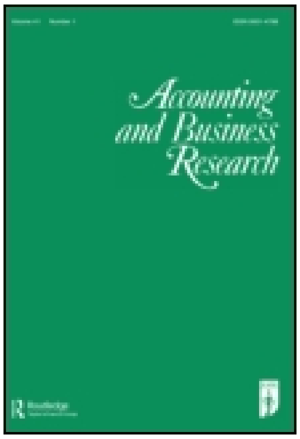

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Does graph disclosure bias reduce the cost of equity capital?

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Does graph disclosure bias reduce the cost of equity capital?

Flora Muiño and Marco Trombetta*

Abstract—Firms widely use graphs in their financial reports. In this respect, prior research demonstrates that companies use graphs to provide a favourable outlook of performance, suggesting that they try to manage the impression created in users' perceptions. This study tests whether by means of distorted graphs managers are able to influence users' decisions in the capital market. By focusing on the effects of distorted graphs on the cost of equity capital, we provide preliminary evidence on one of the possible economic consequences of graph usage. The results of this investigation suggest that graph disclosure bias has a significant, but temporary, effect on the cost of equity. Moreover, our results highlight the important role played by the overall level of disclosure as a conditioning factor in the relationship between graphs and the cost of equity. Consequently, the results of the current study enhance our understanding of the complex interactions that take place in the stock market between information, information intermediaries and investors.
Keywords: cost of equity, disclosure, graph distortion

1. Introduction

Prior research on graph usage in annual reports has documented two important facts. First, graph usage increases when company performance improves (e.g. Steinbart, 1989 and Beattie and Jones, 1992). Second, an important proportion of graphs are distorted to portray a more favourable view of the company than reflected in the financial statements (e.g. Beattie and Jones, 1999 and Mather et al., 1996). Thus, the existing literature supports the notion that managers use distorted graphs to manage the impression created in the perceptions of users of annual reports[1] (e.g. Beattie and Jones, 2000). However, Beattie and Jones (2008: 22), after reviewing the existing literature on graph usage in annual reports, conclude:

> 'A fundamental issue to be addressed by future research is whether an impact on a user's perceptions of the organisation carries through to an impact on their decision. For example, are investment decisions affected by graphical presentation choices? We need, therefore, to carry out research into the effect, if any, of financial graphs on analysts' earnings forecasts, stock prices and the relationship decisions of other key stakeholder groups such as employees, customers and suppliers'

From a theoretical point of view, the potential effect of graph distortion on the functioning of the stock market is a controversial issue. On the one hand, the literature on 'herding' and 'limited attention' in financial markets shows that economic agents may neglect a considerable part of their private information because of reputation and coordination effects or information processing limitations.[2] Consequently, graphs can have an impact on users' judgments and decisions, even when the information represented in graphs can be gathered also in other parts of the annual report. On the other hand, the efficient markets hypothesis (EMH) tells us that prices should include all the publicly available information. Hence, graph distortion should not affect prices because they should be based on all the information available on

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[1] Impression management techniques in annual reports are not limited to the use and distortion of graphs. Extant research provides evidence consistent with the use of narratives as an impression management technique (e.g. Clatworthy and Jones, 2003; Aerts, 2005).

[2] A more detailed review of this literature is provided in the next section of the paper.

the annual report and not only on the image portrayed by graphs. Our aim is to provide empirical evidence that improves our understanding of this controversial issue and take a step forward in the direction indicated by Beattie and Jones (2008).

As an indicator of the capital market effects of graph distortion we use the cost of equity capital, measured both on an ex-ante (i.e. expected) and an ex-post (i.e. realised) basis.[3] The ex-ante measure is based on analysts' forecasts of earnings issued at a certain point in time, soon after the publication of the annual report. This measure depends directly on the expectations of those analysts following the company at the time forecasts are issued. Based on the evidence provided by literature on herding and limited attention, we hypothesise that these expectations can be biased because of distorted graphs included in annual reports. However, on the grounds of the EMH, we do not expect graph distortion to affect our ex-post measure of the cost of equity, realised returns. Since realised returns aggregate the decisions taken by investors over a relatively large period of time (one year), we expect that the potential bias in analysts' perceptions is corrected in the market by means of the aggregation process and the passing of time that allows new information to be impounded in stock prices.[4]

We base our analysis on a sample of Spanish companies quoted in the Madrid Stock Exchange (MSE) between 1996 and 2002. As compared to the US or the UK, where most prior studies on graphs have been developed, Spain has still a relatively underdeveloped capital market, where levels of corporate transparency are generally low.[5] Moreover, prior research documents the existence of a higher level of herding in Spain than in countries with more developed capital markets.[6] If graph distortion is able to bias the perceptions of market participants, that is more likely to be observed in those markets, such as the MSE, with low corporate transparency and high levels of herding. When comparing US and European stock markets (excluding the UK), Bagella et al. (2007) find that the absolute bias in earnings forecasts is significantly higher in Europe than in the US. This is why we believe that the MSE is well suited to investigate whether graph distortion affects perceptions and decisions of market participants.

After controlling for other possible determinants of the cost of equity, we detect a significant negative effect of favourable graph distortion on our ex-ante measure of the cost of equity. This effect is moderated by the overall level of disclosure so that, at high levels of transparency, the relationship between graph distortion and the ex-ante cost of equity becomes positive. However, when we turn to the ex-post analysis, we do not find any significant effect of graph distortion on realised returns. We interpret this result as evidence that the effect on the ex-ante cost of equity is only temporary and confined to expectations. It is really an effect on the bias of the analysts' forecasts that are used to calculate the ex-ante measure of the cost of equity. However, with the passing of time the aggregation process performed in the market corrects this bias.

Our contribution to the literature is twofold. First, to the best of our knowledge, we are the first to provide empirical evidence on the capital market effects of graph distortion for quoted firms. Graph distortion is an ideal item from which to study the economic effects of impression management techniques. As stated by Merkl-Davies and Brennan (2007), the study of these effects is complicated by the difficulty of separating impression management (opportunistic distortion of information) from incremental information (provision of useful additional information). However, graph distortion, as an impression management technique, is not affected by this problem. Given that the information portrayed in graphs is always available in another format in the same annual report, we can assume that distorted graphs are pure impression management tools and do not provide any incremental information.

Second, we provide additional evidence that supports the necessity of distinguishing between estimations by individuals and aggregated market behaviour, when studying the capital market effects of impression management techniques. Short-term effects on individuals' predictions can be corrected with the passing of time by the aggregation role played by market activity, so that they do not have an impact on long-window stock returns.

The structure of the paper is as follows. In the next section we review the existing literature and develop our research hypotheses. In Section 3 we describe our sample and the variables that we use in our empirical analysis. Section 4 contains the

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[3] A review of the issues involved in the empirical measurement of the cost of equity capital can be found, for example, in Botosan (2006).

[4] Temporary differences between ex-ante and ex-post measures of the cost of equity are depicted in Figure 1 and discussed in detail in section 3.2.1.

[5] According to the World Federation of Exchanges, in 2002, the latest year covered in our analysis, total value of share trading in the MSE was $653,221m as compared to $4,001,340m for the London Stock Exchange or $10,310,055m for the New York Stock Exchange. Additionally, La Porta et al. (2006) provide evidence showing that the MSE has a lower index of disclosure requirements (0.50, as compared to 0.83 and 1.00 for the UK and the US, respectively) and public enforcement (0.33 as compared to 0.68 and 0.90 for the UK and the US, respectively) .

[6] Ferruz Agudo et al. (2008) report a level of herding of 13.26% for Spain, a figure similar to that observed by Lobao and Serra (2002) for Portugal, but much higher than the 2% found by Lakonishok et al. (1992) for the US or the 3.3% observed by Wylie (2005) in the UK.

main results of our analysis. Section 5 summarises the analysis, provides some conclusions and draws implications.

2. Background and hypotheses development

The importance of information for the functioning of the stock market is manifest. The whole notion of market efficiency in its different forms is based on how agents in the market react to information and how information is eventually reflected into prices. Graphs included in annual reports do not provide additional information, but they are a vehicle of information dissemination that makes data more visible and, when properly constructed, facilitates its processing (Beattie and Jones, 1992). Extant research, however, shows that a significant proportion of graphs included by companies in their annual reports is materially distorted, generally to portray corporate performance more favourably[7] (e.g. Mather et al., 1996; Beattie and Jones, 1999). Researchers conclude that managers use distorted graphs to manage users' perceptions (e.g. Beattie and Jones, 2000).

Experimental research provides evidence consistent with this conclusion. Taylor and Anderson (1986), Beattie and Jones (2002) and Arunachalam et al. (2002) all provide evidence that users' perceptions are far more favourable when they are based on graphs that are favourably distorted. Arunachalam et al. (2002) explain this phenomenon on the basis of two findings of psychological research. First, Payne et al. (1993) show that people minimise their cognitive effort in order to achieve a certain level of accuracy. Second, Ricketts (1990) finds that people have difficulty at detecting presentation errors. Distorted graphs usually do not reverse or fundamentally change the reality as expressed by the data.

