	0.075	-0.113	1.000						
Esp Exp	-0.026	-0.021	0.028	-0.123	0.578	1.000					
BTM	-0.182	-0.233	0.048	0.035	0.087	-0.000	1.000				
ACC	-0.017	-0.013	0.000	-0.015	-0.023	-0.013	-0.016	1.000			
MV	0.109	0.088	0.232	-0.041	-0.104	0.037	-0.298	0.025	1.000		
AF	-0.035	-0.044	0.212	-0.054	-0.125	0.045	-0.236	0.052	0.683	1.000	
SIGMA	-0.074	-0.186	-0.095	0.028	0.054	-0.024	0.407	0.002	-0.257	-0.224	1.000

Descriptive statistics of the model variables are shown in Panel A. Rec is the analyst investment recommendation, which takes values from 1 (sell) to 5 (buy) or from 1(sell) to 3(buy) (Rec 5-point scale or 3-point scale, respectively). V/P is the ratio of stock value (based on the residual valuation model) to stock price. Sent Global is the global sentiment index and Sent EU is the European sentiment index, both orthogonalised to macroeconomic variables. ConfInt is a proxy for conflict of interests; GenExp and EspExp are general and stock-specific analyst experience proxies, respectively. BTM is the book-to-market ratio, and ACC is individual analyst accuracy with respect to consensus forecast error. MV is the market capitalization, AF is the number of analysts following a firm and SIGMA is volatility. Panel A shows the descriptive statistics of the model variables and Panel B the correlation matrix of the independent variables. All of the correlation coefficients are significant at the 5% level, except BTM with Esp Exp, ACC with BTM and SIGMA with ACC.

Table II. The effect of sentiment on analysts' translational effectiveness. Full Sample.

Panel A: Recommendations on 5-point scale

	Sent Global				Sent EU			
	Model (1)		Model (2)		Model (1)		Model (2)	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	0.361	0.00	0.341	0.00	0.287	0.00	0.245	0.02
V/P	0.082	0.02	0.137	0.00	0.083	0.02	0.143	0.00
V/P*SENT	-0.022	0.39	-0.015	0.63	-0.017	0.49	0.000	0.99
ConfInt			0.012	0.90			0.011	0.91
GenExp			0.010	0.22			0.010	0.22
EspExp			0.010	0.37			0.010	0.37
BTM			-0.042	0.46			-0.045	0.43
ACC			-0.021	0.00			-0.021	0.00
MV			-0.000	0.24			-0.000	0.23
AF			-0.008	0.01			-0.008	0.01
SIGMA			-0.510	0.28			-0.507	0.28
Year Fixed Effects	Yes		Yes		Yes		Yes	
Num Observ	27,733.00		23,020.00		27,733.00		23,020.00	
Pseudo-R2	0.02		0.02		0.01		0.02	
Prob>chi2	0.000		0.00		0.00		0.00	

Panel B: Recommendations on 3-point scale

	Sent Global				Sent EU			
	Model (1)		Model (2)		Model (1)		Model (2)	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	0.311	0.00	0.265	0.03	0.255	0.00	0.190	0.08
V/P	0.085	0.05	0.155	0.00	0.084	0.06	0.160	0.00
V/P*SENT	-0.028	0.38	-0.026	0.51	-0.026	0.37	-0.010	0.78
ConfInt			0.110	0.16			0.111	0.16
GenExp			0.007	0.36			0.007	0.35
EspExp			0.014	0.24			0.014	0.24
BTM			-0.064	0.28			-0.067	0.26
ACC			-0.024	0.00			-0.024	0.00
MV			-0.000	0.18			-0.000	0.18
AF			-0.011	0.00			-0.011	0.00
SIGMA			-0.737	0.16			-0.730	0.16
Year Fixed Effects	Yes		Yes		Yes		Yes	
Num Observ	27,733.00		23,020.00		27,733.00		23,020.00	
Pseudo-R2	0.01		0.02		0.01		0.02	
Prob>chi2	0.00		0.00		0.00		0.00	

Results of the estimation for all UK market stocks. The dependent variable is analyst j's recommendation for stock i on recommendation date t. Recommendations are coded on 5- and 3-point scales. SENT is the global sentiment index (Sent Global) or the European sentiment index (Sent EU), both orthogonalised to macroeconomic variables, V/P is the ratio of stock value, based on the residual valuation model, to price. ConfInt is a proxy for conflict of interests. GenExp and EspExp are general and stock-specific analyst experience proxies, respectively. BTM is the book-to-market ratio, and ACC is individual analyst accuracy with respect to consensus forecast errors. MV is market capitalization; AF is the number of analysts following a firm and SIGMA is volatility. Model (1) is the one shown in equation (12) where the coefficients of all the control variables are restricted to 0 and model (2) is the one shown in equation (12). The estimation uses an Ordered Probit model. The standard errors are clustered by stock and adjusted for heteroskedasticity and serial autocorrelation.

