CORPORATE HEDGING POLICY AND THE ACCURACY OF ANALYSTS' FORECASTS: EVIDENCE FROM LARGE, NON-FINANCIAL U.S. CORPORATIONS

Gabriela Rusu

A Thesis
In
the John Molson School of Business

Presented in Partial Fulfilment of the Requirements
for the Degree of Master of Science in Administration at
Concordia University
Montreal, Quebec, Canada

April 2002

0-612-68426-1

ABSTRACT

Corporate Hedging Policy and the Accuracy of Analysts' Forecasts: Evidence from Large, Non-Financial U.S. Corporations

Gabriela Rusu

This paper examines the accuracy of forecasts of financial analysts in light of the hedging policies of the S&P 500 non-financial companies over the 1994 – 1997 period. Given that hedging reduces the volatility of cash flows, we ask whether it allows financial analysts to provide more accurate forecasts for firms that hedge than for firms that do not. Three data sources are used to construct the data set for this study: the Edgar database, Compustat and I/B/E/S. Univariate and multivariate tests are run in order to determine the effect of the usage of derivative products for hedging purposes, as well as that of the level of the usage, on analysts' forecasts accuracy. Only interest rate risk and foreign exchange risk hedging are considered, separately and together as the total hedging variable. The empirical results show that neither the involvement, nor the degree of involvement in hedging activities of a firm will result in more accurate forecasts, when considering the 1-year forecasts. Interest rate hedging and overall hedging do not impact on the accuracy of forecasts in a statistically significant way. However, surprisingly, the results show an increase in the forecast error when the company is involved in higher levels of foreign exchange hedging. The results also show evidence that the further away in time the forecast is made, the more relevant the hedging policies of a company are to the analyst.

ACKNOWLEDGEMENTS

I would like to express my deep gratitude to professor Dogan Tirtiroglu, for his valuable help, availability, support and unlimited patience. Professor Tirtiroglu was for me more than just a supervisor; he also was, and is a mentor and a friend.

I would like to thank professor Bhabra, for the advice and help provided throughout the period that leaded to the completion of this thesis, as well as for his interesting ideas that inspired this study.

Also, many thanks go to professor Prevost for his advice and comments.

I would like to thank I/B/E/S for providing the data used in this study.

I would also like to thank my friend Michèle Accarisi, for her support, her patience and interesting input.

Finally I would like to thank my family and Michel for supporting and encouraging me, throughout my studies. I would have never completed this thesis without their support and understanding.

Table of Contents

List of Figures

List of Tables

1. Introduction

The past two decades have been ground for important developments in research relating to derivative products and hedging policies. This great interest is mainly due to the drastic development that the business environment has known, through massive globalization and development of new financial instruments. At the same time, this period has experienced an important increase in research relating to analysts' forecasts. Research in both areas (hedging policies and analysts' forecasts) is very important due to the increasingly important place that derivative products take in the business life and the impact of analysts' forecasts on capital markets (Brown, Foster, and Noreen (1985)). This study examines the earnings forecasts of financial analysts in light of the hedging policies of the S&P 500 non-financial companies. The companies in this study are collected as of January 1995, and the sample is kept constant over the period of the study from 1994 to 1997, even though, some companies drop from or get added to the index during the same period. Given that hedging is expected to reduce a firm's volatility of cash flows, we ask whether it allows financial analysts to provide more accurate earnings forecasts for firms that hedge than for firms that do not (or for firms that hedge more than those that hedge less). Pervious studies have shown that forecast accuracy is influenced by different factors, such as the level of disclosure of information (Higgins (1998)), and the experience of the analysts with a specific firm (Mikhail, Walther, and Willis (1998)). However, to our knowledge, there is no previous work in the literature that relates accuracy of analysts' forecasts to firms' usage of derivative products.

Three data sources are used to construct the data set for this study: the Edgar database, Compustat and I.B.E.S.. Univariate and multivariate tests are run in order to determine the effect of the usage of derivative products for hedging purposes, as well as that of the level of the usage, on the accuracy of analysts' forecasts. Only interest rate risk and foreign exchange risk hedging are considered, separately and together as the total hedging variable.

The results obtained in this study show that interest rate risk hedging and overall hedging does not significantly impact on the accuracy of the 1-year forecasts. However, we find that forecast error increases with the level of foreign exchange hedging. The above impacts of hedging policies on the accuracy of forecasts were found to be more significant when the forecasts are made further away in time from the announcement date of the actual earnings.

The paper is organized as follows. The second part describes the previous research that was conducted on hedging activities and the accuracy of analysts' forecasts. The third part formulates the hypotheses that are to be tested in this study. The fourth part describes the data used in this study, as well as the process followed in order to obtain the final data set. The fifth part explains the models that are used in order to test the hypotheses developed in the fourth section. The sixth part shows the effect of hedging activities on the accuracy of analysts' forecasts, as well as results for the other hypotheses. Finally, the seventh part gives a conclusion of the paper.

2. Literature Review

The 1990's were ground for a massive globalization of corporations, as well as important developments for the derivative products. The market of derivative products has experienced a drastic expansion in recent years and, more and more companies are aware of and use hedging as part of their corporate policy. Bodnar, Hayt and Marston (1999) show in their study that even though the percentage of firms using derivatives did not change since their 1994 survey, a significant proportion of the survey respondents indicated increased usage of hedging products. This finding implies that the firms that hedge consider that financial derivative products are helpful to the firm.

The hedging activities of the S&P500 firms is an important part of our research and therefore, we will consider quite a bit of the hedging literature. The accuracy of analysts' forecasts is at the heart of this project. Thus, the previous work on the accuracy of the analysts' forecasts will follow our literature review on hedging.

2.1. Empirical Evidence on Hedging

Previous studies show that there are three main incentives for hedging: 1) the reduction of taxes, 2) the reduction of expected transaction costs of financial distress and 3) agency costs reduction. Different studies show that the weight of one or more of these incentives depends on several factors. Moreover, many articles underline the benefits of hedging; companies seem to have recognized these benefits and try to take advantage of them. However, some of the most recent research questions how optimal the hedging positions of certain firms are (Ahn, Boudoukh, Richardson, and Whitelaw (1999), and Graham and Rogers (1999)). This research suggests that some managers have incentives to invest in derivative products in a manner that would compromise the optimal hedging point, and that would represent a disadvantage for the firm.

2.1.1. Hedging incentives

The interest for corporate risk management seems to have emerged in the 1970's. However, it was not until 1985 that Smith and Stulz (1985) publish an article that examined the possible determinants of corporate hedging. Smith and Stulz (1985) develop a theory that suggests that hedging is part of the corporate financing policy of value-maximizing firms. They examine the factors that encourage some firms to hedge and not others. Smith and Stulz (1985) examine theoretically the motives for risk management; they do not provide empirical evidence. They argue that firms hedge for three main reasons: the reduction of taxes (for companies having convex tax functions), the reduction of the expected costs of financial distress, and because of managerial risk aversion.

Many articles in the late 1990's show great interest in the reasons or incentives that explain corporate hedging practice. Graham and Smith (1999) provide new evidence on the tax determinants of hedging. This is consistent with the idea that firms with convex tax functions have an incentive to hedge. Bodnar, Hayt, Marston and Smithson (1994) survey two thousand companies (530 respondents) on their use of hedging instruments. Summary statistics indicate that 67% of the hedging firms in 1994 were using hedging to minimize the cash flow fluctuations. Bodnar, Hayt and Marston (1996, 1998) report similar and improved survey results for 1995 and 1998 in comparison to their 1994 survey. They find that the percentage of respondent firms that were using derivative products in 1997 was not significantly different from that in 1993. However, they report that the significant proportion of hedging firms increased the usage of derivative products. Their results also show that 83% of hedging respondents in 1998 are large firms and that the reduction of cash flows volatility is still the primary concern of the risk managers.

a) Tax incentives

Hedging has been long viewed as a way to reduce corporate taxes. Miller (1986) finds evidence that the regulatory and tax environment are at the centre of the major financial innovations, which are mainly represented by the development of derivative products. Smith and Stulz (1985) show that it is optimal for firms with a convex tax function of earnings to hedge. Also, Nance, Smith and Smithson (1993) show that firms with the more convex tax function hedge more than those with less convex tax functions. Graham and Smith (1999) use simulation methods to examine convexity of tax functions and conclude that firms with convex tax functions, which they find to be approximately 50% out of 80,000 Compustat tracked companies, will reduce the tax payments by using hedging instruments. However, the reductions in taxes are marginal in most cases, implying that the strength of tax incentive to hedge is highly dependent on the cost of hedging, and that more recent tax regulations and market developments have changed some of the characteristics of companies that are hedging, at least for those which hedge to benefit from tax savings. Moreover, Bodnar and Gebhardt (1999) underline the weight of taxation in the decision of derivative products usage by comparing the general usage of derivative products in the US and Germany. They find that German firms consistently make greater use of derivative products[1] than US firms. The authors justify this observation by a "greater importance of the financial accounting statements in Germany[2] (where they also act as the basis for taxation) relative to the US (where they are purely to provide information to investors)" and by "stricter policies of control over derivative activities within the firm" in Germany, as compared to the U.S. (Bodnar and Gebhardt (1999, pg. 25)).

b) Incentives to reduce costs of financial distress

Hedging is also used to reduce the volatility of future cash flows. This should also lower the expected transactional costs of financial distress. Smith and Stulz (1985) argue that financial distress imposes real costs on the shareholders and the bondholders. Miller and Modigliani (1963) and Miller (1977) show that it is optimal for a firm to take on more debt to benefit from additional value from tax savings. Given that hedging is expected to reduce financial distress costs, then hedging firms can have a higher debt-to-

[1] Bodnar and Gebhardt (1998) consider three classes of derivatives hedging for three different types of risk: exchange rate risk, interest rate risk and commodity risk.

equity ratio than comparable non-hedging firms. However, Nance, Smith and Smithson (1993) do not observe the expected significant positive relationship between hedging and leverage; although Berkman and Bradbury (1996) find evidence that New Zealand firms are using hedging instruments in order to lower their expected financial distress costs.

c) Agency cost reduction incentives

The reduction of volatility of cash flows resulting from hedging also contributes in reducing some agency costs in the hedging firms. The underinvestment[3] problem, suggested first by Myers (1977), is the agency cost that hedging seems to have more effect on. Stulz (1990) and Froot, Scharfstein and Stein (1993) also suggest that underinvestment might be higher in non-hedging firms that find it costly or impossible to have access to external financing. They find evidence that firms with closely correlated cash flows with future investment opportunities will hedge less, while firms with closely correlated cash flows and collateral values will hedge more[4]. Nance, Smith and Smithson (1993) find that companies that have more growth options in their investment opportunity set make more extensive use of derivative products than others, confirming the agency cost reduction hypothesis. Géczy, Minton and Schrand (1997, pg. 1323) report a similar

---

[2] Bodnar and Gebhardt (1998) state that the financial accounting statements are the basis for taxation in Germany.