Participants' perceptions are affected by distorted graphs even when the accurate numeric values are displayed as variable labels in graphs (e.g. Arunachalam et al., 2002). This suggests that participants focus their attention on the image portrayed in graphs and ignore the numeric values. The fact that participants in these experimental studies neglect relevant information could be attributed to their low level of experience (they were students). However, extant research provides evidence showing that even sophisticated users (analysts) do not always make use of all available information.

A substantial body of research in theoretical finance demonstrates that, under certain circumstances, analysts may ignore a significant proportion of their private information. Trueman (1994) demonstrates that analysts tend to release forecasts similar to those reported by other analysts, even when their private information does not justify such forecasts. Similarly, Morris and Shin (2002) analyse the role of public information in contests where an agent needs to co-ordinate with other agents in order to maximise his/her payoff.[8] They show that, in these settings, it can be socially optimal to adopt coarser information systems instead of finer information systems. These theoretical predictions have been confirmed empirically. Stickel (1992), Graham (1999), Hong et al. (2000), and Welch (2000) provide evidence of analysts' herding behaviour and Anctil et al. (2004) use an experimental setting to document the negative social effects of a lack of coordination.

Literature on limited attention provides empirical evidence showing that investors ignore valuable information when making investment decisions. For instance, Doyle et al. (2003) find that the stock market does not fully appreciate the predictive power of expenses excluded from proforma earnings. Similarly, Hirshleifer et al. (2004) demonstrate that investors do not optimally use the information conveyed by net operating assets when assessing the sustainability of corporate performance. Furthermore, experimental studies such as those by Hopkins (1996), Hirst and Hopkins (1998) and Hirst et al. (2004) show that analysts' judgments and valuations are affected by the income-measurement method (recognition versus disclosure in the footnotes) or the classification of items in the financial statements. These studies provide further evidence showing that even experts ignore relevant information when making estimations and valuations; otherwise their valuations would not be affected by classification of information in financial statements. Overall, prior research indicates that users tend to focus their attention on the most salient and easily processed information, neglecting relevant data. This is attributed to limited attention and cognitive processing power (Hirshleifer and Teoh, 2003).

Graphs represent a prominent piece of information in the annual report and the information they convey can be processed by users fairly easily. Then, on the basis of both the theoretical arguments and the empirical and experimental evidence provided by extant literature, we hypothesise that market expectations and analysts' estimations can be affected by favourable graph distortion, despite the fact that accurate values of the variables dis-

[7] Distortion refers to violations of what Tufte (1983) states as an essential principle in graph construction: physical measures on the surface of the graph should be directly proportional to the numerical quantities represented. The use of non-zero axis, broken axis, or non-arithmetic scales leads to graphs where equal distances along the axis do not represent equal amounts, that is, physical measures are not proportional to the underlying numerical values.

[8] The stock market is used by Morris and Shin (2002) as an example of such a contest.

played in graphs are reflected in the financial statements. The ex-ante (expected) measures of the cost of equity capital depend directly on these expectations and estimations in the sense that more optimistic forecasts about the future of the company are associated with a lower level of the ex-ante cost of capital. Hence, we state the following hypothesis to be tested in our study:

H1: Favourable graph distortion is negatively related to the ex-ante cost of equity capital.

Disclosure and time are two additional factors that can affect the relationship between graph distortion and the cost of equity capital. Next, we discuss the moderating effect that can be exercised by disclosure and afterwards we analyse the role played by the passing of time in correcting biases in ex-ante expectations.

The above-mentioned prior experimental research indicates that users have difficulties in detecting graph distortion. Corporate disclosure can ameliorate this situation by providing users with additional data that may turn out to be important clues in identifying distorted graphs.[9] Take, for example, the case of a firm presenting a slight increase in net sales, which is magnified in a distorted graph so that it appears as a strong rising trend. Distortion is difficult to detect because the direction of the change depicted graphically is the same as that shown by data in financial statements. However, if this firm provides operating data showing a decrease in production, readers are more likely to realise the graph is distorted. The role played by disclosure in correcting misperceptions is documented in the literature. Schrand and Walther (2000) observe that the bias introduced by strategic choices of prior-period benchmarks in earnings announcements is eliminated when the financial statements are released. Along the same line, in a controlled experiment, Krische (2005) finds that clear and quantitative information about prior-period transitory gains or losses allows participants to adjust the comparative prior period-earnings stated as a benchmark in earnings announcements. Based on prior evidence we expect that the likelihood of distortion being detected is increasing in the level of disclosure.

Detection of graph distortion can have an impact on users' decisions because of the impairment in corporate disclosure credibility. As stated by Schmid (1992), graph distortion threatens the credibility of the entire report containing such a graphic. Therefore, when distortion is detected, users may perceive a higher risk associated with their decisions.[10] Theoretical studies by Easley and O'Hara (2004) and Leuz and Verrecchia (2005) predict the existence of a negative relationship between the quality of information and the risk premium required by investors. Easley and O'Hara (2004) show that information precision reduces the information-based systematic risk of shares to uninformed investors, thereby reducing the cost of capital. Leuz and Verrecchia (2005) take a different approach and show that information quality increases expected cash-flows and, as a consequence, reduces the firms' cost of capital. Francis et al. (2004) and Francis et al. (2005) provide empirical evidence supporting these predictions. They find that accrual quality and a number of earnings attributes are significantly related to the cost of capital. By analogy we expect that, by reducing the credibility of the annual report, the inclusion of distorted graphs, if detected, will increase the information risk and, as a consequence, the risk premium demanded by investors. On the contrary, as long as distortion is undetected, companies could benefit from a lower cost of equity. Since the overall level of disclosure can be essential in unveiling graph distortion, we test the following hypothesis:

H2: The effect of favourable graph distortion on the ex-ante cost of equity capital is different at low levels of disclosure than at high levels of disclosure.

So far we have focused our attention on users' perceptions and estimations about the future of the company. These perceptions and estimations are at the basis of the so called ex-ante measures of the cost of equity. After estimations have been formed and revealed, investors will take their buying and selling decisions in the stock market and market prices will be formed continuously. The EMH predicts that market prices reflect all available information in an efficient manner. Hence, it could be argued that graph usage and graph distortion should not affect the aggregated ex-post behaviour of the stock market. In other words, as time passes, the aggregation role played by market activity should correct any possible bias contained in the ex-ante perceptions and estimations.

In a paper closely related to our analysis, Easton and Sommers (2007) provide evidence showing that ex-ante measures of the cost of equity are upwards biased because of the bias contained in analysts' forecasts. However, they also show that the

[9] The relationship between the overall level of disclosure and the cost of equity has already been explored in various papers, both from a theoretical and an empirical point of view. For a general introduction to this literature see Botosan (2006). A more analytical perspective can be found in Verrecchia (2001) and Dye (2001).

[10] Prior research referring to managers' explanations for poor performance supports this line of reasoning. Barton and Mercer (2005) find that implausible explanations harm management reputation leading to an increase in the firm's information risk. Although these explanations are given to promote a more favourable view of corporate performance, they end up having the contrary effect.

stock market undoes the bias of analysts' forecasts. Hence, these authors suggest that variation in the proxies used to measure the ex-ante cost of equity capital can be due to variation in analysts' bias rather than to variation in the true cost of equity capital. Starting from this result, we conjecture that the bias in analysts' estimations of earnings per share (the base for the ex-ante measure of the cost of equity) can be influenced by graph distortion, while the ex-post realised cost of equity is not. In other words, stock prices are not biased by distorted graphs. This argument is the basis of our third hypothesis.

H3: Favourable graph distortion does not affect stock market returns, i.e. the ex-post cost of equity capital.

Taken together, our three research hypotheses aim at covering some important aspects of the potential role played by graphs as communication tools in the stock market. In the next section we implement our research design by describing the sample and the variables used for our empirical tests.

3. Research design and variable definitions

3.1. The sample

For our sample we collect information on companies listed on the continuous (electronic) market in the MSE for the period 1996–2002. Information on the graphs and their characteristics is gathered from corporate annual reports. Data on the information disclosed by the company (disclosure index) is obtained from the rankings produced by a pool of analysts and published annually by the business magazine Actualidad Económica.[11] Analysts' forecasts and market data used to calculate the cost of equity capital measures are obtained from the JCF database.[12] Finally, financial data are collected from the OSIRIS database.[13] Companies were removed from our study when the necessary information was not available at least for two consecutive years. Our final sample comprises 259 firm-year observations from 67 companies during 1996–2002.