Table III. The effect of sentiment on analysts' translational effectiveness. Stock characteristics.

	5-point scale				3-point scale			
	Sent Global		Sent EU		Sent Global		Sent EU	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	0.298	0.01	0.202	0.06	0.207	0.10	0.129	0.26
DQ_{HVDA} *SENT	0.145	0.04	0.151	0.06	0.203	0.01	0.207	0.02
DQ_{SEC}*SENT	0.036	0.73	0.026	0.83	0.091	0.41	0.097	0.46
V/P	0.137	0.00	0.143	0.00	0.153	0.00	0.159	0.00
V/P*SENT	-0.001	0.98	0.017	0.65	-0.002	0.97	0.018	0.69
DQ_{HVDA} *SENT*V/P	-0.100	0.06	-0.091	0.08	-0.144	0.02	-0.123	0.03
DQ_{SEC}*SENT*V/P	0.018	0.76	0.010	0.87	-0.010	0.88	-0.027	0.68
Conf Int	0.006	0.95	0.001	1.00	0.108	0.17	0.107	0.18
Gen Exp	0.010	0.22	0.010	0.22	0.007	0.36	0.007	0.36
Esp Exp	0.011	0.36	0.011	0.36	0.014	0.23	0.014	0.23
BTM	-0.048	0.42	-0.048	0.42	-0.071	0.25	-0.070	0.26
ACC	-0.020	0.00	-0.021	0.00	-0.023	0.00	-0.024	0.00
MV	-0.000	0.17	-0.000	0.21	-0.000	0.11	-0.000	0.14
AF	-0.008	0.01	-0.008	0.01	-0.010	0.00	-0.011	0.00
SIGMA	-0.719	0.14	-0.648	0.17	-0.979	0.07	-0.858	0.11
Year Fixed Effects	Yes		Yes		Yes		Yes	
Num Observ	23,018.00		23,018.00		23,018.00		23,018.00	
Pseudo-R2	0.02		0.02		0.02		0.02	
Prob>chi2	0.00		0.00		0.00		0.00	

Results of the estimation for volatility-sorted stocks equation (13). The dependent variable is analyst j's recommendation for stock i on recommendation date t. Recommendations are coded on 5- and 3-point scales. SENT is the global sentiment index (Sent Global) or the European sentiment index (Sent EU), both orthogonalised to macroeconomic variables. V/P is the ratio of stock value, based on the residual valuation model, to price. ConfInt is a proxy for conflict of interests. GenExp and EspExp are general and stock-specific analyst experience proxies, respectively. BTM is the book-to-market ratio, and ACC is individual analyst accuracy with respect to consensus forecast errors. MV is market capitalization, AF is the number of analysts following a firm and SIGMA is volatility. DQHVDA is a dummy variable that takes a value of 1 for stocks in the top quintile in terms of difficulty of valuation and arbitrage, proxied by volatility, and 0 otherwise. DQSEC captures the effect of the stocks in the bottom quintile, that is, it takes a value of 1 for the least hard-to-value (least volatile) stocks and 0 otherwise. The estimation uses an Ordered Probit model. The standard errors are clustered by stock and adjusted for heteroskedasticity and serial autocorrelation.

Table IV. Analyst coverage, stock characteristics and translational effectiveness.

Panel A: Stocks in the fifth volatility quintile

	5-point scale				3-point scale			
	Sent Global		Sent EU		Sent Global		Sent EU	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	1.050	0.00	0.800	0.00	1.050	0.00	0.789	0.00
V/P	0.017	0.78	0.036	0.55	-0.005	0.94	0.022	0.74
V/P*SENT	-0.159	0.00	-0.107	0.02	-0.226	0.00	-0.153	0.00
Num Observ	4,065.00		4,065.00		4,065.00		4,065.00	

Panel B: Stocks in the fourth or fifth volatility quintile

	5-point scale				3-point scale			
	Sent Global		Sent EU		Sent Global		Sent EU	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	0.609	0.00	0.488	0.00	0.581	0.00	0.473	0.00
V/P	0.103	0.02	0.105	0.02	0.118	0.02	0.120	0.02
V/P*SENT	-0.062	0.07	-0.051	0.11	-0.091	0.01	-0.078	0.02
Num Observ	8,591.00		8,591.00		8,591.00		8,591.00	