[3] The underinvestment problem is described as the eventuality where the management of a heavily leveraged firm will not undertake a positive Net Present Value investment, knowing that most of the incremental value of the project goes to bondholders.

[4] Closely correlated cash flows with future investment opportunities suggest that necessary financing will be available when investment opportunities will be undertaken, and that low availability of cash flows will correspond to a period where there will be no valuable investment opportunity to take advantage of.

result; they state that 'firms with greater growth opportunities and tighter financial constraints are more likely to use currency derivatives'.

d) Impact of managerial risk aversion

Hedging is viewed as a financial strategy to reduce agency costs of a firm, by increasing its internal financing possibilities and reducing its dependence on external financing. Several studies have shown support for this theory that hedging enhances the value of a company by reducing underinvestment costs: see Stulz (1990), Froot, Scharfstein and Stein (1993), Nance, Smith and Smithson (1993), and Géczy, Minton and Schrand (1997). However, Tufano (1996), in his study of the gold and mining industry, questions whether the value of a company for shareholders is maximized under hedging. He shows no strong support for the reduction of financial distress costs, nor for the reduction of the need for external financing, as consequences of hedging. On the other hand, Tufano (1996) finds evidence showing that hedging is positively affected by the number of shares of stock that managers own, and negatively affected by the amount of options managers hold. Managers who own more options are considered to be less risk averse, while managers holding more stock are considered to tolerate less volatility in their returns, and to be more risk averse. The relationships between hedging and management's stock or option holding, found by Tufano (1996), support the managerial risk aversion theory. Schrand and Unal (1998) support Tufano's (1996) findings by providing evidence on 571 mutual-to-stock conversions. The authors find that the volatility of returns of a stock is negatively related to the number of shares that managers purchase at conversion. Also, Schrand and Unal's (1998) results show that the volatility of returns is significantly higher for stocks that have managers that are granted options at conversion, than for those that do not. Graham and Rogers (1999) also find support for the managerial risk aversion theory, using probit and truncated regressions. However, support for the managerial risk aversion theory is statistically significant only, when studying interest rate hedging. For foreign exchange hedging, there is no statistically significant relationship between the levels of stock, or the number of options owned by managers and the hedging levels.

2.1.2. Determinants of hedging

Although the interest in derivative products dates back to the 1970's, it was not until Nance, Smith and Smithson (1993) that the determinants of hedging policies were analysed from an empirical point of view, where the actual use of derivative products was included in an empirically testable model. Nance, Smith and Smithson (1993) use survey data on the use of hedging instruments and a logistic model to determine the reasons behind hedging. They find that firms with 1) convex tax functions, 2) large firms, 3) firms with high research and development expenditures, 4) and firms with higher growth opportunities hedge more than others. However, Nance, Smith and Smithson (1993) do not find that highly levered companies are more likely to be engaged in hedging. This finding does not support their hypothesis. They also find that hedging could be substituted by other financial policies; lower levels of liquidity and higher dividends characterize companies using derivative instruments.

Mian (1996) provides new evidence on the determinants of hedging using data from the annual reports of companies as compared to survey data. Using univariate tests, the author finds that hedging firms are larger in size than non-hedging firms. However, there is no evidence that hedgers have a higher market-to-book ratio than non-hedgers. Using multivariate logistics regressions, Mian (1996) confirms his previous result of a positive relationship between the size of a company and its derivative use. But, surprisingly, a statistically significant negative relationship between market-to-book ratio and hedging is also evident. This does not support the hypothesis that the possibility to reduce transaction costs and agency costs is an incentive for hedging. The author explains this result as a possible inhibition of companies 'from cost effectively hedging their growth option-related exposures', due to 'costs associated with financial reporting requirements' (Mian (1996, pg. 433)). Also, through a correlation table Mian (1996) reports no correlation between hedging and leverage, while dividend yield and dividend payout are positively correlated to hedging, and liquidity is negatively correlated with hedging.

Samant (1996), in his study of interest rate swap usage, reports that fixed-rate payers that hedge exhibit higher levels of leverage, profitability and growth options, as well as greater inaccuracy in earnings forecasts, than those that do not hedge. However, results are inconclusive for the floating-rate payers. No significant difference is reported between the characteristics of hedgers and non-hedgers for the floating-rate payers. These results are obtained using both binary and continuous variables for hedging.

When studying the characteristics of hedging firms, only one of these characteristics seems to bring all authors to a consensus. All recent studies find evidence that firms using derivatives instruments for hedging are consistently larger in size than firms that do not use derivatives. Géczy, Minton, and Schrand (1997) support the above statements in their study where they assume that the size is a proxy for economies of scale. They explain this positive relationship between size and hedging by "the presence of cost-driven motives for hedging" (Géczy, Minton, and Schrand (1997, pg. 1340)). Haushalter (2000) also supports the hypothesis of economies of scale being the reason for hedging. He reported that "larger companies and companies whose production is located primarily in regions where prices have a high correlation with the prices on which exchange-traded derivatives are based are more likely to manage risks". Along the same line of research Goldberg, Godwin, Kim and Tritschler (1998) find evidence, that both interest-rate risk and foreign-exchange risk hedging are positively related to the size of the U.S. non-financial firms. Similar results are reported by Fehle (1999), who finds that there is a highly significant positive relationship between size and hedging.

Growth opportunities of a firm is another firm characteristic that is of interest to researchers. This is due to its impact in reducing the underinvestment incentives. Most studies find evidence that greater growth opportunities increase the likelihood of hedging. Géczy, Minton and Schrand (1997, pg. 1323) report that "firms with greater growth opportunities and tighter financial constraints are more likely to use currency derivatives". Howton and Perfect (1998) who study 451 Fortune 500/ S&P500 firms and

461 randomly selected firms, also find support for the agency cost hypothesis, reporting a significant relationship between the level of hedging and the growth opportunities (proxied by the ratio of research and development expenses to sales). However, Howton and Perfect (1998) do not find a statistically significant relationship between hedging and growth opportunities for the random sample; although the coefficient was positive. Supporting evidence for the agency cost model is also provided by Goldberg, Godwin, Kim and Tritschler (1998) who find a positive relationship between the level of hedging and the growth opportunities of a firm (proxied by the research and development expenses). However, Fehle (1999) find some mixed evidence for the hypothesis that hedging companies are more growth oriented companies. Using univariate tests, Fehle (1999) reports that derivative users are less value and more growth oriented companies than non-users. However, when using a probit model, Fehle (1999) finds that the book-to-market ratio has a statistically significant positive relationship with hedging. This result implies that more value oriented firms are more likely to hedge, which does not support the agency cost hypothesis.

Leverage of a company affects its ability to raise external financing. Thus, a positive relationship between the levels of leverage and hedging is expected, in order to support the agency cost model. Most recent studies tend to agree on this relationship of leverage levels with hedging levels. Howton and Perfect (1998) find support for a positive association of hedging and leverage for both Fortune 500 / S&P500 and random samples for the total hedging and for interest rate hedging. However, when studying currency hedging, Howton and Perfect (1998) report a negative coefficient estimate for the relationship between leverage and currency hedging. This coefficient estimate is not statistically significant for both samples. Haushalter (2000) also finds evidence that greater levels of leverage are associated with greater hedging activities (in order to manage price risk) for a sample of oil and gas producers between 1992 and 1994. Goldberg, Godwin, Kim and Tritschler (1998) report results supporting the Howton and Perfect (1998) findings. Their results show that interest rate hedging is significantly positively affected by the levels of leverage, while foreign-exchange hedging exhibit a negative but not significant relationship with leverage. Fehle (1999) also finds supporting evidence of a positive relationship between the levels of leverage and the levels of hedging, when using a probit model. Also, when using univariate tests, Fehle (1999) finds that firms that use derivatives have significantly higher debt-to-equity ratio than those that do not.

Liquidity levels is another firm characteristic that is likely to influence its hedging activities. Consistent with the need for external financing, it is expected that higher levels of liquidity will result in lower levels of hedging, given that higher liquidity implies a lesser need for external financing. Goldberg, Godwin, Kim and Tritschler (1998) find support for this statement in their study, where the liquidity levels are negatively related to the levels of hedging for all three measures of hedging: foreign-exchange hedging, interest rate hedging and total hedging. Similar results are reported by Howton and Perfect (1998), who confirm a negative relationship between liquidity levels and all three measures of hedging, for the Fortune 500 / S&P500 sample. However, Howton and Perfect (1998) do not find a statistically significant relationship between liquidity and currency hedging, for the random sample; although interest rate hedging and total hedging exhibit a statistically significant negative relationship with the level of liquidity, for the same sample. Fehle (1999) reports, using univariate tests, that users of derivative products are significantly less liquid than non-users. Also, Fehle's (1999) multivariate probit estimation results confirm the negative relationship between the levels of liquidity and the levels of hedging.