3.2. Definition of variables

3.2.1. Cost of capital measures

Ex-ante cost of capital (R_{PEG_PREM})

An ex-ante measure of cost of equity capital is a measure based on some valuation model and it infers the discount rate that it should have been used to calculate the observed price of the stock if that particular valuation model had been used. The question of which is the best proxy for the ex-ante cost of equity capital of a company has received a great deal of attention in the recent literature. To produce a comprehensive review of this literature is beyond the scope of this study. However, one of the common results of these studies is that all the measures proposed in the literature are highly correlated among each other. Consequently, the choice of a particular proxy instead of another should not have a major effect on the overall results of the study. Botosan and Plumlee (2005) assess the relative merits of five alternative proxies in terms of their association with credible risk proxies. They find that the measure proposed by Easton (2004) is one of the two measures that clearly dominate the other three. They observe that it correlates with a number of risk indicators in the expected direction. This result, combined with the relative simplicity of this measure, made us decide to use it as our primary proxy for the ex-ante cost of equity capital.[14] Following Easton (2004) we calculate the ex-ante cost of equity capital for year t as[15]

$$r_{peg} = \sqrt{\frac{eps_2 - eps_1}{P_0}}$$

where:

P_0 = price of the stock of the company at 30 June of year t+1

eps_1 = one year ahead consensus forecast of earnings per share at 30 June of year t+1

eps_2 = two years ahead consensus forecast of earnings per share at 30 June of year t+1

Following Botosan and Plumlee (2005) we then calculate the equity risk premium (R_{PEG_PREM}) by subtracting from the cost of equity capital the risk free rate, proxied by the interest rate on five-year Spanish Treasury bills.[16] To avoid an unduly effect of outliers, R_{PEG_PREM} is then winsorised at the 1 and 99 percentiles of its distribution (i.e. values in the top and bottom 1% of the distribution are set equal to next value counting inwards from the extremes).

[11] The process of elaboration of this index is similar to that followed in constructing the AIMR index and it is discussed in detail in Section 3.2.3.

[12] JCF provides a global database of consensus earnings estimates and other financial projections to the professional investment community.

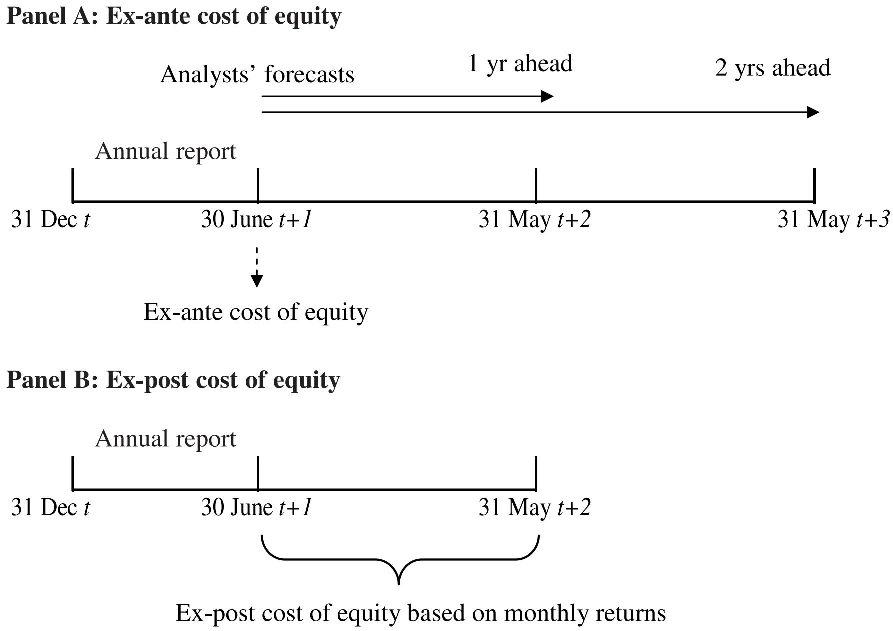
[13] The OSIRIS database, compiled by Bureau Van Dijk, provides financials for the world's publicly quoted companies from over 130 countries. It has been used in prior studies (e.g. García Lara et al., 2007; Surroca and Tribó, 2008). After comparing a number of databases, including OSIRIS, García Lara et al. (2006) conclude that when using the same set of companies results are not affected by the choice of the database.

[14] We check the robustness of our results to the use of other proxies for the ex-ante cost of equity. Results of these sensitivity analyses are discussed in Section 4.2.1.

[15] For the exact derivation of the formula the reader can refer to Easton (2004).

[16] We subtract the risk-free rate to obtain an indicator of the premium for risk required by investors to fund the company.

Figure 1
Ex-ante and ex-post cost of equity



Ex-post cost of capital (stock returns)
Besides the ex-ante measure of the cost of equity, we use the one-factor asset-pricing model to assess the actual effect of graphs on the aggregated market.[17] Similar to Francis et al. (2005), when analysing the effect of accruals quality in stock returns, we add a variable capturing the level of graph distortion to the traditional capital asset pricing model (CAPM). To obtain this graph distortion factor we use a similar procedure to that employed by Fama and French (1993) in constructing the size and book-to-market factor-mimicking portfolios. We start by constructing two mimicking portfolios for graph distortion. To obtain these portfolios we divide stocks into two groups: distorting and non-distorting companies. Distorting companies are those which materially distort the graphs included in their annual reports to portray a more favourable view of the company.[18] Non-distorting companies are those that present fairly constructed graphs or distorted graphs presenting a more unfavourable view of the company. We calculate monthly excess returns for companies in each group from June of year t+1 to May of year t+2.[19] The graph distortion factor mimicking portfolio equals mean monthly excess return for distorting companies portfolio less mean monthly excess return for non-distorting companies portfolio. For our sample period (1996–2002) we obtain a series of 84 monthly returns for the graph distortion factor. Then, we estimate the CAPM including the graph distortion factor for each of the 67 companies included in our sample. In these regressions, the coefficient of the graph distortion factor indicates whether this factor adds to market risk premium in explaining returns, our proxy for the ex-post cost of equity.

The ex-ante and ex-post measures of the cost of equity differ not only in the nature of the information on which they are based (analysts' forecasts as opposed to realised returns), but also in the period of time when they are formed. The relationship between the ex-ante and the ex-post measure of the cost of equity capital in terms of time is represented in Figure 1.

As we can see, the ex-ante measure is based on analysts' forecasts of earnings per share one and two years ahead at 30 June of year t+1, whereas the ex-post measure is based on realised returns (i.e. we estimate firm-specific asset-pricing models running from June 1997 to May 2004). For the period June of year t+1 to May of year t+2, returns

[17] Similar results obtain when using the three-factor model proposed by Fama and French (1993).

[18] Material distortion refers to a mean favourable graph distortion index above 2.5%. The selection of this cut-off point is explained in detail in Section 3.2.2, when describing the measure of graph distortion. The direction of the results remains unchanged if distorting and non-distorting portfolios include companies in the top and bottom 40% percentiles of the distribution of the variable used to measure graph distortion, respectively.

[19] Following prior literature on disclosure in Spain (e.g. Espinosa and Trombetta, 2007), calculations start in June of year t+1, given that financial reporting regulation in Spain requires companies to release their annual report by that date at the latest.

Table 1
Measures of graph distortion

Panel A: Distortion measure for individual graphs

Trend in data	*Nature of distortion*	*RGD*
Increasing	Exaggeration	>0
Decreasing	Understatement	>0
Increasing	Understatement	<0
Decreasing	Exaggeration	<0

Panel B: Distortion measure across all graphs in the annual report

Graphs in the annual report	*RGDFAV*	*RGDUNF*
All graphs are properly constructed	0	0
There are favourably distorted graphs There are unfavourably distorted graphs	>0	>0
There are favourably distorted graphs There is not any unfavourably distorted graph	>0	0
There is not any favourably distorted graph There are unfavourably distorted graphs	0	>0

to the graph distortion factor incorporated in the asset pricing models are calculated using the level of graph distortion in the annual report of year t. Then, when using the ex-ante measure of the cost of equity, the analysis of the effect of graph distortion is based on expectations observed at a certain point time (June of year t+1). However, when employing the ex-post measure, the analysis is based on monthly realised returns covering one year (from June of year t+1 to May of year t+2). Accordingly, the latter measure allows for two types of corrections: those arising from the aggregation of all investors' decisions and those resulting from the passing of time which permits new information to be impounded in stock prices.

3.2.2. Graph distortion measures

Relative graph discrepancy (RGD) index

Graph distortion is measured in our study by using the relative graph discrepancy (RGD) index (Mather et al.,2005),[20] which is defined as

$$RGD = \frac{g_2 - g_3}{g_3}$$

where g_2 represents the actual height of the last column and g_3 is the proportionately correct height of the last column, based on the formula:

$$g_3 = \frac{g_1}{d_1} d_2$$

d_1 = value of first data point (corresponding to the first column)

d_2 = value of last data point (corresponding to the last column)

g_1 = actual height of first column

g_2 = actual height of last column.

In the absence of distortion, the index takes the value of zero (0), that is, the change portrayed in the graph is the same as that observed in the data. The RGD takes a positive value both when an increasing trend is exaggerated and when a decreasing trend is understated. Negative values result from understatement of increasing trends and exaggeration of decreasing trends (Table 1, Panel A).