Panel C: Stocks in the third, fourth or fifth volatility quintile

	5-point scale				3-point scale			
	Sent Global		Sent EU		Sent Global		Sent EU	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	0.515	0.00	0.407	0.00	0.438	0.00	0.346	0.01
V/P	0.148	0.00	0.150	0.00	0.167	0.00	0.170	0.00
V/P*SENT	-0.039	0.12	-0.030	0.24	-0.047	0.10	-0.037	0.18
Num Observ	13,373.00		13,373.00		13,373.00		13,373.00	

Panel D: Stocks in the fifth quintile and random volatility sample

	5-point scale				3-point scale			
	Sent Global		Sent EU		Sent Global		Sent EU	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	0.484	0.01	0.375	0.01	0.442	0.01	0.344	0.02
V/P	0.106	0.01	0.110	0.01	0.113	0.02	0.119	0.01
V/P*SENT	-0.038	0.26	-0.025	0.45	-0.063	0.12	-0.046	0.23
Num Observ	8,837.00		8,837.00		8,837.00		8,837.00	

Results of the estimation for all UK market stocks. All the estimations include the control variables and year fixed effects to control for time effects. The dependent variable is analyst j's recommendation for stock i on recommendation date t. Recommendations are coded on 5- and 3-point scales. SENT is the global sentiment index (Sent Global) or the European sentiment index (Sent EU), both orthogonalised to macroeconomic variables, V/P is the ratio of stock value, based on the residual valuation model, to price. ConfInt is a proxy for conflict of interests. GenExp and EspExp are general and stock-specific analyst experience proxies, respectively. BTM is the book-to-market ratio, and ACC is individual analyst accuracy with respect to consensus forecast errors. MV is market capitalization, AF is the number of analysts following a firm and SIGMA is volatility. The estimation uses an Ordered Probit model. The standard errors are clustered by stock and adjusted for heteroskedasticity and serial autocorrelation. Panel A includes all stocks in the fifth volatility quintile. Panel B shows the results for stocks grouped in the fourth and fifth volatility quintiles. Panel C aggregates stocks in the third volatility quintile with those included in the previous estimation. Panel D incorporates stocks in the fifth quintile plus a random sample taken from the first and fourth quintiles. PseudoR2 values range between 0.0 and 0.03. In all cases Prob>chi2=0.00.

Table V. The effect of sentiment on analysts' translational effectiveness. Market Abuse Directive.

	5-point scale				3-point scale			
	Sent Global		Sent EU		Sent Global		Sent EU	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	0.503	0.00	0.611	0.00	0.315	0.02	0.388	0.02
SENT*PostMAD	-0.309	0.01	-0.486	0.00	-0.196	0.19	-0.329	0.04
DQ_{HVDA} *SENT	0.144	0.05	0.159	0.10	0.247	0.01	0.281	0.02
DQ_{HVDA} *SENT*PostMAD	0.071	0.67	0.037	0.82	0.005	0.98	-0.046	0.79
DQ_{SEC}*SENT	0.090	0.45	0.104	0.53	0.090	0.50	0.116	0.53
DQ_{SEC}*SENT*PostMAD	-0.309	0.13	-0.251	0.26	-0.231	0.33	-0.196	0.44
V/P	0.125	0.07	0.120	0.09	0.180	0.06	0.174	0.08
V/P*PostMAD	0.057	0.47	0.062	0.44	0.010	0.92	0.018	0.86
V/P*SENT	-0.034	0.29	-0.052	0.20	-0.044	0.31	-0.068	0.21
V/P*SENT*PostMAD	0.092	0.17	0.112	0.09	0.096	0.21	0.128	0.10
DQ_{HVDA} *SENT*V/P	-0.140	0.05	-0.150	0.10	-0.241	0.01	-0.260	0.03
DQ_{HVDA} *SENT*V/P*PostMAD	0.044	0.69	0.054	0.64	0.128	0.34	0.146	0.31
DQ_{SEC}*SENT*V/P	0.027	0.68	0.023	0.79	0.051	0.50	0.050	0.61
DQ_{SEC}*SENT*V/P*PostMAD	0.059	0.63	0.032	0.79	-0.018	0.90	-0.038	0.79
Conf Int	0.006	0.95	0.007	0.94	0.107	0.18	0.107	0.18
Gen Exp	0.010	0.22	0.010	0.22	0.007	0.36	0.007	0.36
Esp Exp	0.011	0.36	0.010	0.36	0.014	0.23	0.014	0.23
BTM	-0.047	0.43	-0.046	0.44	-0.072	0.24	-0.071	0.24
ACC	-0.019	0.00	-0.020	0.00	-0.022	0.00	-0.023	0.00
MV	-0.000	0.10	-0.000	0.13	-0.000	0.06	-0.000	0.08
AF	-0.008	0.01	-0.008	0.01	-0.010	0.00	-0.010	0.00
SIGMA	-0.398	0.46	-0.489	0.34	-0.552	0.39	-0.623	0.30
Year Fixed Effects	Yes		Yes		Yes		Yes	
Num Observ	23,018.00		23,018.00		23,018.00		23,018.00	
Pseudo-R2	0.02		0.02		0.02		0.02	
Prob>chi2	0.00		0.00		0.00		0.00	