The evidence on the characteristics of firms that use derivative products for the purpose of hedging, described above, comes from studies on U.S. companies. However, there is international support for these findings. Jalilvand (1999) shows in his results that users of derivative products are larger in size and have higher levels of leverage than the non-users for Canadian firms. Berkman and Bradbury (1996), in their study of New-Zealand firms, find in their univariate tests that firms using derivative products are significantly larger in size, more levered, less liquid and pay more dividends than non-users. Their univariate results are supported by their multivariate Tobit regression results, where size, leverage, and dividend payout are positively related to hedging, and liquidity is negatively related to hedging. He and Ng (1998), who study foreign exchange hedging in Japan, support previous findings suggesting that hedgers are larger in size than non-hedgers. Also, still using firm-characteristics as proxies for hedging policies, the authors report that low levels of liquidity and higher levels of leverage are characteristics of hedging firms. Bodnar and Gebhardt (1999) find, in their study of German firms, that hedgers are larger in size than non-hedgers.

2.2. Empirical Evidence on Accuracy of Analysts' Forecasts

The research interest in the accuracy of the analysts' forecasts and the factors that might influence them, seems to have started in the 1970's and has continued with an increasing research output until today. Analysts' forecasts play an important role in the capital markets, given that they have proven to influence stock prices, (Brown, Foster and Noreen (1985), Stickel (1992), and Lim (2001)). Due to this importance of forecasts, many studies attempt to find evidence on the factors that affect their accuracy. Although, many firm characteristics are found to affect the accuracy of analysts' forecast, analyst bias is reported to affect accuracy.

2.2.1. Importance of Analysts' Forecast

DeBont and Thaler (1990) find evidence that the majority of investors do not produce their own forecasts in taking their investment decision, but rely on those of analysts. Thus, it is only expected that these forecasts influence stock prices through the actions of investors. The influence of analysts' forecasts is documented by several studies. Stickel (1992), in his comparison of All-American and Non All-American analysts finds that All-American analysts provide more accurate forecasts. Also, Stickel (1992, pg. 1811) reports that "stocks return immediately following large upward forecast revisions suggest that All-Americans impact price more than other analysts". Lim (2001, pg. 370) also shows the importance of analysts' forecasts, and justifies analysts' positive bias by the firm managers' preference for favourable forecasts. Lim (2001) states that this managerial preference is due to more favourable forecasts supporting "higher capital market valuations". Finally, analysts' forecasts are important to investors given that they might provide the most accurate appraisal of expectations of market earnings. Several studies provide evidence that analysts' forecasts are more accurate than the forecasts obtained with time-series model (Fried and Givoly (1982), Conroy and Harris (1987), and Brown and Kim (1991)). Wiedman (1996) also supports this statement, by finding a stronger relationship between expectations of market earnings with variables associated with analysts' forecasts accuracy, than that of expectations of market earnings with variables associated with the time-series model forecasts.

2.2.2. Determinants of Analysts' Forecasts Accuracy

Being aware of the importance of analysts' forecasts, academics have extensively studied for the past decades, the different factors that could affect the accuracy of these forecasts. A very wide range is represented by these factors; from firm characteristics to human factors affecting the analysts, by the environment the company finds itself in at the proximity of the forecast date, and the tools that analysts use to collect the data necessary to make an informed forecast.

a) Disclosures by the Company

The disclosure level of a company seems to be a natural factor in the accuracy of analysts' forecasts. Lys and Sohn (1990), and Lang and Lundholm (1996) find results that show that the disclosure of information positively contributes to the accuracy of forecasts. The hypothesis that larger levels of disclosure increase the accuracy of analysts' forecasts is also supported by Higgins (1998) in his international study. Studying firms in France, Germany, Japan, the Netherlands, Switzerland, the United Kingdom and the United States, Higgins (1998) reports evidence that the accuracy of analysts' forecasts was significantly higher and the optimistic bias significantly lower for firms in countries that mandate high levels of disclosure compared to those in countries that impose lower disclosure levels. Moreover, other empirical evidence shows that the degree of disclosure increases with the size of a company (Ho and Michaely (1998)) and with the number of analysts following the company (Lim (2001)). Lim (2001), also, states that the FASB's and SEC's disclosure requirements seem to support the hypothesis of decreasing disclosure costs with an increase in the size of the company. Thus, due to this relationship between size and disclosure of a company, Lim (2001) test the association between size and analysts' forecast accuracy. Lim (2001) reports a statistically significant positive relationship between the size of the company and the level of accuracy of analysts' forecasts, for the entire sample, as well as for different sub-periods and size-based sub-samples. Lim (2001) also reports a similar type of relationship for the level of analysts coverage (as given by the number of analysts providing forecasts) with the level of accuracy of analysts' forecasts (Lim (2001)).

b) Human Factors Affecting Analysts' Forecasts

It seems intuitive that the greater the experience of an analyst in making earnings forecasts the more accurate his/her forecasts should be. Several studies have documented the effect of the experience of the analysts on the forecasts (Mikhail, Walther and Willis (1997), Clement (1997), and Bailey and Gupta (1999)). However, this relation between experience and forecast accuracy seems also to be dependent on the way that experience is considered. When studying the forecast accuracy among industries, O'Brien (1990) does not find any significant difference in the accuracy of forecasts between the analysts' earnings forecasts for different industries. Mikhail, Walther and Willis (1997) also find no evidence that accuracy of the forecasts is affected by the degree of involvement of an analyst in a specific industry. On the other hand, Mikhail, Walther and Willis (1997), in their study of 990 analyst-firm combinations, find evidence for a positive relationship between analysts' forecast accuracy and their firm-specific experience, measured as the number of prior quarters for which the analysts has issued an earnings forecast for the firm. This relationship between forecasts and the degree of experience has been documented both in the finance and statistics literature. Bailey and Gupta (1999) find support for this relationship and its human component, in a laboratory environment. They report that human performance was statistically superior to the [statistical] model when few data points were available and when forecasting further into the future.

e) Accounting Information

Several studies that focus on analysts' forecasts have documented the importance of the use of accounting information by the analysts in order to reach a best possible forecast (Anderson (1988), and Hunton and McEwen (1997, 1999)). Hunton and McEwen (1999) find evidence for a relationship between the accuracy of analysts' forecasts and the accounting information used to reach these forecasts. They report that analysts that focus on Balance Sheet items in the Annual Report and footnotes provide less accurate forecasts than analysts that base their forecasts on company information, such as the Key ratios and the five-year earnings summary.

2.2.3. Analysts' Forecast Bias

The important effect that earnings forecasts have on the capital markets and the increasing interest in studying the accuracy of these forecasts has resulted in several studies reporting that analysts tend to give overly optimistic earnings estimates (Butler and Lang (1991), Francis and Philbrick (1993), Dreman and Berry (1995), Olsen (1996), Chopra (1998), Hayes (1998), and Lim (2001)). Chopra (1998), in his study of the earnings forecasts of the S&P500 companies, reports that forecasted earnings are on average 11.2 percent greater than actual earnings at the beginning of the year, although, this gap decreases over the year. The author also finds that the growth rate of earnings forecasts is, on average, double of the growth rate of actual earnings for the past 13 years. These results confirm the findings of Butler and Lang (1991, pg. 155), who conclude that analysts "persist over time in their optimism or pessimism relative to consensus earnings forecasts, for firms of both high and low earnings predictability". Although, Butler and Lang (1991) suggest that pessimistic bias is also present in analysts' forecasts, most studies consistently support only the optimistic bias. The greater support for the optimistic bias could be justified by the underreaction of analysts to negative earnings news and their overreaction to positive earnings news (Easterwood and Nutt (1999)). Hayes (1998) studies one possible incentive for the optimistic bias in analysts: the trading commission. The author models the interaction between an analyst and an investor, and finds that analysts have greater incentives to gather information for stock they expect will perform well than for stocks expected to have a poor performance. Thus, stocks that perform well should exhibit more accurate forecasts and less bias than those that perform poorly. Moreover, Hayes (1998, pg. 313) states that the holding of a stock is also related to the accuracy of the forecasts: "if a stock is not widely held, an analyst will initiate coverage only if the stock's performance is expected to be good; this would imply that earnings forecasts for such stocks should be especially precise". These results show support for previous findings, demonstrating that analysts are more optimistic in their forecasts for sell stock than for buy stock (Francis and Philbrick (1993)). Also, studying incentives for optimistic bias on earnings forecasts, Lin and McNichols (1997) find evidence that analysts would provide more optimistic forecasts for companies that have an investment banking relationship with their employer. Lim (2001, pg. 369), agrees with the persistent optimistic bias of analysts. However, the author using a quadratic-loss utility function, finds results implying that 'positive and predictable bias may be a fundamental property of statistically optimal earnings forecasts'.

3. Development of Hypotheses

The accuracy of analysts' forecasts has been studied and analysed from many points of view; however, there is no study that we know of, that has used the hedging activity of a company as an explanatory variable. A company is believed to engage in hedging activities when it faces some sort of market risk. In the 1990s, due to the increasing globalization, most companies are expected to face increased market risk. The companies that use derivative securities for hedging purposes should have less volatile cash flows than companies that do not get involved in hedging activities, given that derivative products are traded for this main reason.

The first hypothesis takes its essence from the above mentioned reason for hedging. It is expected that in the event the volatility of cash flows of a company is reduced, the volatility of earnings per share will be reduced as well. Also, it is expected that when analysts deal with less volatile earnings, they will be able to give more accurate forecasts for these figures. Therefore, the first hypothesis is as follows:

Hypothesis 1a: Analysts' forecasts for earnings are expected to be more accurate for companies that hedge in comparison to those that do not hedge.

Hypothesis 1b: The accuracy of analysts' forecasts are expected to increase with higher levels of involvement in hedging activities, assuming that higher levels of hedging are closer to the optimal levels of hedging.

The next hypothesis explores the effect of time and hedging over the analysts' forecast accuracy. We conjecture that there is an inverse relationship between forecast horizon and accuracy. This implies that when the forecast is made on a date far from the actual earnings announcement date, the uncertainty due to the possible unexpected events is higher. So, the effect of hedging will be more evident. Or, alternatively, when the forecast is made on a date not far from the announcement date for the actual earnings, the uncertainty will be less and therefore, the effect of hedging will be less evident. When a forecast is made well in advance of the earnings announcement date, the forecast accuracy for the companies that are involved in hedging activities is likely to be better than that for companies that are not involved in hedging activities. All the above arguments are also applicable when the levels of hedging are taken into consideration.