Measures of favourable and unfavourable graph distortion

The RGD index gives us an indication of the level of distortion of a particular graph, either if distortion is favourable or unfavourable to the firm. To test our hypotheses we need to isolate those distortions that are favourable to the company and design an indicator of favourable (unfavourable) graph distortion across all graphs in the annual report.

[20] This measure was developed by Mather et al. (2005) to overcome some of the limitations of the graph discrepancy index (GDI), the measure of graph distortion used in previous studies. The GDI is defined as $(\frac{a}{b}-1)\times 100$, where a is the percentage of change in centimetres depicted in the graph and b is the percentage of change in the data. We repeated all our analysis using the GDI, instead of the RGD, and results do not vary.

Favourably distorted graphs are those graphs manipulated to present a more favourable view of the company. Examples of favourable distortion are the magnification of a positive trend in sales growth or the understatement of a decreasing trend in the same variable. Conversely, understatement of an increasing trend in sales and exaggeration of a decreasing trend in this variable are examples of unfavourable distortion.

We measure the level of favourable distortion across all graphs included by a firm in the annual report as follows:

$$RGDFAV = \frac{\sum_{j=1}^{n} |rgd\ fav_j|}{n}$$

where:

$|rgd\ fav_j|$ = Absolute value of the RGD index for graph j in the annual report.[21] $rgd\ fav_j$ is set to zero when graph j is distorted to portray a more unfavourable view of the company.

n = total number of graphs in the annual report.

The RGDFAV provides us with an indication of the mean level of favourable graph distortion in the annual report. This measure is increasing in the number of favourably distorted graphs and the corresponding RGD indices. Zero (0) value for the RGDFAV indicates that the annual report does not contain any favourably distorted graph. Panel B in Table 1 describes the values that correspond to the RGDFAV measure depending on whether the annual report includes properly constructed, favourably, and unfavourably distorted graphs.

Similarly, we measure unfavourable graph distortion across all graphs in the annual report as follows:

$$RGDUNF = \frac{\sum_{j=1}^{n} |rgd\ unf_j|}{n}$$

where:

$|rgd\ unf_j|$ = Absolute value of the RGD index for graph j in the annual report. $rgd\ unf_j$ is set to zero when graph j is distorted to portray a more favourable view of the company.

The RGDUNF is increasing in the number and the RGD of distorted graphs presenting a more unfavourable image of the company and takes the value of zero (0) when the annual report does not include any unfavourably distorted graph (Table 1, Panel B).

We also calculate mean favourable distortion index for financial (RGDFFAV) and non-financial graphs (RGDRFAV). These indices are defined in the same way as the RGDFAV but taking into consideration exclusively financial graphs (i.e. graphs depicting financial variables) for the RGDFFAV and non-financial graphs for the RGDRFAV.

In estimating the regression models we use the fractional ranks of our graph distortion measures (RGDFAV, RGDUNF, RGDFFAV and RGDRFAV). Fractional ranks for each of these measures are computed by dividing, within each year, the rank of a firm's distortion measure by the number of firms in the sample in this year. The rank is increasing in the level of distortion.

Finally, in order to distinguish between materially and non-materially distorted graphs we have to choose a cut-off point for the RGD measure. Mather et al. (2005) conclude that an RGD of 2.5% would be similar to a GDI of 5%, the cut-off point suggested by Tufte (1983) and used in previous studies. This is why we decided to use the 2.5% cut-off point as suggested by Mather et al. (2005).[22]

3.2.3. Control variables

Following prior literature, we add a number of risk factors as controls in our regression models (i.e. number of analysts' estimations, beta, leverage, book-to-price ratio, volatility of profitability, growth, and disclosure). These factors are standard controls in the cost of equity literature, which widely documents their association with measures of the cost of equity (e.g. Gebhardt et al., 2001; Gietzmann and Ireland, 2005; Francis et al., 2008).

Number of estimates (NEST)
In order to proxy for the level of attention received by a company we use the number of analysts' estimations of one-year-ahead EPS. This is a standard control variable used in disclosure-related studies. Starting from the seminal work by Botosan (1997), the previous literature has documented a strong influence of the level of analysts' attention on the relationship between disclosure and cost of equity capital.

Beta (BETA)
The capital asset pricing model (CAPM) predicts a positive association between the market beta of a stock and its cost of capital. However, previous studies do not consistently show such an expected relationship. While Botosan (1997) or Hail (2002) confirm the expected positive sign, Gebhardt et al. (2001) observe the expected sign but beta loses its significance when they add their industry measure. Finally, Francis et al. (2005) observe a negative relationship between beta and their measure of the cost of equity. We obtain the beta of each stock using a market model for the 60 months prior to

[21] As we are interested in obtaining an indicator of the level of distortion, absolute values are used in order to avoid the offsetting of positive and negative values of the individual RGD's.

[22] The direction of the results does not change when we use a GDI of 10% as the cut-off point. This level of distortion was found to affect users' perceptions in the study by Beattie and Jones (2002).

June of t+1, requiring, at least, 12 monthly return observations.

Leverage (LEV)
We measure leverage as the ratio between long-term debt and the market value of equity at 31 December of year *t*. Modigliani and Miller (1958) predict that the cost of equity should be increasing in the amount of debt in the financial structure of the company. This prediction is supported by results of studies such as those by Gebhardt et al. (2001) or Botosan and Plumlee (2005). In line with previous literature we expect to find a positive relationship between leverage and the cost of equity capital.

Book-to-price ratio (BP)
This is the ratio between book value of equity and market value of equity at 31 December of year *t*. Prior research documents a positive association between the book-to-price ratio and average realised returns (e.g. Fama and French, 1993 and Davis et al., 2000) as well as different ex-ante measures of the cost of equity (e.g. Gebhardt et al., 2001 and Botosan and Plumlee, 2005). These results are interpreted as evidence that the book-to-price ratio proxies for risk.

Volatility of profitability (V_NI)
Based on practitioners' consideration of the variability of earnings, Gebhardt et al. (2001) argue that this variable can be regarded as a source of risk. In our study, the volatility of the profitability of the firm is calculated as the standard deviation of net income scaled by mean of net income over a period of five years ending at December of year t.

Growth (GROWTH)
Following Francis et al. (2005) we control for the recent growth experienced by the company measured as the log of 1 plus the percentage change in the book value of equity along year t.

Disclosure (RINDEX)
Finally, to test whether there is an interaction between graph distortion and disclosure (H2), we introduce a measure of overall corporate disclosure. The relationship between corporate disclosure and the cost of equity is widely documented in the literature (e.g. Botosan and Plumlee, 2002; Espinosa and Trombetta, 2007; Francis et al., 2008). As an indicator of the information provided by the company we use the disclosure index published annually by the business magazine *Actualidad Económica*. This index is based on the information disclosed by companies in their annual reports. These reports are reviewed by the panel of experts who assign a score to a list of information items. For each company, the scores for each item are then added up to obtain a global score intended to represent the disclosure policy of the entity. Finally, the disclosure index is calculated as the ratio between the actual score of the company and the maximum possible score. Similar to Botosan and Plumlee (2002) or Nikolaev and Van Lent (2005), we use fractional ranks of the annual report indexes. Firms are ranked from 1 to N for each year and then the rank of each firm is divided by the total number of firms in this year to obtain the fractional ranks.

Table 2 provides a summary of the definition and data source of variables used in our analyses.

4. Results

4.1. Descriptive statistics

Descriptive statistics are presented in Table 3, where it can be seen that companies in our sample make wide use of graphs in their annual reports. At least one graph is included by 92% of the companies and the mean number of graphs per annual report (GRAPH) is 16. These figures are similar to those observed for other countries (e.g. Beattie and Jones, 2001). Although not reported in Table 3, mean RGDFAV is higher than 2.5% for 38% of the companies included in our study; that is, more than one third of the companies in our sample have favourably distorted the graphs included in their annual reports above the cut-off point chosen as an indication of material distortion. Unfavourable distortions are less frequent; mean RGDUNF is higher than 2.5% for 11% of the companies in our sample.

The correlation matrix presented in Table 4 shows that our ex-ante measure of the cost of equity is significantly correlated with all the risk proxies included in our study. As expected, the cost of equity is positively related to beta, book-to-price ratio, leverage and earnings variability and negatively related to growth and the number of estimates that acts also as a proxy for corporate size. Table 4 also shows a significant negative correlation between the cost of equity and our indicators of graph distortion.