Results of the estimation for volatility-sorted stocks: equation (14). The dependent variable is analyst j's recommendation for stock i on recommendation date t. Recommendations are coded on 5- and 3-point scales. SENT is the global sentiment index (Sent Global) or the European sentiment index (Sent EU), both orthogonalised to macroeconomic variables. V/P is the ratio of stock value based on the residual valuation model to price. ConfInt is a proxy for conflict of interests, GenExp and EspExp are general and stock-specific analyst experience proxies, respectively. BTM is the book-to-market ratio, and ACC is individual analyst accuracy with respect to consensus forecast errors. MV is the market capitalization, AF is the number of analysts following a firm and volatility (SIGMA). DQ_{HVDA} is a dummy variable that takes a value of 1 for stocks in the top quintile in terms of difficulty of valuation and arbitrage, proxied by volatility, and 0 otherwise. DQ_{SEC} captures the effect of the stocks in the bottom quintile, that is, it takes a value of 1 for the least hard to value (least volatile) stocks and 0 otherwise. PostMAD dummy takes a value of 1 for the post-regulation period. The estimation uses an Ordered Probit model. The standard errors are clustered by stock and adjusted for heteroskedasticity and serial autocorrelation.

Table VI. Strategy returns.

Strategy		N	Nb	Ns	Mean	St.dev.	t (H_0=0)	p-value
Buy (V/P)>1 Sell (V/P)<1	5Q	144	16	17	0.374%	3.567%	1.258	0.211
	5QHS	71	7	17	0.885%	4.608%	1.617	0.110
	N5QHS	73	51	44	-0.093%	2.365%	-0.337	0.737
Buy (V/P)>1.05 Sell (V/P)<0.95	5Qa	144	16	16	0.474%	3.601%	1.580	0.116
	5QHSa	71	6	16	1.067%	4.634%	1.940	0.057
	N5QHSa	73	47	40	-0.128%	2.461%	-0.444	0.659
Buy (V/P)>1.10 Sell (V/P)<0.90	5Qb	143	15	15	0.387%	3.681%	1.258	0.210
	5QHSb	70	5	15	1.024%	4.781%	1.792	0.078
	N5QHSb	73	45	35	-0.231%	2.295%	-0.860	0.392
Full Sample (Benchmark)		151	127	59	0.048%	1.414%	0.416	0.678

N is the number of strategies that can potentially be implemented with the sample. Mean and Stand. dev. refer to the mean monthly return and standard deviation of the implemented strategies, respectively. Nb (Ns) is the mean number of stocks in the buy (sell) portfolio. t is the value of the statistic for the null hypothesis of the strategy yielding a zero twelve-month return, using the White (1980) correction and the p-value is the significance level of the null hypothesis. 5Q/5Qa/5Qb denote the strategies based on buying stocks with an earnings forecast during that month, belonging to the fifth volatility quintile, and with a V/P ratio higher than 1/1.05/1.1 and selling those with a V/P ratio lower than 1/0.95/0.90. The 5QHS/5QHSa/5QHSb strategies are identical but implemented only during periods of high market sentiment. N5QHS/N5QHSa/N5QHSQb are identical but implemented only during periods of high market sentiment and using stocks not belonging to the fifth volatility quintile. Full Sample is the benchmark strategy based on buying all those stocks whose V/P ratio is higher than 1 and selling those for which it less than 1. If there is a month in which it is not possible to buy or to sell one of the portfolios, it is assumed that it has been possible to invest or borrow at the risk-free rate for that month.

Table VII. Risk-adjusted strategy returns.