Hypothesis 2: The longer the forecast horizons are, the more significant the impact of hedging activities would be on the forecast accuracy.

Standard deviation of earnings forecasts is also analysed in this study as a proxy for forecast accuracy. The hedging activity of a company is also expected to affect the standard deviation of earnings forecasts of a company. As companies are more involved in hedging activities, the number of analysts following these companies is expected to be higher. One could think that the higher the number of analysts issuing a forecast, the higher the standard deviation of forecasts among analysts will be. However, we expect the effect of the higher number of forecasts to be offset by the expected advantages of hedging. Also, analysts should exhibit a better consensus when a company is hedging their market risks.

Hypothesis 3: The higher the involvement of the company in hedging activities, the lower the standard deviation of forecasts among analysts.

The number of revisions over the forecast period of interest is also used as a proxy for forecast accuracy in this study. As mentioned before, companies with higher levels of hedging are expected to be followed by a larger number of analysts. A larger number of analysts following a company could lead one to believe that the number of revisions would be higher. However, the hedging activities of a company are expected to reduce the volatility of that firm's cash flows and improve the accuracy of analysts' forecasts. Therefore, in order to be consistent with the above expectations, the number of revisions should be lower for companies that are involved in hedging activities than for those that are not. Also, in order to ensure that the number of revisions is not directly affected by the number of estimates, and that the latter effect would not drive the results, the total revisions are expressed as a percentage of total estimates[5] when running the models. The same logic is applied for the up and down revisions. The percentage of up revisions is likely to be higher than that of down revisions for the companies that use derivative products. The above statements are expected to also hold when the level of hedging is taken into account.

[5] The number of up and down revisions are also expressed as a percentage of total estimates.

Hypothesis 4a: There will be fewer revisions for firms with higher levels of hedging than for those with lower levels or for those that do not hedge.

Hypothesis 4b: The companies with higher levels of hedging, are expected to have less up revisions than the ones with lower levels or those that do not participate in hedging activities.

Hypothesis 4c: The higher the level of hedging, the lower the number of down revisions will be.

The last hypothesis explores the effect of fiscal year end of the company. In our sample the majority of companies have a fiscal year end of December, while some have fiscal years ending in one of the other months. It is widely believed that for most companies that have a fiscal year ending in December, greater amounts of information will be available for companies with a fiscal year ending in December than for the others. Thus, more analysts are expected to issue estimations of future earnings for December fiscal year end companies, and these estimations are expected to be affected to a higher extent by the usage or not of derivatives, as well as the level of usage of derivatives by these companies.

Hypothesis 5: Companies with a fiscal year ending in December will have a higher improvement in the forecast accuracy for hedging companies than companies with fiscal year ending in any other month.

4. DATA

4.1. Sample construction

In order to analyse the accuracy of earnings forecasts in relation to the hedging policy of companies, we construct our sample based on the 500 companies listed on the S&P500 index as of January 1995. The 500 companies are kept constant throughout the data collection process and over the entire time period of 1994 - 1997. The decision to keep the same companies for the four-year period, instead of collecting data for the S&P500 companies as of each of the four years, is due to the fact that several companies are deleted from and added to the index over time. Keeping the companies constant for the entire time period is important for the consistency of the sample and allows us to study the evolution of the hedging activities over time of the same companies. The time frame of 1994-1997 is chosen in order to ensure robustness of the results over time, and to avoid the possibility that a unique event specific to one year may considerably affect the results in a specific manner. Also, one has to consider that it is likely that fewer number of companies were involved in hedging activities in 1994 than in 1997.

4.2. Hedging data

The overall data used in the statistical analyses come from three major data sources. The first source consists of the hedging data for the chosen companies; the second one deals with the data that gives an overall description of the companies; and the third one consists of the analysts' earnings forecasts. A company is considered as being involved in hedging activities only if it was hedging its exposure to the interest rate and the currency risks[6]. Therefore, there are three measures of hedging used in this study: interest rate hedging, currency hedging, and total hedging. The notional amounts of these hedging activities are collected from the 10-K reports from the EDGAR database. EDGAR is part of SEC (Securities and Exchange Commission) and can be found on the web at the following address: http://www.sec.gov./edgar.shtml. The SEC requires all public companies (except foreign companies and companies with less than $10 million in assets and 500 shareholders) to file registration statements, periodic reports, and other forms electronically through EDGAR. We searched the database through the quick form lookup, using the company name. The quick form lookup contains the most recent data. Data that was filed in 1994 or earlier, for periods preceding 1993, are reported in the EDGAR Archives. The notional amounts given in the annual reports are aggregated amounts that do not take into account a positive or negative sign that would be assigned by the type of transaction (payable and receivable amounts are added), but rather gives an account of the overall involvement of each company in the hedging activities. For each company the 10-K reports were opened for each year from 1995 to 1999. These reports provide the data for the fiscal year ends for the 1994 - 1997 time period. The 10-K reports are the annual report that most companies file with the Commission. The information that is related to the hedging policies of the sample firm is found through a find-path that consists of key words or expressions. The most commonly used find-paths are 'financial instruments' and 'market risk'. For most companies, these two find-paths reveal the

[6] Some companies were using commodity hedging as well. However, our study is limited to the most widely used types of hedging, being interest rate and currency hedging, given that commodity hedging is specific to only one industry type.

hedging policies of the sample firms in relation to the interest rate risk and the currency risk. However, in the event where these two find-paths do not provide any results, the key words 'derivative', 'hedging', 'swap' and 'forward' are used. In the instance where any of these key expressions or words do not provide any information on the hedging activities of the firms, a more through study of the document is performed. Then, if any of these research efforts do not result in any hedging information, the firm is labelled as being a non-hedging firm for that particular year[7].

Table 1 shows the number of firms that participated in hedging activities in each year for the 1994 - 1997 time frame. Given that our sample is composed of the S&P500 companies, our sample mainly consists of large companies from a variety of industries. Panel (a) reports currency hedging results for our sample. The number of currency hedgers per year varies between 216 and 231 companies[8], while the number of companies that are not involved in currency hedging varies between 181 and 220 companies for the 1994 - 1997 period. Panel (b) provides the hedging information for the interest rate risk. The number of hedgers in this case varies from 204 to 237, while the number of non-hedgers varies between 201 and 216. Finally, Panel (c) shows how many firms were involved in either currency or interest rate hedging during the same period.

---

[7] This rigorous screening is performed, even though most of the companies identified as non-hedgers through our process, were clearly stating in their annual statements that they were not using any derivative products for risk management purposes, given that they were considering their market risk to have no significant effect on their revenues.

[8] The number of currency hedgers appears to be lower at the fiscal year end 1997 than that at fiscal year end 1994. However, the lower number of currency hedgers is not due to a lower number of companies interested in hedging their currency risks, but to an increasing number of companies with missing data. The greater

4.3. Control Variables

The control variables are collected for the same 500 companies (for the 1995 - 1999 time period). The data for the control variables are collected from the Research Insight (Compustat) and I/B/E/S databases. Table 2 provides the descriptive statistics for the control variables. These variables are included in the regressions in order to control for as many factors, other than hedging, as possible. Following the relevant literature, we conjecture that these variables have an effect on the analysts' forecasts and their accuracy.

One of the control variable that was previously shown in the literature to have an effect on the accuracy of the analysts' forecasts is the size of the company for which the forecast is made. In this study, the company size is measured by the natural logarithm of the net sales of the company[9]. Logic dictates that larger companies will be followed by more analysts, given that larger companies are usually better known by the public and have a stronger presence. Supporting the previous statement, the study of O'Brien and Bhushan (1990) has shown that the larger the company, the higher the number of analysts following it, and the higher the number of forecasts given. The fact that larger companies are followed by more analysts could be justified by lower costs of disclosure for the larger companies (Ho and Michaely (1988)). Also, given that larger companies are of higher public interest and that the media is following them more closely, analysts are expected to have a better sense of the future performance of the company.

---

missing data are due to missing 10-K reports for some companies for specific years. This might be explained by mergers, bankruptcies, or name changes for these companies.

Tangibility ratio is another factor that can affect the accuracy of the analysts' forecasts. Tangibility ratio is measured as the ratio of tangible assets over total assets[10]. The lower the tangibility ratio of a company implies a greater amount of current assets, and thus a lower need for external financing and a lower probability of financial distress for the firm. Therefore, a company with a low tangibility ratio has a lower probability to experience negative financial surprises, and by consequent is considered to be a more stable company. Thus, companies with low tangibility ratios are expected to have more accurate analyst's forecasts. However, high tangibility ratio means more availability of collateral in obtaining external financing, when the need for additional financing appears unexpectedly, either due to potential investment opportunities or debt payments. Therefore, the evidence on the effect of tangibility ratio on the accuracy of analysts forecasts' is expected to be mixed.

The leverage ratio is a measure that is related to the under-investment problem and the growth opportunities of a company. In this study, we measure leverage as the ratio of total debt[11] to total assets[12]. A company with a relatively high leverage ratio is generally believed to have taken on more debt in order to invest in new opportunities that are expected to allow the company to grow. In this case, analysts will believe that the

---

[9] Total assets are also used as an alternative measure for the company's size; however, results are not reported in this paper.
[10] In this paper, tangible assets are calculated as follows:
Tangible Assets = Total Assets - Current Assets - Intangible Assets
[11] Total debt is the sum of long-tern and short-term debt.
[12] In order to insure the robustness of our results, Debt-to-Equity ratio is used as an alternative in the tests. However, the results with the Debt-to-Equity ratio are not included in this paper. These results can be obtained from the author upon request.

company will experience some positive outcomes in the future. Also, companies with higher levels of debt are more closely monitored by the creditors. Thus, holding all else constant, their future earnings are expected to be predicted more accurately. However, from another point of view, companies with higher levels of debt generally are proven to have more volatile earnings, increasing the likelihood that analysts' forecasts will be less accurate. Which tendency will be dominant is an empirical question.