4.2. Multivariate analysis

4.2.1. Ex-ante measure of the cost of equity (R_{PEG_PREM})

This section presents the results obtained for the ex-ante measure of the cost of equity (i.e. the RPEG measure as developed by Easton, 2004). To asses the validity of this measure, we start our analysis by estimating a model similar to that developed by Botosan and Plumlee (2005) and used to test the relation between the cost of capital and a number of indicators of firm risk. We estimate the following equation:

$$R_{PREM\,it+1} = \alpha_i + \beta_1\,NEST_{it} + \beta_2 LEV_{it} + \beta_3\,V\_NI_{it} + \beta_4\,BETA_{it} + \beta_5\,BP_{it} + \beta_6\,GROWTH_{it} + e_{it}, \quad (1)$$

Table 2
Definition of variables

Variables	*Definitions and data source*
Dependent variables	
R_{PEG_PREM}	Estimated risk premium calculated as the R_{PEG} in Easton (2004) less the risk-free rate (source JCF database).
R_{PEF_PREM}	Estimated risk premium calculated as the R_{PEF} in Easton and Monahan (2005) less the risk-free rate (source JCF database).
R_{MPEG_PREM}	Estimated risk premium calculated as the R_{MPEG} in Easton (2004) less the risk-free rate (source JCF database).
R_{AVRG_PREM}	Estimated risk premium calculated as the average of R_{PEF}, R_{PEG}, and R_{MPEG} less the risk-free rate (source JCF database).
$R_{jm} – R_{fm}$	Monthly excess return for firm *j* (source JCF database).
Independent variables	
GRAPH	Total number of graphs in the annual report of year t (source corporate annual reports).
RRGDFAV	Fractional rank of RGDFAV. RGDFAV is mean favourable Relative Graph Discrepancy (RGD) index across all graphs in the annual report. This index measures graph distortion and (0) means no distortion or distortion that is unfavourable to the company (source corporate annual reports).
RRGDUNF	Fractional rank of RGDUNF. RGDUNF is mean unfavourable Relative Graph Discrepancy (RGD) index across all graphs in the annual report. This index measures graph distortion and (0) means no distortion or distortion that is favourable to the company (source corporate annual reports).
RRGDFFAV	Fractional rank of RGDFFAV. RGDFFAV is mean favourable RGD of financial graphs (source corporate annual reports).
RRGDRFAV	Fractional rank of RGDRFAV. RGDRFAV is mean unfavourable RGD of non-financial graphs (source corporate annual reports).
$R_{Mm} – R_{fm}$	Monthly excess return on the market portfolio (source JCF database).
$RGDFAVfactor_m$	Return to the graph distortion factor mimicking portfolio (source JCF database).
Control variables	
NEST	Number of analysts' estimations of one-year-ahead EPS (source JCF database).
BETA	Capital market beta estimated via the market model with a minimum of 12 monthly returns over the 60 months prior to June of year t+1 (source JCF database).
BP	Book value of equity scaled by market value of equity (source OSIRIS database).
LEV	Long-term debt scaled by market value of equity (source OSIRIS database).
V_NI	Standard deviation of net income scaled by mean net income over a period of five years ending at December of year t (source OSIRIS database) .
GROWTH	Log of 1 plus the percentage change in the book value of equity along year t (source OSIRIS database).
ROA	Return on total assets (source OSIRIS database).
CDA	Current discretionary accruals estimated by using the model developed by Dechow and Dichev (2002) as modified by McNichols (2002) (source OSIRIS database).
RINDEX	Fractional rank of the disclosure index prepared by the business magazine *Actualidad Económica* for year t (source business magazine *Actualidad Económica*).

Table 3
Descriptive statistics

	Mean	*Std. Dev.*	*Minimum*	*Maximum*	*25th perc.*	*50th perc.*	*75th perc.*
R_{PEG_PREM}	5.972	4.448	–0.693	25.031	3.134	5.128	7.682
NEST	15.927	9.103	1	40	9	16	21
BETA	1.125	0.549	0.034	4.594	0.773	1.038	1.348
BP	0.637	0.403	0.049	3.018	0.362	0.558	0.818
LEV	0.398	0.603	0	6.315	0.065	0.221	0.469
V_NI	0.579	1.646	–2.670	19.930	0.180	0.320	0.558
GROWTH	0.103	0.235	–1.769	1.515	0.013	0.079	0.148
GRAPH	16.087	15.461	0	84	4.25	12	23
RGDFAV	0.106	0.307	0	3.685	0	0	0.095
RGDUNF	0.012	0.062	0	0.878	0	0	0
RGDFFAV	0.108	0.326	0	3.685	0	0	0.068
RGDRFAV	0.043	0.151	0	1.5	0	0	0
ROA	6.273	5.820	–21.190	28.100	2.680	5.145	8.150
CDA	0.021	0.065	–0.318	0.238	–0.011	0.017	0.048
INDEX	0.637	0.150	0.230	0.960	0.550	0.630	0.750

The sample consists of 259 firm-year observations for the period 1996–2002. The definition of variables is provided in Table 2.

where:

R_{PREM} = Proxy for the equity risk premium = $R_{PEG} - R_f$

R_f = the risk-free rate, proxied by the interest rate on five-year Spanish Treasury bills.

The rest of the variables are defined in Table 2.

We estimate all our models using the fixed effects technique. The importance of using proper panel data estimation techniques when dealing with financial pooled data has been stressed by Nikolaev and Van Lent (2005) and Petersen (2005). If a simple OLS method is used to compute the estimated coefficients, their significance is very likely to be overstated. A traditional way to correct for this problem is to estimate yearly regressions and then take the average of the estimated coefficients, evaluating the statistical significance of these estimates by using the Fama-Macbeth t-statistic. This corrects for cross-sectional dependence, but not for time dependence. Nikolaev and Van Lent (2005) show how important firm effects can be when studying cost of capital determinants for a pooled sample of companies. This is our reason for estimating our model by using the fixed effects technique.[23]

Results of estimating equation (1) are presented in Table 5, Panel B (Model 1). The coefficients of the number of estimates, leverage, and variability of profitability have the expected sign and are statistically significant. The fact that the coefficients of beta and the book-to-price ratio are not statistically significantly different from zero could be due to the use of the fixed effect estimation technique. Beta and the book-to-price are risk factors that are specific for each company. Given that with the adopted estimation technique a specific intercept is estimated for each company, it is highly likely that the effect of these variables is already captured by these constants. Overall, our results confirm those already obtained for the Spanish market by Espinosa and Trombetta (2007) and support the validity of the measure of the cost of equity capital and the choice of the control variables.

We now move on to the main part of our empirical study and insert in our specification the indicators of mean favourable and unfavourable graph distortion across all graphs included in the annual report. Specifically, we now estimate the following equation (Model 2):

$$R_{PREM\ it+1} = \alpha_i + \beta_1 NEST_{it} + \beta_2 LEV_{it} + \beta_3\ V\_NI_{it} + \beta_4\ BETA_{it} + \beta_5\ BP_{it} + \beta_6\ GROWTH_{it} + \beta_7\ RRGDFAV_{it} + \beta_8\ RRGDUNF_{it} + \varepsilon_{it} \quad (2)$$

All variables are defined in Table 2.

We now find that favourable graph distortion is significantly and negatively related to the ex-ante measure of the cost of equity. A negative coefficient is also observed for unfavourable graph distortion but results show that it is insignificantly different from zero. These results suggest that favourably distorted graphs introduce a bias on users' perceptions. According to our results, annual report users perceive a better image of corporate performance when the annual report includes

[23] However, at least for our main analysis, we also provide the results obtained by running an OLS regression on the pooled sample. These results can be found in Table 4, Panel A.

Table 4
Correlation matrix

	R_{PEG_PREM}	NEST	BETA	BP	LEV	V_NI	GROWTH	RGDFAV	RGDUNF	RGDFFAV	RGDRFAV	ROA	CDA
NEST	–0.200												
	(0.001)												
BETA	0.222	–0.124											
	(0.000)	(0.046)											
BP	0.379	–0.329	0.099										
	(0.000)	(0.000)	(0.112)										
LEV	0.172	0.161	0.023	0.417									
	(0.006)	(0.009)	(0.707)	(0.000)									
V_NI	0.192	–0.121	0.168	0.091	–0.020								
	(0.002)	(0.053)	(0.007)	(0.144)	(0.745)								
GROWTH	–0.165	0.104	–0.011	–0.193	–0.028	0.088							
	(0.008)	(0.093)	(0.854)	(0.002)	(0.651)	(0.159)							
RGDFAV	–0.175	0.172	0.031	–0.036	0.081	–0.096	0.014						
	(0.005)	(0.005)	(0.616)	(0.559)	(0.195)	(0.122)	(0.822)						
RGDUNF	–0.077	0.180	–0.014	–0.073	0.095	–0.041	0.066	0.339					
	(0.217)	(0.004)	(0.825)	(0.243)	(0.127)	(0.516)	(0.291)	(0.000)					
RGDFFAV	–0.202	0.112	0.025	–0.048	0.034	–0.086	0.089	0.872	0.276				
	(0.001)	(0.073)	(0.689)	(0.444)	(0.590)	(0.168)	(0.152)	(0.000)	(0.000)				
RGDRFAV	–0.102	0.268	–0.004	–0.024	0.131	–0.057	–0.101	0.597	0.311	0.301			
	(0.103)	(0.000)	(0.955)	(0.698)	(0.036)	(0.357)	(0.106)	(0.000)	(0.000)	(0.000)			
ROA	–0.250	0.065	–0.153	–0.343	–0.543	–0.012	0.213	–0.046	–0.111	–0.010	–0.054		
	(0.000)	(0.298)	(0.014)	(0.000)	(0.000)	(0.853)	(0.001)	(0.456)	(0.073)	(0.871)	(0.387)		
CDA	0.093	–0.088	0.007	0.062	0.076	–0.081	0.002	0.131	–0.021	0.090	0.071	0.166	
	(0.163)	(0.191)	(0.920)	(0.356)	(0.259)	(0.225)	(0.976)	(0.050)	(0.754)	(0.177)	(0.288)	(0.013)	
RINDEX	–0.220	0.466	–0.003	–0.064	0.247	–0.055	0.010	0.212	0.238	0.170	0.283	–0.323	–0.143
	(0.000)	(0.000)	(0.959)	(0.304)	(0.000)	(0.375)	(0.876)	(0.001)	(0.000)	(0.006)	(0.000)	(0.000)	(0.032)

Table reports Spearman correlations. Significance levels are shown in brackets. The definition of variables is provided in Table 2.