	α	RMRF	SMB	HML
5Q	0.436	-0.096	0.002	-0.155
	(0.16)	(0.14)	(0.98)	(0.14)
5QHS	0.943	-0.283	-0.118	-0.317
	(0.09)	(0.03)	(0.33)	(0.12)
N5QHS	-0.108	0.028	0.101	-0.165
	(0.69)	(0.62)	(0.08)	(0.10)
5Qa	0.552	-0.078	-0.008	-0.181
	(0.08)	(0.28)	(0.90)	(0.10)
5QHSa	1.064	-0.285	-0.08	-0.300
	(0.06)	(0.03)	(0.49)	(0.11)
N5QHSa	-0.019	0.107	0.003	-0.246
	(0.95)	(0.07)	(0.96)	(0.03)
5Qb	0.463	-0.074	-0.008	-0.167
	(0.15)	(0.30)	(0.90)	(0.13)
5QHSb	1.074	-0.303	-0.120	-0.339
	(0.07)	(0.03)	(0.34)	(0.10)
N5QHSb	-0.174	0.099	0.039	-0.195
	(0.50)	(0.07)	(0.50)	(0.03)
Full Sample (Benchmark)	0.042	-0.042	0.019	-0.039
	(0.73)	(0.10)	(0.43)	(0.33)

Risk-adjusted monthly returns and associated p-values (in parentheses) using the Fama-French risk factors. Ecuación (15). α coefficients are multiplied by 100. 5Q/5Qa/5Qb denote the strategies based on buying stocks with an earnings forecast during that month, belonging to the fifth volatility quintile, and a V/P ratio higher than 1/1.05/1.1 and selling those with a V/P ratio lower than 1/0.95/0.90. The 5QHS/5QHSa/5QHSb strategies are identical but implemented only during periods of high market sentiment. N5QHS/N5QHSa/N5QHSQb are identical but implemented only during periods of high market sentiment and using stocks not belonging to the fifth volatility quintile. Full Sample is the benchmark strategy based on buying all those stocks whose V/P ratio is higher than 1 and selling those for which it less than 1. If there is a month in which it is not possible to buy or to sell one of the portfolios, it is assumed that it has been possible to invest or borrow at the risk-free rate for that month.

Table VIII. Changes in variables

	5-point scale				3-point scale			
	Sent Global		Sent EU		Sent Global		Sent EU	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	0.647	0.01	0.511	0.01	0.585	0.02	0.460	0.02
DQ_{HVDA} *SENT	0.214	0.03	0.235	0.04	0.214	0.03	0.238	0.04
DQ_{SEC}*SENT	0.187	0.23	0.116	0.47	0.203	0.17	0.136	0.37
ΔV/P	0.282	0.00	0.283	0.00	0.279	0.00	0.280	0.00
ΔV/P*SENT	-0.046	0.46	-0.019	0.79	-0.041	0.50	-0.011	0.87
DQ_{HVDA} *SENT*ΔV/P	-0.137	0.32	-0.176	0.18	-0.132	0.32	-0.175	0.17
DQ_{SEC}*SENT*ΔV/P	-0.048	0.62	-0.057	0.55	-0.055	0.55	-0.074	0.44
Conf Int	1.899	0.02	1.881	0.02	0.316	0.16	0.312	0.17
Gen Exp	0.015	0.51	0.016	0.51	0.014	0.54	0.014	0.54
Esp Exp	0.015	0.67	0.015	0.67	0.020	0.57	0.020	0.57
BTM	-0.201	0.17	-0.190	0.19	-0.221	0.13	-0.210	0.15
ACC	-0.055	0.00	-0.056	0.00	-0.059	0.00	-0.059	0.00
MV	-0.000	0.26	-0.000	0.31	-0.000	0.26	-0.000	0.32
AF	-0.022	0.01	-0.022	0.01	-0.023	0.01	-0.023	0.01
SIGMA	-2.534	0.06	-2.319	0.09	-2.622	0.05	-2.415	0.07
Year Fixed Effects	Yes		Yes		Yes		Yes	
Num Observ	12,411.00		12,411.00		12,902.00		12,902.00	
Pseudo-R2	0.04		0.04		0.04		0.04	
Prob>chi2	0.00		0.00		0.00		0.00	