The growth opportunity of a company can also affect the way an analyst is making a forecast. In this study, we use the price-to-book ratio as a proxy for a firm's growth opportunities[13]. A firm with high growth opportunities is expected to have higher positive earnings in the future than a value firm. However, value firms have less volatile earnings than growth firms do. Thus, one would expect a less accurate forecast for the firms with a higher price to book ratio.

The profitability of a company is another factor that may affect the accuracy of the analysts' forecasts. The ratio of operation income before depreciation-to-total assets is the measure of profitability used in this paper. A company with a high profitability ratio tends to drive analysts towards being positively biased, in the event where this is not the regular pattern for this company. Thus, one could believe that forecast accuracy will be lower for companies with higher profitability ratios. However, companies with high profitability ratios are companies that are more likely to be followed closely by analysts and,

[13] The ratio of research and development expenditures-to-total assets is an other proxy used for growth opportunities. However, the results are not reported in this paper. The results obtained with this proxy are

consequently these companies would have a more accurate forecast than the ones with low profitability ratios. Also, companies with a high profitability ratio are more likely to be able to meet their expenses and take advantage of future investment opportunities, without being caught in a position of financial distress or facing any big surprises. Therefore, we expect that firms with higher profitability ratios will tend to have more accurate analysts' forecasts.

In order to ensure the robustness of our results, we incorporate in our model a proxy for the stability of earnings. This proxy is represented by the standard deviation of quarterly earnings over a period of five years[14]. The standard deviation of quarterly earnings is calculated after actual quarterly earnings are deflated by the actual price at the end of the fiscal year for the company. The actual quarterly earnings and the fiscal year end closing price are collected from the I/B/E/S database[15]. The more stable the historical earnings of a company are, the more accurate the analysts' forecasts are expected to be.

The "number of estimates" is included in the model as another variable that will affect the accuracy of analysts' forecasts. The number of analysts following a firm is provided in the I/B/E/S database, and is taken at the time when the forecast that is of

---

not as strong, due to a considerable reduction in the number of observations, caused by missing data on this variable.

[14] Another proxy used to measure the stability of earnings is the standard deviation of operating income over 5 years, with the exception of the measure for the fiscal year end of 1994, where only 16 quarter of data are available. This is due to the fact that we have access to quarterly data only as far back as the quarters of fiscal year 1990, on the Compustat database. The standard deviation of operating income is calculated after quarterly earnings are deflated by total assets of the company at the end of the fiscal year end.

[15] I/B/E/S provides far more complete and consistent price and quarterly earnings data than Compustat does.

interest to us was issued. It seems that the larger the number of analysts for a company, the more information is available for that company. Also, it is possible that a greater number of analysts providing an estimate for a company, will result in a higher variance of the forecasts. However, the effect of the greater availability of information is expected to dominate. Therefore, we expect that a large number of analysts following a company will result in more accurate earnings' forecasts.

Preferred equity and convertible debt are considered in some papers to be substitutes for hedging (Nance, Smith, and Smithson 1993)[16]. Preferred equity could be considered as a substitute to hedging, given that the issue of preferred equity is expected to confer similar advantages as hedging. Some of the recognized benefits of preferred equity issues are the possible reduction of under-investment costs and financial distress costs, by raising funds without increasing the debt level. Similar attributes can be recognized for convertible debt. Thus, the expectations that apply to hedging, also extend to preferred equity and convertible debt. Companies with higher levels of preferred equity (or convertible debt) should have lower likelihood of financial distress, and more stable earnings. Therefore, companies with higher levels of preferred equity (or convertible debt) should result in analysts providing more accurate forecasts.

We also include dummy variables for the industry, after dividing the companies into four major industry groups: financial, utilities, manufacturing, and services. All companies belonging to the financial industry are excluded from this study since these firms have an important role as dealers and intermediaries in the derivative markets. These dummy variables are included, given that companies in different industries have different needs for hedging. The different types of operations from one industry to another expose the firms to different types of risk. For example, the manufacturing industry seems to be exposed to currency risk to a greater extent than the services industry. On the other hand, services industries seems to be exposed to interest rate risk, to a greater extent than the manufacturing industry. Thus, it would seem that hedging of currency risk would have a greater impact on the forecast accuracy of the manufacturing industry, while the hedging of interest rate risk would have a greater impact on the forecast accuracy of the services industry.

Dummy variables for each year are included as well, in order to take into account any specific events that might have happened in a given year. The economic outlook for a specific year could have an impact on forecast accuracy. For example, in a year when the U.S. experiences an unexpected recession, the forecasts will be much greater than the actual earnings.

[16] Only preferred equity will be used as a proxy for hedging substitute. Results with convertible debt can be

4.4. Dependent Variables

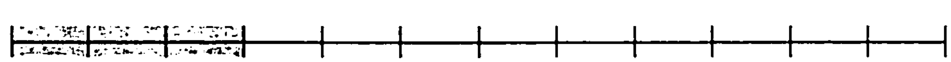
4.4.1. Dependent variables for forecast accuracy

In this study we analyse the effects of hedging on the a) 1-year earnings' forecasts, b) the 2-year earnings' forecasts, and c) the 1-month earnings' forecast prior to fiscal year end. The forecasts measures given in I/B/E/S are the means of forecast estimates among analysts given in a month. For the 1-year forecasts, the first forecasts for each sample firm in the fiscal years 1995 through 1998 are included and are related to actual earnings at the end of the same fiscal year. For the 2-year forecasts, the first forecasts available are collected as they are issued in fiscal years 1995 to 1998. These 2-year forecasts are related to actual earnings as of fiscal year ends 1996, 1997, 1998, and 1999. The 1-month forecasts are collected as the last forecasted earnings for the last fiscal years 1995 to 1998.

The relationship between forecast horizons and actual earnings is depicted below in figures 1,2, and 3.

Figure 1: Collection of 1-year Forecasts

The grey area is the period of the year when first forecasts are collected. For the 1-year forecasts, only the first forecasts made in the 3 months at the beginning of the fiscal year are considered in the study (represented by the grey area in the figure).



Month of the fiscal year   1   2   3   4   5   6   7   8   9   10   11   12

<u>1-year Forecasts</u>	<u>Actual Earnings</u>
<u>Fiscal years end</u>	<u>Fiscal year end</u>
1995	1995
1996	1996
1997	1997
1998	1998

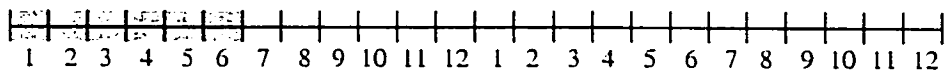
---

obtained from author upon request.

Figure 2: Collection of 2-year Forecasts

The grey area is the period of the year when first forecasts are collected. For the 2-year forecast period, only the first forecasts made in the 6 months at the beginning of the first fiscal year are considered in the study (represented by the grey area in the figure).

Month of
the fiscal year

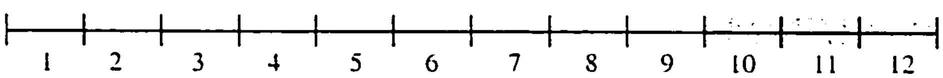


2-year Forecasts Fiscal years end	End of First Fiscal Year	Actual Earnings Fiscal year end
1995	1995	1996
1996	1996	1997
1997	1997	1998
1998	1998	1999

Figure 1: Collection of 1-month Forecasts

The grey area is the period of the year when last forecasts are collected. For the 1-month forecast period, only the last forecast made in the last 3 months of the fiscal year are considered in the study (represented by the grey area in the figure).

Month of
the fiscal year



1-year Forecasts Fiscal years end	Actual Earnings Fiscal year end
1995	1995
1996	1996
1997	1997
1998	1998

For the 1-year forecast, the first available forecast earnings for the respective fiscal year, is made at least nine months away from the fiscal year end (Figure 1). In most cases, the first available 1-year forecast is given 10 months before the fiscal year end. All 2-year forecasts are included in the study for as long as the forecast is made at least 18 months before the fiscal year end, at which time the actual earnings are announced (Figure 2). The 1-month forecasts figures are collected as the last forecasts available before the fiscal year end; only values that are forecasted up to 3 months in advance of the fiscal year end are included (Figure 3).

The forecasts and actual earnings are collected from Institutional Brokers Estimate System (I/B/E/S) for fiscal years from 1995 to 1998. However, when collecting the actual annual earnings and the fiscal year closing prices for the fiscal year 1998, the data are collected from the Compustat database, given that the I/B/E/S database available to us has no complete data for the whole year further than the fiscal year 1997. There are six dependent variables for forecast accuracy that are used in this study. As indicated, these variables are collected from the I/B/E/S database, and to our knowledge, they have not been used in the risk management literature yet.

The first measure of forecast accuracy is given by the following ratio:

$$\textbf{Faccu1}_i = |\textbf{Forecast earnings}_i - \textbf{Actual earnings}_i| \,/\, \textbf{Fiscal Year End Closing Price}_i \quad \textbf{(1)}$$

where i indicates sample firm i.

The absolute value of the forecast error is used in order to capture only its magnitude, and exclude the effect of an optimistic or pessimistic bias. The absolute value of the forecast error is deflated by the closing stock price at the fiscal year end to bring the observed values to a common basis across all firms.

The second measure of forecast accuracy is given as a percentage of actual annual earnings:

$$\textbf{Faccu2}_i = |\textbf{Forecast earnings}_i - \textbf{Actual earnings}_i| \,/\, \textbf{Actual earnings}_i \qquad (2)$$

where i indicates sample firm i.

In both equations, the mean of forecast earnings among analysts is used. We construct equations (1) and (2) for the 1-year, 2-year and 1-month forecasts.

4.4.2. Other dependent variables

The standard deviation of forecasts is also used as a proxy of forecast accuracy. This figure is given in the I/B/E/S database. We collect the value of the standard deviation only on the date on which the forecasts for a sample firm are made by the analysts. These forecasts must also be used in equations (1) or (2). The value of the standard deviation for a sample firm is given as the standard deviation of forecasts among analysts at the time the forecasts are made.