Table 5
Regression of the ex-ante measure of cost of equity (R_{PEG_PREM}) on risk proxies and graph distortion

Model 1: $R_{PEG\_PREM\ it+1} = \alpha_i + \beta_1\ NEST_{it} + \beta_2 LEV_{it} + \beta_3\ V\_NI_{it} + \beta_4\ BETA_{it} + \beta_5\ BP_{it} + \beta_6\ GROWTH_{it} + \varepsilon_{it}$

Model 2: $R_{PEG\_PREM\ it+1} = \alpha_i + \beta_1 NEST_{it} + \beta_2 LEV_{it} + \beta_3\ V\_NI_{it} + \beta_4\ BETA_{it} + \beta_5\ BP_{it} + \beta_6\ GROWTH_{it} + \beta_7\ RRGDFAV_{it} + \beta_8\ RRGDUNF_{it} + \varepsilon_{it}$

Model 3: $R_{PEG\_PREM\ it+1} = \alpha_i + \beta_1 NEST_{it} + \beta_2 LEV_{it} + \beta_3\ V\_NI_{it} + \beta_4\ BETA_{it} + \beta_5\ BP_{it} + \beta_6\ GROWTH_{it} + \beta_9\ RRGDFFAV_{it} + \beta_{10} RRGDRFAV_{it} + \varepsilon_{it}$

Panel A: Pooled OLS regression

	Model 1		*Model 2*		*Model 3*	
Variable	*Coeff.*	*P-val*	*Coeff.*	*P-val*	*Coeff.*	*P-val*
Intercept	4.382	0.000	4.936	0.000	5.101	0.000
NEST	–0.059	0.039	–0.051	0.091	–0.057	0.064
LEV	1.149	0.128	1.122	0.145	1.136	0.143
V_NI	0.096	0.325	0.075	0.435	0.083	0.403
BETA	0.791	0.149	0.892	0.105	0.895	0.096
BP	2.089	0.010	2.111	0.010	2.053	0.011
GROWTH	–2.172	0.087	–2.131	0.097	–1.839	0.160
RRGDFAV			–1.721	0.072		
RRGDUNF			0.162	0.900		
RRGDFFAV					–2.604	0.005
RRGDRFAV					0.910	0.530
Adj. R^2	0.135		0.138		0.149	

Panel B. Fixed effects regressions

	Model 1		*Model 2*		*Model 3*	
Variable	*Coeff.*	*P-val*	*Coeff.*	*P-val*	*Coeff.*	*P-val*
NEST	–0.147	0.011	–0.130	0.027	–0.126	0.032
LEV	2.537	0.004	2.491	0.005	2.516	0.005
V_NI	0.264	0.022	0.270	0.021	0.279	0.018
BETA	–0.378	0.453	–0.271	0.593	–0.293	0.567
BP	–0.109	0.912	–0.127	0.897	–0.182	0.851
GROWTH	0.160	0.867	0.208	0.831	0.296	0.766
RRGDFAV			–2.351	0.013		
RRGDUNF			–0.182	0.828		
RRGDFFAV					–2.230	0.015
RRGDRFAV					–1.032	0.260
Adj. R^2	0.547		0.554		0.555	

The sample consists of 259 firm-year observations for the period 1996–2002. The definition of variables is provided in Table 2. Estimates of the firm-specific constant terms are omitted for readability.

graphs that have been distorted to portray a more favourable view of the company. The same is true if we focus our attention only on financial graphs (RRGDFFAV), as we do in Model 3. These results support our hypothesis H1. The information represented in graphs is usually included in the financial statements or other parts of the annual report. However, users get a different picture of the company when the annual report includes favourably distorted graphs. These results are consistent with the experimental evidence of the impact of improperly constructed graphs on subjects' choices provided by Arunachalam et al. (2002). They observe that students' decisions are affected by graph design. We extend these results by showing that, in a real setting, experts' (analysts') forecasts are biased because of distorted graphs included in annual reports.

We test the robustness of these results to the choice of the ex-ante measure of the cost of equity and to the inclusion of additional control variables. As for the proxy for the cost of equity, we calculate two alternative measures: R_{PEF} and R_{MPEG}. The definition of these measures is given in the appen-

Table 6
Regression of the cost of equity on risk proxies and graph distortion using fixed effects

$$R_{PREM\ it+1} = \alpha i + \beta_1 NEST_{it} + \beta_2 LEV_{it} + \beta_3\ V\_NI_{it} + \beta_4\ BETA_{it} + \beta_5\ BP_{it} + \beta_6\ GROWTH_{it} + \beta_7\ RRGDFAV_{it} + \beta_9\ ROA_{it} + \beta_{10} CDA_{it} + \varepsilon_{it}$$

	Panel A R_{PEG_PREM}		Panel B R_{PEF_PREM}		Panel C R_{MPEG_PREM}		Panel D R_{AVRG_PREM}	
Variable	*Coeff.*	*P-val*	*Coeff.*	*P-val*	*Coeff.*	*P-val*	*Coeff.*	*P-val*
NEST	–0.121	0.029	–0.177	0.000	–0.085	0.111	–0.125	0.003
LEV	1.590	0.075	1.032	0.071	1.847	0.046	1.410	0.021
V_NI	0.168	0.280	–0.020	0.800	0.082	0.578	0.094	0.314
BETA	–0.454	0.350	–1.191	0.012	–0.689	0.193	–0.892	0.049
BP	0.510	0.701	0.971	0.253	0.774	0.573	0.692	0.451
GROWTH	1.082	0.287	0.748	0.299	1.150	0.283	0.726	0.307
RRGDFAV	–2.232	0.012	–1.327	0.041	–2.645	0.002	–2.296	0.001
ROA	–0.334	0.000	–0.037	0.378	–0.327	0.000	–0.172	0.000
CDA	3.090	0.277	5.413	0.010	5.793	0.049	5.296	0.014
Adj. R^2	0.630		0.599		0.653		0.659	

The sample consists of 259 firm-year observations for the period 1996–2002. The definition of variables is provided in Table 2. Estimates of the firm-specific constant terms are omitted for readability.

dix. We also use the average (R_{AVRG}) of the three proxies calculated in our study. Additionally, we check if our results are driven by factors such as corporate performance or accruals quality. Prior literature documents a positive association between corporate performance and graph distortion (e.g. Beattie and Jones, 1999, 2000). Therefore, the effect of graph distortion on the cost of equity that we observe in this study could be driven by the fact that distorting companies are also those with the highest performance. Hence, we add a measure of corporate performance (i.e. ROA) as a control variable. Second, Francis et al. (2005) and Francis et al. (2008) show the existence of a positive relationship between the cost of equity capital and the (poor) quality of accruals. The negative relationship between graph distortion and the cost of equity observed in this study could be reflecting this association. Therefore, we test for the robustness of our results by adding a measure of accruals quality (i.e. discretionary accruals) to our model (CDA).[24]

Table 6 reports the results of these sensitivity analyses and shows that the effect of favourable graph distortion on the ex-ante cost of equity is robust to the choice of the measure of the cost of equity. Favourable graph distortion is found to be negatively and significantly related to all the alternative measures of the ex-ante cost of equity calculated in our study. Additionally, we observe that, although corporate performance and accruals quality can be highly significant variables in explaining the ex-ante cost of equity, its inclusion in the model does not qualitatively change our results. That is, the effect of favourable graph distortion on the ex-ante measures of the cost of equity remains.