Results of the estimation for volatility-sorted stocks. The dependent variable is change in the recommendation proxied by a dummy variable which takes a value of 1 for upgrades to buy ratings and reiterations on both scales and 0 for downgrades to sell ratings and reiterations. SENT is the global sentiment index (Sent Global) or the European sentiment index (Sent EU), both orthogonalised to macroeconomic variables. ΔV/P reflects change in forecasts. ConfInt is a proxy for conflict of interests. GenExp and EspExp are general and stock-specific analyst experience proxies, respectively. BTM is the book-to-market ratio, and ACC is individual analyst accuracy with respect to consensus forecast errors. MV is market capitalization, AF is the number of analysts following a firm and SIGMA is volatility. DQHVDA is a dummy variable that takes a value of 1 for stocks in the top quintile in terms of difficulty of valuation and arbitrage, proxied by volatility, and 0 otherwise. DQSEC captures the effect of the stocks in the bottom quintile, that is, it takes a value of 1 for the least hard-to-value (least volatile) stocks and 0 otherwise. The estimation uses a Logit model. The standard errors are clustered by stock and adjusted for heteroskedasticity and serial autocorrelation.

Table IX.: Endogeneity.

	5-point scale				3-point scale			
	Sent Global		Sent EU		Sent Global		Sent EU	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	0.422	0.00	0.310	0.01	0.336	0.02	0.244	0.06
DQ_{HVDA} *SENT	0.190	0.02	0.188	0.04	0.269	0.01	0.267	0.01
DQ_{SEC}*SENT	0.042	0.75	-0.005	0.97	0.107	0.44	0.070	0.66
$\hat{V}/P$	0.126	0.01	0.130	0.02	0.139	0.02	0.142	0.03
$\hat{V}/P$ *SENT	-0.024	0.57	-0.005	0.91	-0.026	0.61	-0.007	0.89
DQ_{HVDA} *SENT* $\hat{V}/P$	-0.188	0.01	-0.196	0.02	-0.260	0.01	-0.262	0.02
DQ_{SEC}*SENT* $\hat{V}/P$	0.024	0.76	0.031	0.68	-0.009	0.91	-0.007	0.93
Conf Int	0.078	0.45	0.077	0.45	0.137	0.16	0.136	0.16
Gen Exp	0.012	0.20	0.012	0.20	0.008	0.41	0.008	0.41
Esp Exp	0.012	0.39	0.012	0.39	0.019	0.21	0.019	0.21
BTM	-0.050	0.47	-0.051	0.47	-0.078	0.29	-0.077	0.30
ACC	-0.020	0.00	-0.021	0.00	-0.023	0.00	-0.024	0.00
MV	-0.000	0.12	-0.000	0.17	-0.000	0.12	-0.000	0.17
AF	-0.005	0.11	-0.005	0.10	-0.008	0.03	-0.008	0.03
SIGMA	-0.396	0.48	-0.427	0.43	-0.472	0.47	-0.469	0.46
Year Fixed Effects	Yes		Yes		Yes		Yes	
Num Observ	13,112.00		13,112.00		13,112.00		13,112.00	
Pseudo-R2	0.02		0.02		0.02		0.02	
Prob>chi2	0.00		0.00		0.00		0.00	

Results of the estimation for volatility-sorted stocks. The dependent variable is analyst j's recommendation for stock i on recommendation date t.Recommendations are coded on 5- and 3-point scales. SENT is the global sentiment index (Sent Global) or the European sentiment index (Sent EU), both orthogonalised to macroeconomic variables. $(\hat{V}/P_{i,j,t})$ is predicted V/P derived from the estimates of $\hat{\beta}_o$, $\hat{\beta}_1$ and $\hat{\beta}_2$ in the regression (16). ConfInt is a proxy for conflict of interests. GenExp and EspExp are general and stock-specific analyst experience proxies, respectively. BTM is the book-to-market ratio, and ACC is individual analyst accuracy with respect to consensus forecast errors. MV is market capitalization, AF is the number of analysts following a firm and SIGMA is volatility. DQHVDA is a dummy variable that takes a value of 1 for stocks in the top quintile in terms of difficulty of valuation and arbitrage, proxied by volatility, and 0 otherwise. DQSEC captures the effect of the stocks in the bottom quintile, that is, it takes a value of 1 for the least HVDA (least volatile) stocks and 0 otherwise. The estimation uses an Ordered Probit model. The standard errors are clustered by stock and adjusted for heteroskedasticity and serial autocorrelation.