Also, analysts' revisions as a percentage of total estimates are used as a different proxy for analysts' forecasts accuracy. The "up" revisions, "down" revisions and "total" revisions are analysed separately in order to determine the effects of hedging on each type of forecast revision. The up revisions are calculated as follows:

$uprevi_i$ = (sum of number of upward revisions over the time frame of the $forecast_i$) / the total number of estimates over the time frame of the $forecast_i$ (3)

where *i* indicates sample firm *i*.

The number of up revisions is added over the 10 months that forecasts are made for the 1-year forecasts. For the 2-year forecasts the number of up revisions is added over the 23-or-22 month period[17], over which the 2-year forecasts are made. The sum of the total number of estimates over the forecast period is computed in the same manner as the sum of up revisions.

The down revisions are also calculated as a percentage of the total forecast over the forecast period, as follows:

$dwnrevi_i$ = (sum of number of down revisions over the time frame of the $forecast_i$) / the total number of estimates over the time frame of the $forecast_i$ (4)

where *i* indicates sample firm *i*.

The number of down revisions is obtained in the same way the number of up revisions is obtained.

[17] The number of months over which the up revisions are added depends on when the first forecast is made for the forecast period.

The percentage total revisions over total forecasts, over the forecast period, is calculated using the following equations:

allrevi$_i$ = (sum of number of total revisions over the time frame of the forecast$_i$) / the total number of estimates over the time frame of the forecast$_i$[18] **(5)**

4.5. Final Data Sample

The three data sources discussed above are merged in order to obtain a final data set on which different statistical models are run. Several SAS programs are run in order to obtain this final data set. Table 3 describes the process followed to obtain it. We start by reading the forecast data from the I/B/E/S tapes, for the forecasts made between 1992 and 1998 for the fiscal years ending in 1993 through 1998. The 18,788 observations read by this first program include the initial and all of the revised 1-year, and the 2-year forecasts, I/B/E/S has data for 482 out of the 500 sample companies we are interested in. In the second program, the difference between the time the forecast is made at and the fiscal year end is calculated, in order to find the exact time frame of the forecast. Only the first forecasts for each sample firm is kept; for the 1-year and 2-year time periods. For the 1-month forecasts, only the forecast that is closest to the fiscal year end is considered. This results in a reduction of the number of observations to 1,843 for the 1-year forecasts, to 1849 for the 2-year forecasts, and to 1820 for the 1-month forecasts. Since we have a sample of 500 companies a total of 2000 observations for the 1-year forecasts, the 2-year

[18] The time frame of forecasts is the same as for the up and down revisions.

forecasts, and the 1-month forecasts over the four year, sampling period are the maximum total number of observations possible. Also, in this second program, we obtain the sum of the number of forecasts made for the entire forecast period, and the total number of revisions, as well as the sum of upward and downward revisions. Then we obtain the annual and quarterly earnings per share for a sample firm and its respective closing prices from the "actuals" file in I/B/E/S, to calculate the standard deviation of the quarterly earnings scaled by the closing price for this firm. Using 5 years of data on the quarterly earnings scaled by the closing price, the standard deviation of quarterly earnings is calculated for the fiscal year ends 1994, 1995, 1996 and 1997. The standard deviation of quarterly operating income before depreciation is also calculated for the same fiscal year ends as an alternative to standard deviation of quarterly earnings. Before calculating this standard deviation, the quarterly operating income is scaled by the fiscal year end total assets. At this point, two files are built: one that contains 1) all the forecast data, 2) the standard deviation of quarterly earnings scaled by price and 3) actual earnings deflated by price[19], and another that contains 1) all other control variables collected from Compustat, and 2) the standard deviation of operating income before depreciation scaled by total assets. In each of these two files, there is an identification number assigned to each company according to their alphabetical order. After assigning an identification number to each company in the forecast data file and including the actual earnings scaled by price, the forecast data file is reduced to 1,707 observations for the 1-year forecasts, to 1588 for the 2-year forecasts, and to 1721 for the 1-month forecasts. The number of observations decreases due to missing data in the Compustat database. These identification numbers

[19] As mentioned above the actual annual earnings scaled by price is calculated from the data obtained on

are assigned from a common identification file that contains the names, tickers, cusip numbers and identification numbers, specific to each of the initial 500 companies. In the next step, the forecast data file is merged with the Compustat data file, using the identification number. This reduces further the number of observations to 1,410 observations for the 1-year file, to 1,415 observations for the 2-year file, and to 1,358 observations for the 1-month file. The forecast data are for the fiscal year ending from 1995 to 1998 for the 1-year and 1-month forecasts, and from 1996 to 1999 for the 2-year forecasts. The Compustat data are for fiscal years ending from 1994 to 1997. These fiscal years are combined with the forecast data with the fiscal year ends as described above. Then, we add to this merged file the file containing the hedging data, reducing even further the number of observations to 1,323 for the 1-year forecasts, to 1,267 observation for the 2-year forecasts, and to 1,333 observations for the 1-month forecasts. The hedging data correspond to the same fiscal years as the Compustat data, namely 1994 to 1997. Thus, we endow the typical financial analyst with the hedging and other control variables at the end of a fiscal year before the analyst formulates his/her forecast for the coming fiscal year, or 2-years, or the month. Several operations are made on the data in the last file, to scale all control and hedging variables and to compute all the dependent variables. The final data set is reduced to 1,135 observations for the 1-year forecast due to missing data, only 955 observations are read for the 2-year forecasts, and 1,227 observations are read for the 1-month forecasts. This final data set is used in the OLS regressions. When we run the univariate tests the data set used is composed of only the hedging and the forecast data. This merged data set used for the univariate tests has 1,344 observations for

---

Compustat, for fiscal year ending in 1998, due to missing data on I/B/E/S for this fiscal year end.

the 1-year forecasts, 1,133 observations for the 2-year forecasts, and 1,338 observations for the 1-month forecasts. The final data sets used for the OLS regressions or the univariate tests only include the data needed in order to run the respective tests.

5. Methodology

Both univariate and multivariate tests are used in order to study the relationship between hedgers and the accuracy of analysts' forecasts.

In order to test for the mean difference of forecast accuracy between hedgers and non-hedgers, we use the t-distribution. The sample used in the univariate tests to examine the mean differences between hedgers and non-hedgers for the dependent variables is the merged sample of I/B/E/S data and hedging data (Table 3, data step 8). However, when testing the mean differences for the independent variables, the sample used is the final data set of the merged data from Compustat, I/B/E/S and hedging data (Table 3, data step 7). The degree of significance of the difference is given by the critical t-statistic values. A critical value of 2.59 or higher corresponds to a 1-percent significance level, of 1.96 corresponds to a 5-percent significance level, and of 1.69 corresponds to 10-percent significance level. In this study, we consider a result as statistically significant only in the case where critical t-statistic values correspond to a significance level of 10-percent or lower.

To study the relationship between forecast accuracy and hedging, multivariate ordinary least square regressions are run. The dependent variables, as well as the independent variables are scaled in order to standardize them, to make the comparison among companies more appropriate. We use up to ten control variables. The sample used in the ordinary least square regressions is the final data sample of the merged data from

Compustat, I/B/E/S, and the hedging data, as shown in Table 3, data step 7. The empirical model for the 1-year forecast horizon with continuous data is as follows:

$$Y_{i,t} = \alpha + \Sigma^{1998}{}_{t=1996}\gamma_t DY_{i,t} + \Sigma^{2}{}_{j=1}\eta_j DI_{j,i,t} + \Sigma^{m}{}_{k=1} (\beta_k X_{k,i,t}) + \varepsilon_{i,t} \tag{1}$$

In using binary data for hedging, equation (1) becomes:

$$Y_{i,t} = \alpha + \delta DH_{i,t} + \Sigma^{1998}{}_{t=1996}\gamma_t DY_{i,t} + \Sigma^{2}{}_{j=1}\eta_j DI_{j,i,t} + \Sigma^{m-1}{}_{k=1} (\beta_k X_{k,i,t}) + \varepsilon_{i,t} \tag{2}$$

where,

Y = the value of the forecast accuracy,

DY = the dummy variable for fiscal years ending in 1996 through 1999,

DI = the dummy variable for manufacturing and services industries,

DH = the dummy variable for hedging, when binary variables are used for the hedging activities,

X = the independent variables, as described in section 4.2. and 4.3. ,

α = is the intercept also reflecting the effect of the dummy variables for the fiscal year of 1995 and the dummy variable for the utilities industry on the dependent variables,

δ = the coefficient to be estimated for the dummy variable for hedging variables,

γ_t = the coefficients to be estimated for the dummy variables for fiscal years ending in 1996 through 1998,

η_j = the coefficients to be estimated for the dummy variables for the manufacturing and services industries,

β_k = the coefficients to be estimated for the k^{th} variable,

$\varepsilon_{i,t}$ = the error term of the empirical model, t = fiscal years 1995, 1996, 1997, and 1998,

i = 1,..., 500 (the company),

k = the number of independent variables in the model.

It is important to note that k = 1 to m in equation (1) while k = 1 to (m-1) in equation (2). This is because the continuous hedging variable is included in the X matrix in equation (1).

We make the necessary modifications to equations (1) and (2) to test for hypotheses using the 2-year and 1-month forecast horizons.

6. Results

Three different measures of hedging activities are used in both the univariate and multivariate tests. These measures of hedging only take into consideration two major types of hedging activities: interest rate risk hedging and foreign exchange risk hedging. In all tables, three sets of results are provided. One set of results shows the impact that hedging of interest rate risk alone has on the forecast accuracy; this set of results is given under the column that has the title: **Interest Rate**. Another set of results gives the impact of hedging of foreign exchange risk on the forecast accuracy. This set of results is listed under the column entitled: **Currency**. The third set of results shows the effect of both interest rate risk and foreign exchange risk hedging together on forecast accuracy. This last set of results is given under the column entitled: **Total Hedging**.