Interaction analysis

To investigate whether the relationship between graph distortion and the ex-ante measure of the cost of equity varies depending on the overall level of disclosure, as stated in our second hypothesis, we introduce a measure of the voluntary information provided by the company in their annual report (RINDEX) and an interaction term between disclosure and graph distortion. Specifically, we estimate the following equation:

$$R_{PREM\ it+1} = \alpha_i + \beta_1 NEST_{it} + \beta_2 LEV_{it} + \beta_3\ V\_NI_{it} + \beta_4\ BETA_{it} + \beta_5\ BP_{it} + \beta_6\ GROWTH_{it} + \beta_7\ RRGDFAV_{it} + \beta_8\ RINDEX_{it} + \beta_9\ RRGDFAV_{it} * RINDEX_{it} + \varepsilon_{it} \quad (3)$$

All variables are defined in Table 2.

Table 7, Panel A presents the results of the estimation of Equation (3). Consistent with the results reported previously, the coefficient on RRGDFAV is found to be negative and significant. A negative relationship is also observed between the overall level of disclosure and the cost of equity, although it is not significant at conventional levels. Finally, the interaction term is positive and significant, which means that graph distortion and disclosure interact in shaping their effects on the cost of equity. Since the sign of the interaction term is posi-

[24] To obtain this measure we use the model developed by Dechow and Dichev (2002) as modified by McNichols (2002).

Table 7
Regression of the cost of equity on risk proxies, graph distortion, and disclosure using fixed effects

Model 1: $R_{PEG\_PREM\ it+1}$ (Panel A) = $\alpha_i + \beta_1 NEST_{it} + \beta_2 LEV_{it} + \beta_3\ V\_NI_{it} + \beta_4\ BETA_{it} + \beta_5\ BP_{it} + \beta_6\ GROWTH_{it} + \beta_7\ RRGDFAV_{it} + \beta_8\ RINDEX_{it} + \beta_9\ RRGDFAV_{it} * RINDEX_{it} + \varepsilon_{it}$

Model 2: $R_{PEG\_PREM\ it+1}$ (Panels B–C) = $\alpha_i + \beta_1 NEST_{it} + \beta_2 LEV_{it} + \beta_3\ V\_NI_{it} + \beta_4\ BETA_{it} + \beta_5\ BP_{it} + \beta_6\ GROWTH_{it} + \beta_7\ RRGDFAV_{it} + \beta_8\ RINDEX\_D_{it} + \beta_9\ RRGDFAV_{it} * RINDEX\_D_{it} + \varepsilon_{it}$

	Panel A		Panel B		Panel C	
Variable	*Coeff.*	*P-val*	*Coeff.*	*P-val*	*Coeff.*	*P-val*
NEST	–0.148	0.032	–0.148	0.028	–0.153	0.022
LEV	2.433	0.001	2.456	0.001	2.495	0.001
V_NI	0.284	0.050	0.266	0.066	0.276	0.058
BETA	–0.350	0.555	–0.345	0.564	–0.161	0.786
BP	–0.202	0.829	–0.147	0.876	–0.135	0.885
GROWTH	0.181	0.856	0.111	0.911	0.237	0.809
RRGDFAV	–6.227	0.002	–4.198	0.003	–3.909	0.002
RINDEX	–4.204	0.099				
RRGDFAV*RINDEX	8.106	0.024				
RINDEX_D			–1.517	0.178	–2.093	0.143
RRGDFAV*RINDEX_D			3.785	0.058	4.871	0.028
Adj. R^2	0.564		0.561		0.565	

The sample consists of 259 firm-year observations for the period 1996–2002. The definition of variables is provided in Table 2. Estimates of the firm-specific constant terms are omitted for readability.

tive, results indicate that the effect of graph distortion on the cost of equity is moderated by the level of overall disclosure. Stated in other words, the effect of graph distortion on the cost of equity is partially (or eventually completely) offset by its interaction with the overall level of disclosure. To get a clearer picture of the interaction between graph distortion and disclosure we dichotomise the RINDEX variable and estimate the following equation:

$$R_{PREM\ it+1} = \alpha_i + \beta_1 NEST_{it} + \beta_2 LEV_{it} + \beta_3\ V\_NI_{it} + \beta_4\ BETA_{it} + \beta_5\ BP_{it} + \beta_6\ GROWTH_{it} + \beta_7\ RRGDFAV_{it} + \beta_8\ RINDEX\_D_{it} + \beta_9\ RRGDFAV_{it} * RINDEX\_D_{it} + \varepsilon_{it} \quad (4)$$

where all the variables are defined as before except for:

RINDEX_D = A dichotomy variable which, in Panel B (C), takes the value of one (1) when the value of the RINDEX is in the top 50% (33%) percentile of the distribution of this variable, and a value of zero (0) otherwise.

Results of this estimation are presented in Table 7, Panels B and C. Since the selection of the cut-off point used to dichotomise the RINDEX variable is arbitrary, Table 7 reports the results obtained by using two different cut-off points. In panel B, the set of high disclosers comprises those companies the disclosure index of which is above the median, while in Panel C high disclosers are those firms falling in the top 33% percentile of the distribution of the RINDEX variable.

Consistent with the results presented in Panel A, we find that the cost of equity is negatively associated with RRGDFAV and positively related to the interaction term. The dichotomisation of the variable RINDEX facilitates the interpretation of the results. When RINDEX_D takes the value of zero (0), the relationship between graph distortion and the cost of equity is given by β_7 and is negative, both in Panels B and C. This means that for low disclosers, graph distortion is negatively related to the cost of equity. However, when RINDEX_D takes the value of one (1), the effect of graph distortion is given by the addition of the coefficients on RRGDFAV and the interaction term (i.e. $\beta_7 + \beta_9$). This addition results in a negative figure (–0.413) in Panel B, which is much lower than the coefficient on RRGDFAV, and a positive figure (0.962) in Panel C. Thus, for transparent companies, disclosure partially removes the effect of graph distortion (Panel B) or even transforms it into a positive effect (Panel C). These results indicate that disclosure moderates the relationship between graph distortion and the cost of equity and provide support for our second hypothesis. Furthermore, differences between Panels B and C indicate that the moderating effect is increasing in

Table 8
Firm-specific regressions of stock returns on the market portfolio and the graph distortion factor

Model 1: $R_{jm} - R_{fm} = a_j + b_j (R_{Mm} - R_{fm}) + \varepsilon_{jm}$

Model 2: $R_{jm} - R_{fm} = a_j + b_j (R_{Mm} - R_{fm}) + c_j$ RGDFAVfactor$_m + \varepsilon_{jm}$

	Model 1		Model 2	
Variable	*Coeff.*	*P-val*	*Coeff.*	*P-val*
Constant	0.004	0.529	0.005	0.520
$R_{Mm} - R_{fm}$	0.836	0.020	0.851	0.012
RGDFAVfactor$_m$			–0.130	0.326
R-squared	0.264		0.296	

The table reports the average coefficient estimates obtained from the estimation of the asset-pricing models for each company included in our sample. A minimum of 18 monthly stock returns for the period June 1997 to May 2004 is required. The definition of variables is provided in Table 2.

the level of disclosure, so that when transparency is sufficiently high, the relationship between graph distortion and the ex-ante measure of the cost of equity becomes positive. Results suggest that while at low levels of transparency graph distortion remains undetected, high levels of disclosure uncover graph distortion, which results in an increase in the risk perceived by users. Hence, users' predictions can only be potentially affected by graph distortion when the level of information provided by the company is low.

So far we have used an ex-ante measure of the cost of equity based on analysts' estimations of earnings per share. Hence, our results could be interpreted as evidence that graph distortion affects users' (analysts') perceptions of corporate performance. However, it is important to check that the market is able to correct individuals' biases. With this aim, in the next section we present the results obtained using average ex-post returns as a proxy for the cost of equity.

4.2.2. Ex-post measure of the cost of equity (stock returns)

As a starting point in our ex-post analysis, we estimate a one-factor asset-pricing model for each of the 68 companies in our sample.[25] The average coefficients and adjusted R's squared of these estimations are presented in Table 8 (Model 1).

Results show a mean beta of 0.84 and a mean adjusted R-squared of 26.4%. We proceed by adding a factor aimed at representing favourable graph distortion (RGDFAVfactor). Specifically, we estimate the following equation:

$$R_{jm} - R_{fm} = a_j + b_j (R_{Mm} - R_{fm}) + c_j \text{ RGDFAVfactor}_m + \varepsilon_{jm} \quad (5)$$

where:

$R_{jm} - R_{fm}$ = monthly excess return for firm j.