Table X. Influence of Post MAD and economic cycle

	5-point scale				3-point scale			
	Sent Global		Sent EU		Sent Global		Sent EU	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT	0.489	0.01	0.597	0.00	0.243	0.20	0.305	0.17
SENT*PostMAD	-0.286	0.05	-0.464	0.01	-0.129	0.45	-0.249	0.20
DQ_{HVDA} *SENT	0.144	0.05	0.158	0.10	0.245	0.01	0.278	0.02
DQ_{HVDA} *SENT*PostMAD	0.072	0.66	0.038	0.81	0.007	0.97	-0.043	0.81
DQ_{SEC}*SENT	0.089	0.46	0.103	0.54	0.089	0.51	0.113	0.54
DQ_{SEC}*SENT*PostMAD	-0.310	0.13	-0.250	0.26	-0.231	0.33	-0.195	0.45
V/P	0.125	0.07	0.120	0.09	0.178	0.06	0.173	0.08
V/P*PostMAD	0.058	0.47	0.062	0.43	0.011	0.91	0.019	0.85
V/P*SENT	-0.035	0.29	-0.052	0.19	-0.045	0.31	-0.069	0.21
V/P*SENT*PostMAD	0.092	0.17	0.112	0.09	0.095	0.22	0.127	0.10
DQ_{HVDA} *SENT*V/P	-0.139	0.06	-0.150	0.11	-0.238	0.01	-0.257	0.03
DQ_{HVDA} *SENT*V/P*PostMAD	0.043	0.70	0.053	0.65	0.125	0.35	0.144	0.31
DQ_{SEC}*SENT*V/P	0.027	0.68	0.024	0.78	0.052	0.49	0.052	0.60
DQ_{SEC}*SENT*V/P*PostMAD	0.059	0.63	0.031	0.80	-0.018	0.90	-0.039	0.78
Conf Int	0.012	0.90	0.013	0.89	0.106	0.18	0.107	0.18
Gen Exp	0.009	0.22	0.009	0.22	0.007	0.37	0.007	0.37
Esp Exp	0.011	0.36	0.011	0.36	0.014	0.23	0.014	0.23
BTM	-0.047	0.43	-0.046	0.44	-0.071	0.24	-0.070	0.25
ACC	-0.019	0.00	-0.020	0.00	-0.023	0.00	-0.023	0.00
MV	-0.000	0.10	-0.000	0.13	-0.000	0.06	-0.000	0.08
AF	-0.008	0.01	-0.008	0.01	-0.010	0.00	-0.010	0.00
SIGMA	-0.395	0.46	-0.486	0.34	-0.550	0.39	-0.622	0.31
CDI	-0.097	0.73	-0.082	0.77	-0.307	0.35	-0.292	0.37
IPI	-0.857	0.37	-0.908	0.34	-0.712	0.51	-0.764	0.48
NDI	-0.469	0.46	-0.454	0.48	-0.587	0.39	-0.574	0.40
UR	0.979	0.84	0.901	0.85	3.397	0.49	3.320	0.50
Year Fixed Effects	Yes		Yes		Yes		Yes	
Num Observ	23,018.00		23,018.00		23,018.00		23,018.00	
Pseudo-R2	0.02		0.02		0.02		0.02	
Prob>chi2	0.00		0.00		0.00		0.00	

Results of the estimation for volatility-sorted stocks equation (14). The dependent variable is analyst j's recommendation for stock i on recommendation date t. Recommendations are coded in 5 and 3-point scale. SENT is the global sentiment index (Sent Global) or the European sentiment indicator (Sent EU), both orthogonal to macroeconomic variables. V/P is the ratio of stock value based on the residual valuation model to price. ConfInt is a proxy for conflict of interests, GenExp and EspExp are general and stock-specific analyst experience proxies, respectively. BTM is the book-to-market ratio, and ACC is individual analyst accuracy with respect to consensus forecast errors. MV is the market capitalization, AF is the number of analysts following a firm and volatility (SIGMA). DQ_{HVDA} is a dummy variable that takes a value of 1 for stocks in the top quintile in terms of difficulty of valuation and arbitrage, proxied by volatility, and 0 otherwise. DQSEC captures the effect of the stocks in the bottom quintile, that is, it takes a value of 1 for the least hard to value (least volatile) stocks and 0 otherwise. PostMAD dummy takes a value of 1 for the post-regulation period. The macroeconomic variables considered are the industrial production index (IPI), consumption of durable (CDI) and non-durable goods (NDI) and the rate of unemployment (UR). The estimation uses an Ordered Probit model. The standard errors are clustered by stock and adjusted for heteroskedasticity and serial autocorrelation.