6.1. Impact of Hedging on Analysts' Forecasts Accuracy

Table 4 reports the results from the univariate and multivariate tests on the first fundamental research question of the influence of hedging on the forecast accuracy. Panel A shows the results of the univariate tests on the 1-year forecasts. The first two rows of Panel A show that there is no statistically significant difference in the accuracy of analysts' forecasts between hedgers and non-hedgers for any type of hedging considered. T-statistics range from 0.04 to -1.27 for the first measure of forecast error that is scaled by the closing price, and from -0.14 to 0.58 for the second measure of forecast error. These results reject Hypothesis 1a, that posits that analysts' forecasts for companies using derivative products for hedging purposes are more accurate than for companies that are not using derivative products. Total Hedging in Panel A shows that the forecasts for hedgers are less accurate than those for non-hedgers. However, none of these results are statistically significant. Panel B of Table 4 shows the results of the ordinary least square (OLS) regressions, also testing for Hypothesis 1a. These results are obtained using binary variables for the hedging activities. If a sample firm is engaged in hedging activities, then we assign a value of 1 for the hedging variable for this firm and 0 otherwise. The results in Panel B, also reject Hypothesis 1a. Only companies that engage in interest rate risk management exhibit a slightly negative, but insignificant coefficient estimate of -0.00005867. On the other hand, companies that hedge only their foreign exchange risks, or both their interest rate risk and foreign exchange risk, have positive and insignificant coefficient estimates. These results suggest that observing the hedging position of a firm does not contribute to an analyst's forecast accuracy. Panel C of Table 4, shows the results of the OLS regression on Hypothesis 1b, which posits that the degree of accuracy of analysts' forecasts is increasing with an increase in the level of hedging activities. The coefficient estimates for all three types of hedging fail to support Hypothesis 1b. The coefficient estimates for interest rate hedging and total hedging are both negative (-0.00042394, and -0.00036789 respectively), as expected by Hypothesis 1b. However, none of these two coefficient estimates is statistically significant. The coefficient estimate for foreign exchange hedging, on the other hand, is positive (0.00703) and statistically significant at the 10% level. This result implies that analysts increase their forecast errors with an increase in the level of hedging of foreign exchange risk, which contradicts Hypothesis 1b. Overall, these results are surprising, under the assumption that companies maintain optimal hedging positions, be it for interest rate risk management, and/or foreign exchange risk management. A firm with an optimal hedging position should be able to reduce the risk it is hedging against and as a result, the volatility of its future cash flows should also be reduced. However, our results do not support this hypothesis. One possible explanation is that firms do not maintain optimal hedging positions. However, when an analyst makes a forecast, there are many human factors that could influence his/her judgement. Several studies have shown that analysts' forecasts are significantly affected by their experience with a specific firm (for example, Mikhail, Walther and Willis (1997), Clement (1997), and Bailey and Gupta (1999)). In our study, we have no information that would indicate which analyst makes a specific forecast and for how many quarters the same analyst provides forecasts for a specific company. Therefore, the fact that we do not control for the firm-specific experience of analysts, might have affected our results. Another possible explanation for our results can be that the majority of analysts providing forecasts for our sample firms that are involved in hedging activities is less experienced with these firms. In this case, the effect of hedging on the accuracy of analysts' forecasts is offset by the effect of the lack of experience. Also, many past studies show that analysts consistently provide overly optimistic earnings estimates (Butler and Lang (1991), Chopra (1998), Hayes (1998), and Lim (2001)). The presence of an optimistic bias could also, in part, explain our results. Analysts might estimate that volatility of cash flows would decrease more than they actually do and that hedging would have more positive effects on the stock performance than it does. These kind of estimations would result in overly optimistic forecasts. Therefore, the greater optimistic bias of analysts for companies involved in hedging activities could cancel the effects of hedging on the accuracy of analysts' forecasts. Although, this is just a possible explanation, it could be tested using the same type of forecast accuracy measures without taking the absolute value of the difference between the forecast and the actual earnings. Finally, our results could be explained by the way analysts collect and use the accounting information. All the data documenting hedging activities for the 1994 - 1997 period are only available in the footnotes of annual reports of each company. Hunton and McEwen (1999) show in their study that many analysts choose not to focus on balance sheet items and the footnotes in the annual reports, and to focus on the key ratios of these companies. The authors also show that analysts that focus on the key ratios provide more accurate forecasts than others. Therefore, if analysts do not consider the data available in the footnotes of the annual reports, they will not consider the hedging activities of a company when making an earnings forecast. Moreover, we are not aware of any financial ratio formulated specifically to account for a firm's hedging activities and their effectiveness. Also, according to Hunton and McEwen (1999) analysts that focus on footnotes and take hedging into consideration should be expected to give less accurate forecasts than those that focus on key ratios. This could in part explain the positive coefficient of currency hedging in Panel C. However, a more plausible explanation for the positive coefficient estimate of currency hedging is that this type of hedging activity would only decrease the volatility of earnings from the company's foreign operations, but not for the earnings from the company's domestic operations. Therefore, analysts might overestimate the effect of hedging on the volatility of total earnings of the company. This could then result in analysts giving overly optimistic forecasts for companies that are involved in foreign exchange risk hedging.

Variables that have a statistically significant effect on forecast accuracy in Table 4 for both Panels B and C are tangibility ratio, profitability ratio, indicator variables for industry categories and indicator variables for the fiscal year 1998. Preferred equity attains significance in models with interest rate risk hedging. In Panel C, sales exhibit a statistically significant impact on forecast accuracy, when currency hedging is used in the model as an independent variable. The tangibility ratio has a statistically significant positive coefficient estimate indicating that an increase in the tangibility ratio will result in an increase in the forecast error. Lower tangibility ratios correspond to higher levels of current assets. Thus, they indicate lower needs of external financing and higher stability of the firm. Analysts are likely to give more accurate forecasts for companies with lower levels of tangibility and higher levels of liquidity. This relationship between tangibility and accuracy of analysts' forecasts, for the 1-year period, is consistent through all regressions, for all different types of hedging and both measures of forecast accuracy. The profit ability ratio's negative coefficient estimate is statistically significant at the 1% level, in both Panels B and C, when using all types of hedging, for the 1-year forecast period. These results support the hypothesis that companies with higher profitability ratios would have lower needs of external financing and lower probability of facing financial distress. Consequently, higher levels of profitability would result in more accurate forecasts. It is important to notice that although the size of a firm does not exhibit a statistically significant coefficient estimate in all cases, the coefficient estimates are negative as expected and close to the 10% significance level. Panel C, shows that an increase in size significantly decreases the error of analysts' forecasts (at the 10% significance level), in currency hedging. This result is consistent with O'Brien and

Bhushan (1990) and Ho and Michaely (1988), who show that a higher number of analysts follow larger companies and that larger companies have lower disclosure costs.

6.2. Effect of Forecast Timing on the Relationship between Hedging and the Accuracy of Analysts Forecasts[20]

Table 5 reports the results from the multivariate tests, inquiring the influence of hedging activities on analysts' forecasts accuracy. Panel A shows the results for the forecast revisions 1-month prior to the announcement of actual earnings. Panel B shows the results of the regression where 1-year forecasts are used in the computation of the dependent variable. Panel C shows the results of the regression when 2-year forecasts are used in the computation of the dependent variable. All these regressions are run using continuous variables for all types of hedging activities. The three panels in Table 5 test for our second hypothesis which posits that the longer the forecast horizon is the more significant the impact of hedging activities should be on the accuracy of analysts' forecasts. In Panel A, we see that the coefficient estimates of interest rate hedging and total hedging are negative, while the coefficient estimate of foreign exchange risk hedging is positive[21]. However, none of these three coefficient estimates are statistically significant.

---

[20] We are reporting results only for faccu1 in Table 5. Results for faccu2 are similar to those reported, and can be obtained from the author upon request.

[21] See 6.1 for a possible explanation of a positive coefficient for foreign exchange risk hedging.

Panel B provides the results for the 1-year forecasts. We see that the coefficient estimates of interest rate risk management and total hedging are also negative, as in panel A. Although these coefficient estimates are still not statistically significant, one can observe that the significance levels of these coefficient estimates have increased as compared to those in panel A. The t-statistics for the coefficient estimate of interest rate hedging is -1.09 in Panel B, as compared to -0.67 in Panel A; and the t-statistics for the coefficient estimate of total hedging is of -0.95 in Panel B, as compared to -0.62 in Panel A. The coefficient estimate of currency hedging is still positive in Panel B, but it becomes statistically significant at the 10% level in this panel (t-statistics is 1.69 in Panel B, as compared to 0.38 in Panel A).

Panel C provides the results for the 2-year forecasts. We see that the coefficient estimates of interest rate hedging and total hedging are still negative. Although the coefficient estimate of total hedging is still not statistically significant, it is closer to the 10% significance level in Panel C than in Panel B (the t-statistics is of -1.55 in Panel C, while it is -0.95 in Panel B). The coefficient estimate of interest rate hedging becomes statistically significant at the 10% level in Panel C (the t-statistics is of -1.71 in Panel C, as compared to -1.09 in Panel B). The coefficient estimate of currency hedging, although still positive, is more statistically significant in Panel C, than in Panel B, passing from a 10% significance level to a 5% significance level (the t-statistics is of 2.34 in Panel C, as compared to 1.69 in Panel B).

When we consider the regressions results given in all three panels of Table 5, we can conclude that we fail to reject Hypothesis 2. Thus, the impact of hedging activities seems to be more important the further away from the announcement date of the actual earnings, the forecasts are made. More precisely, in this study, the longer the forecast horizon is, the more likely it is that the interest rate risk hedging activities will decrease analysts' forecast errors. On the other hand, the longer the forecast horizon is, the more likely it is that the foreign exchange risk hedging will increase the analysts' forecast error.

It is worthwhile to observe that none of the coefficient estimates of the other independent variables follows the same pattern as those of the hedging activities. This underlines the effect of hedging activities on analysts' forecast accuracy.