$R_{Mm} - R_{fm}$ = monthly excess return on the market portfolio

RGDFAVfactor$_m$ = return to the graph distortion factor mimicking portfolio

Average coefficients obtained from firm-specific estimations of Equation (5) are reported in Table 8 (Model 2). Results show that stock returns are not affected by the distortion of graphs included in the annual report. The coefficient of the RGDFAV factor is negative but it is insignificantly different from zero. Hence, we find support for our hypothesis H3. Results (unreported) are similar when we construct the RGDFAV factor relaying on favourably distorted graphs representing financial variables. Although these variables might exert a higher influence on users' decisions than non-financial variables, results show that stock returns are not affected by the distortion of financial graphs. These results are in accordance with the EMH and suggest that decision makers (at the aggregated level) are able to see through distortion. Their decisions cannot be biased by means of 'rosy' graphs depicting a much more favourable view of corporate performance than that reflected in the financial statements. Nonetheless, results presented in the previous section show the existence of a negative and significant relationship between favourable graph distortion and the ex-ante measure of the cost of equity. One way to explain these apparently contradicting findings is that individuals' perceptions can be biased because of distorted graphs, but the aggregation process performed by the stock market leads to unbiased decisions. Prior research shows that the aggregation of individual's predictions leads to higher levels of accuracy (e.g. Solomon, 1982 and Chalos, 1985). Furthermore,

[25] A minimum of 18 monthly returns is required in these estimations.

Easton and Sommers (2007) provide evidence showing that the market undoes the optimistic bias in analysts' forecasts. Therefore, the possibility exists that analysts' estimations of earnings per share (the base for the ex-ante measure of the cost of equity) are influenced by graph distortion, even though stock prices resulting from the aggregation of a large number of decisions are not biased by distorted graphs.

To further investigate this issue, following Easton and Sommers (2007), we recalculate the R_{PEG} measure using realised earnings instead of analysts' earnings forecasts. By doing so the R_{PEG} measure becomes an ex-ante measure of the cost of equity based on perfect foresight, since it is not based on estimations but on realised earnings. We re-estimate Equation (2) using this measure as the dependent variable. Unreported results, available from the authors, show that this measure of the cost of equity is not affected by graph distortion. Even when we focus our attention on financial graphs we do not observe any significant relationship between graph distortion and this perfect foresight measure of the cost of equity. These results corroborate the intuition gathered from previous analyses. Individuals' (analysts') perceptions are biased and distorted graphs affect this bias, but the market is able to correct these misperceptions. Once this bias in expectations is removed, the effect of graph distortion on the cost of equity disappears. Our results are consistent with those reported in previous experimental studies showing that individuals' perceptions are affected by graph distortion (e.g. Beattie and Jones, 2002 and Arunachalam et al., 2002). We extend these results by providing evidence of the effect of graph distortion on individuals' (analysts') estimations in a real setting, instead of a controlled experiment. Additionally, we show that the bias in individuals' expectations is corrected in the capital market. Hence, despite the efforts made by companies to create a more favourable impression on users, we provide evidence showing that the aggregated market response is not biased by distorted graphs.

5. Conclusions

The wide use of graphs in corporate annual reports together with the frequency with which they are distorted to portray a more favourable view of corporate performance, suggest that companies expect benefits from using and distorting graphs. In other words, distorted graphs are used by companies as an impression management technique. This 'manipulation hypothesis' is confirmed, for example, by the time-series analysis of Beattie and Jones (2000). However, the information depicted in graphs is usually presented also in a numerical format in the annual report. Using the terminology of Merkl-Davies and Brennan (2007), graphs do not provide any 'incremental information'. Consequently, market efficiency would imply that stock prices should not be affected by the use of distorted graphs to display information already available in the financial statements or other sections of the annual report. We can call this second hypothesis the 'absence of incremental information' hypothesis. To the best of our knowledge, our study is the first to test these two hypotheses by investigating the effect of graph distortion on the cost of equity capital both on an ex-ante and an ex-post basis.

Using a sample of companies quoted on the MSE, we obtain the following results. In accordance with the EMH, we find that ex-post stock returns are not affected by the distortion of graphs included in the annual report. Nonetheless, we observe a robust negative relationship between favourable graph distortion and ex-ante measures of the cost of equity. This negative relationship, however, is moderated by the overall level of disclosure, so that at high levels of transparency the relationship between graph distortion and the ex-ante measure of the cost of equity becomes positive. Results suggest that disclosure uncovers graph distortion which in turn leads to a higher risk being perceived.

In order to understand our results, it is important to distinguish between analysts' expectations and aggregated market behaviour. Since ex-ante measures of the cost of equity are based on analysts' forecasts, results indicate that analysts' estimations can be biased when graphs are distorted to portray a more favourable view of the company, especially when the overall level of information provided is low. These results are consistent with existing theories on the effects of herding and limited attention on the use of information in capital markets.[26] These theories predict that a focus on relative performance evaluation can induce analysts to neglect some of their detailed private information and to focus on coarser and more readily available indicators that summarise the existing information.

After analysts' forecasts have been formed, investors take their buying and selling decisions and these decisions determine the ex-post measure of the cost of equity, which is not found to be affected by distorted graphs. Hence, the limited attention effects are only transitory, because they disappear once the market settles. This means that with the passing of time, market activity is able to correct individuals' misperceptions, so that stock returns are not affected by distorted graphs. These results are related to those reported by Easton and Sommers (2007) showing that the market undoes the optimistic bias in analysts' forecasts. However, we extend their analysis in two ways. First, we

[26] These theories have been reviewed in the previous sections.

highlight graph distortion as a significant determinant of this bias. Second, we show that their result is robust to the use of a three-factor model as a measure of ex-post cost of equity as proposed by Fama and French (1993).

Since the analysis was conducted in a relatively underdeveloped capital market, where herding behaviour and heuristic trading are more likely, we conjecture that, in spite of the documented prevalence of graph usage and graph distortion in countries with highly developed capital markets (e.g. the UK and the US), it is unlikely that firms in these countries will achieve a reduction in their realised cost of equity by means of distorted graphs. However, further research is needed to investigate whether analysts' estimations are also biased because of distorted graphs in highly developed capital markets.

Our empirical evidence also sheds some additional light on the relationship between disclosure and the cost of equity. Both Espinosa and Trombetta (2007) and Gietzmann and Ireland (2005) show the important role played by accounting policy choice as a conditioning factor in this relationship. Our results show that disclosure interacts also with graph distortion as a determinant of the cost of equity.

More generally, we provide some initial evidence on the economic effects of materially distorted graphs. The previous literature had already documented the fact that a considerable number of graphs presented in annual reports are distorted. The minimum level of distortion necessary to influence users' perceptions was also established through experimental studies. Building on these important findings, we have extended the analysis and investigated the effects of graph bias on the cost of equity. However, this is only one of the possible economic variables that can be affected. The task of investigating the effects of distorted graphs on other economic variables is left to future research.

Finally, Steinbart (1989) and Beattie and Jones (2002) advocate regulatory intervention and the involvement of auditors in order to eliminate graph distortion. This proposal is based on the presumption that any misrepresentation of firms' financial performance potentially misleads users of annual reports. Our results have some important implications for this debate. Drawing on prior experimental evidence, we enhance our understanding of the significant economic effects of graph distortion outside a controlled laboratory environment. The fact that, over time, the market is able to correct individuals' misperceptions caused by distorted graphs does not diminish their importance with regard to the continuous functioning of the stock market. Consequently, our results support the notion that there is a rationale for the enforcement of regulatory action to avoid significant graph distortion. At the same time, our findings also underscore the complexity of the influences that graphs have on economic decisions and they call for an increased effort to advance knowledge on how graphs affect economic behaviour.

Appendix

Measures of the ex-ante cost of equity capital

All three alternative proxies for the ex-ante cost of equity capital that we use in the paper are based on the valuation model known as the Abnormal Earnings Growth Valuation Model. The general valuation formula according to this model is as follows:

$$P_t = \frac{x_{t+1}}{r} + \sum_{\tau=2}^{+\infty} \frac{x_{t+\tau} + rd_{t+\tau-1} - (1+r)x_{t+\tau-1}}{r} = \frac{x_{t+1}}{r} + \sum_{\tau=2}^{+\infty} \frac{AEG_{t+\tau}}{r(1+r)^{\tau}} \quad \text{(A.1)}$$

where:

P_t = closing price of the month of June
x_t = earnings at time t
r = cost of equity capital
d_t = the dividend payout at time t
AEG_t = abnormal earnings growth rate at time t.

Starting from this general valuation formula, each of the three proxies is obtained by making some restrictive assumptions on the parameters of the model (cf. Easton and Monahan, 2005). The expressions for each of the three measures are as follows:

a) Price to Forward Earnings Model (PEF)

$$P_0 = \frac{eps_1 + r_e d + eps_2}{(r_e + 1)^2 - 1} \quad \text{(A.2)}$$

Appendix *(continued)*

b) Price to Earnings Growth model (PEG)

$$P_0 = \frac{eps_2 - eps_1}{(r_e)^2} \quad (A.3)$$

c) Modified Price to Earnings Growth models (MPEG)

$$P_0 = \frac{eps_2 + r_e d - eps_1}{(r_e)^2} \quad (A.4)$$

P_0 = price of the stock of the company at 30 June of year t+1
d = dividend payout ratio for year t
eps_1 = one year ahead consensus forecast of earnings per share at 30 June of year t+1
eps_2 = two years ahead consensus forecast of earnings per share at 30 June of year t+1
Solving for r_e in each of these equations produces the estimates of the ex-ante cost of equity.

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