Table XI. Optimism Differential and Investor Sentiment

	5-point scale						3-point scale					
	OPT		Sent Global		Sent EU		OPT		Sent Global		Sent EU	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
SENT			0.319	0.02	0.216	0.07			0.222	0.11	0.139	0.27
DQ_{HVDA} *SENT			0.155	0.03	0.157	0.06			0.219	0.01	0.218	0.02
DQ_{SEC}*SENT			0.049	0.67	0.037	0.78			0.115	0.35	0.119	0.40
OPT	0.475	0.00	0.477	0.00	0.473	0.00	0.518	0.00	0.520	0.00	0.517	0.00
DQ_{HVDA} *OPT	-0.369	0.16	-0.420	0.11	-0.410	0.12	-0.347	0.24	-0.437	0.14	-0.423	0.15
DQ_{SEC}*OPT	0.594	0.34	0.495	0.38	0.519	0.36	0.014	0.98	-0.130	0.83	-0.130	0.83
V/P	0.149	0.00	0.140	0.00	0.147	0.00	0.168	0.00	0.155	0.00	0.163	0.00
V/P*SENT			-0.004	0.91	0.017	0.68			-0.001	0.98	0.021	0.67
DQ_{HVDA} *SENT*V/P			-0.114	0.04	-0.101	0.06			-0.163	0.01	-0.138	0.02
DQ_{SEC}*SENT*V/P			0.011	0.87	0.002	0.97			-0.024	0.75	-0.043	0.55
V/P*OPT	-0.068	0.54	-0.072	0.53	-0.070	0.54	-0.074	0.53	-0.077	0.52	-0.076	0.53
DQ_{HVDA} *OPT*V/P	0.176	0.33	0.209	0.27	0.204	0.28	0.161	0.44	0.226	0.32	0.216	0.33
DQ_{SEC}*OPT*V/P	0.075	0.85	0.140	0.68	0.135	0.69	0.391	0.32	0.466	0.19	0.480	0.17
Conf Int	0.019	0.86	0.014	0.89	0.006	0.96	0.137	0.12	0.133	0.13	0.132	0.13
Gen Exp	0.013	0.16	0.012	0.17	0.012	0.17	0.009	0.31	0.009	0.33	0.009	0.33
Esp Exp	0.007	0.62	0.007	0.61	0.007	0.60	0.012	0.38	0.012	0.37	0.012	0.37
BTM	-0.055	0.36	-0.057	0.37	-0.058	0.37	-0.081	0.20	-0.083	0.21	-0.083	0.21
ACC	-0.018	0.00	-0.018	0.00	-0.018	0.00	-0.021	0.00	-0.021	0.00	-0.021	0.00
MV	-0.000	0.15	-0.000	0.11	-0.000	0.14	-0.000	0.14	-0.000	0.08	-0.000	0.11
AF	-0.006	0.04	-0.006	0.05	-0.006	0.04	-0.009	0.01	-0.009	0.01	-0.009	0.01
SIGMA	-0.363	0.47	-0.648	0.22	-0.571	0.27	-0.546	0.32	-0.848	0.15	-0.716	0.22
Year Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes	
Num Observ	19,142.00		19,142.00		19,142.00		19,142.00		19,142.00		19,142.00	
Pseudo-R2	0.02		0.02		0.02		0.02		0.02		0.02	
Prob>chi2	0.00		0.00		0.00		0.00		0.00		0.00	

Results for the effect of Investor Sentiment (SENT) and the Optimism Differential (OPT) on translational effectiveness. The dependent variable is analyst j's recommendation for stock i on recommendation date t.SENT is the global sentiment index orthogonalised to macroeconomic variables. OPTi,j,t is defined as the difference between the forecast issued by analyst j for firm i at time t, relative to the consensus forecast for firm i at time t. Both the optimism differential and investor sentiment values are lagged, although in the case of the latter it is its value in December of the previous year. In the joint estimations of OPT and SENT, OPT is orthogonalised to the sentiment variable. V/P is the ratio of stock value, based on the residual valuation model, to price. DQHVDA is a dummy variable that takes a value of 1 for stocks in the top quintile in terms of difficulty of valuation and arbitrage, proxied by volatility, and 0 otherwise. DQSEC captures the effect of the stocks in the bottom quintile, that is, it takes a value of 1 for the least hard-to-value (least volatile) stocks and 0 otherwise. The estimation uses an Ordered Probit model. The standard errors are clustered by stock and adjusted for heteroskedasticity and serial autocorrelation. The control variables are ConfInt, which is a proxy for conflict of interests, and GenExp and EspExp, which are general and stock-specific analyst experience proxies, respectively. BTM is the book-to-market ratio, and ACC is individual analyst accuracy with respect to consensus forecast errors. MV is market capitalization, AF is the number of analysts following a firm and SIGMA is volatility.