6.3. Impact of Hedging Activities on the Standard Deviation of Forecasts Among Analysts

Table 6 reports the results from the OLS regressions, testing whether firm's hedging activities are likely to reduce the standard deviation of forecasts among analysts[22] for the 1-year forecast period. Panels A and B, show the results testing Hypothesis 3, that states that the higher the involvement of a company in hedging activities is, the lower the standard deviation of forecasts among analysts would be for

this company. Panel A shows the estimation results using binary variables for the hedging activities, while Panel B shows the estimation results using continuous variables for the

[22] At the time the first forecasts of a fiscal year are made.

hedging activities. Panel A of Table 6 shows that only the coefficient estimate of interest rate hedging is negative, implying that the usage of derivative products for interest rate hedging purposes would reduce the standard deviation of forecasts among analysts, as posited in Hypothesis 3. However, the t-statistics of this coefficient estimate is not statistically significant. The coefficient estimate of currency hedging and total hedging are positive. This suggests that the usage of derivatives for the purpose of hedging foreign exchange risk and both interest rate and foreign exchange risks, increases the disagreement among analysts on earnings forecasts. However, once again these coefficients are not statistically significant. These results show that the usage of derivative products has no significant effect on the standard deviation of forecasts among analysts. Thus we reject our third hypothesis.

In Panel B of Table 6, it can be seen that both interest rate hedging and total hedging exhibit negative coefficient estimates, but they are not significant. On the other hand, currency hedging exhibits a large positive coefficient estimate, implying that the level of derivative usage for the purpose of hedging foreign exchange risk has an important effect on the dispersion of forecasts among analysts. The t-statistics of 4.69 of this coefficient estimate shows that there is a 99% likelihood that an increase in the level of derivative usage for foreign exchange risk management will increase the standard deviation of forecasts among analysts at the moment the forecasts are made. The third hypothesis is once again rejected by these results. It is worthwhile to notice the similarities of these results and those reported in Panels B and C of Table 4. One can conclude hedging foreign exchange risk has a different effect on analysts' forecast accuracy.

Other independent variables with a significant impact on the dispersion of analysts' forecasts in Table 6 are sales, the tangibility ratio, the profit ratio, the price-to-book ratio, the preferred equity, the indicator variables for the fiscal years and the indicator variables for the industry categories. All these independent variables have coefficient estimates that are consistent with the results reported in Panels B and C of Table 4 (except for sales). It is expected that all these variables affect the standard deviation of forecasts among analysts in the same way they affect their forecast errors[23]. It is surprising to see that in both Panels B and C sales has positive coefficient estimates that are statistically significant at the 1% and 5% levels. These results suggest that the larger a company is, the greater the forecast dispersion among analysts is. This is not expected given that larger firms have lower disclosure costs (Ho and Michaely (1988)). Lower disclosure costs suggest that analysts would be able to make more informed forecasts, and consequently, they would be more likely to agree with each other. One possible explanation for the increase in forecast dispersion with the increase in size might be that larger companies have more analysts following them (O'Brien and Bhushan (1990)). A large number of analysts might increase the standard deviation of forecasts.

[23] The lower the consensus among analysts is, the greater the forecast error is expected to be.

6.4. Impact of Hedging Activities on the Number of Revisions

Table 7 reports the results from the multivariate tests, inquiring the influence of hedging activities on the number of total revisions for the 1-year forecasts. Panels A and B report the empirical results on Hypothesis 4a. It posits that there will be fewer revisions for firms with higher levels of hedging positions than for those with lower levels (Panel B), or those that do not hedge (Panel A). The results in Panel A are obtained using binary variables for the hedging activities, while those in Panel B are obtained using continuous variables for hedging activities. Panel A shows that the coefficient estimates of all hedging activity types are negative. However, the impact of the hedging activities is only statistically significant, at the 5 and 10% levels, when we consider interest rate risk hedging and foreign exchange risk hedging separately. But, when these two types of hedging activities are considered together, the influence of these hedging activities on the number of revisions becomes insignificant at the 10% level. Panel B shows that the level of hedging of interest rate risk and of both interest rate and foreign exchange risks have the expected negative impact on the number of total revisions for the 1-year forecasts. But, this impact is not statistically significant for either of these two measures. Surprisingly, the results in Panel B show that an increase in the level of involvement in derivative usage for the management of the foreign exchange risks results in an increase in the number of total revisions. The impact of the level of derivative usage of hedging purposes is significant at the 1% level in this case. It is important to note that the level of foreign exchange risk hedging also has a significant positive impact on the analysts' forecast error for the first forecast of the year. It is possible that the higher error of the first 1-year forecasts for firms with higher levels of foreign exchange risk hedging drives the higher number of revisions for these firms. This is a possible explanation, although, it still has to be tested. According to the results in Table 7, Hypothesis 4a is rejected.

It is interesting to note that both Panels A and B show that the number of revisions is greater for companies with higher tangibility ratios, and lower price-to-book ratios. Both panels report a 1% significance level of the impact of the tangibility ratios, and a 5% significance level of the impact of the price-to-book ratio. The influence of the tangibility ratio on the number of revisions could be explained by the lower current assets that implies a higher dependence on external financing. Although, the influence of the price-to-book ratio on the number of revisions is surprising, it could be explained by a possible greater optimism or lack of experience for analysts providing estimates for value companies.

Table 8 reports the results of the OLS regressions, testing for the influence of hedging activity on the number of upward revisions, over the 1-year period for the 1-year forecasts. Panels A and B reports the empirical results testing for Hypothesis 4b. The results in Panel A are testing whether the usage of derivative products influences the number of upward revisions of forecasts over the 1-year period. These results are obtained using binary data for the hedging activity. The results in Panel B are testing whether the level of usage of derivative products for hedging purposes affects the number of upward revisions for the 1-year forecasts. These results are obtained using continuous variables for the hedging activity. Panel A reports results similar to those in Table 7, Panel C. The coefficient estimates of all types of hedging activities are negative. These results suggest that the usage of derivatives for hedging purposes decreases the number of upward revisions for the 1-year forecasts. However, only the impacts of interest rate risk hedging and foreign exchange risk hedging, separately, are statistically significant at the 5% level. The t-statistics of -1.57 for the coefficient estimates of total hedging is only close to the 10% significance level. Panel B reports positive coefficient estimates for all the hedging types, but the effect of the level of hedging activity is only significant for the hedging of foreign exchange risk, as in Table 7. The same reasoning, proposed for the results in Table 7 could be used to explain the statistically significant positive relationship between the level of usage of derivative products for hedging the foreign exchange risks and the number of upward revisions. Therefore, it could be concluded that the Hypothesis 4b is rejected.

It is also interesting to note that in both Panels A and B of Table 8, the tangibility ratio and the price-to-book ratio do not significantly impact the number of upward revisions. These two panels show that the specific characteristics of a firm do not significantly impact the number of upward revisions. However, in the year the 1-year forecasts are made seems to have an overall negative impact on the number of upward revisions. The economic set-up at the time might explain this relationship, although further investigation is needed. Also, the industry the firm belongs to has an impact on the number of upward revisions for the 1-year forecasts.

Table 9 reports the empirical results testing for the influence of hedging activities on the number of downward revisions for the 1-year forecasts. Panels A and B show results testing for Hypothesis 4c. Panel A provides the results for whether the usage of derivative products affects the number of downward revisions. These results are obtained using binary variables for the hedging activities. Panel B shows the estimation results, inquiring whether the level of derivative products usage has an impact on the number of downward revisions. These results are obtained using continuous variables for the hedging activities. The results in Panel A of Table 9 show that all types of hedging activities have positive coefficient estimates. None of these three coefficient estimates is statistically significant. Thus we reject Hypothesis 4c.

The results in Panel B report negative coefficient estimates for the interest rate hedging and total hedging. Neither of these coefficient estimates is statistically significant. Also, currency hedging exhibits a positive coefficient estimates in Panel B of Table 9. Like others, this estimate is not statistically significant. Therefore, the results in Panel B, of Table 9, also lead to the rejection of Hypothesis 4c.

Moreover, it is worthwhile to note that the economic environment and the industry classification are not the only factors affecting the number downward revisions as for the upward revisions, but, some firm-specific characteristics also influence the number of downward revisions. In both panels in Table 9, the tangibility and leverage ratios are significantly affecting the number of downward revisions for the 1-year forecasts.

6.5. Empirical Results for December and Non-December Samples

Table 10 reports the results for the influence of hedging activities on the accuracy of analysts' forecasts, using two different samples. One consists of companies having fiscal years ending in December, and another that consists of companies having fiscal years ending in any other month of the year. Panels A and B show the results on Hypothesis 5. It posits that analysts will provide more accurate forecasts for firms with a December fiscal year end than for those with fiscal years ending in any of the other months. Panel A provides the results for the 1-year forecasts using the ratio of the forecast error to the closing price of the stock as the dependent variable. The ratio of the forecast error to the actual earnings is the dependent variable used in Panel B. In both panels, the forecast error is given by the difference between the forecast and actual earnings. Panel A shows that companies that have a fiscal year ending in December exhibit positive coefficients for all types of hedging. These results suggest that for companies with December fiscal year ends, an increase in the level of usage of derivative products for hedging purposes will increase the analysts' forecast errors for the1-year forecasts. However, none of these three coefficient estimates is statistically significant. Also, Panel A shows that companies that do not have fiscal years ending in December exhibit results similar to those of the entire sample (shown in Panel C of Table 4), even though none of the coefficients is statistically significant. The results for companies that do not have fiscal years ending in December show that the level of derivative usage for interest rate risk management and both interest rate and foreign exchange risks management improve the forecast accuracy. But, the improvement of the forecast accuracy in these cases are not significant at the 10% level. Also, results show that an increase in the level of derivative usage for foreign exchange risk management reduces forecast accuracy for the 1-year forecasts for the companies that do not have a fiscal year ending in December. However, in this case the increase in forecast error is not significant at the 10% level.

Panel B shows that the results obtained using the difference between the forecast and actual earnings, divided by the actual earnings, as the dependent variable are very similar to the results in Panel A where the dependent variable is scaled by the closing price. Companies with December fiscal year ends are likely to have their forecasts improved to a greater extent by the hedging activities than companies with fiscal years ending in any other month. We conclude that Hypothesis 5 is rejected. However, we note that for foreign exchange risk hedging and total hedging, the coefficient estimates are closer of the 10% significance level for companies with fiscal years ending in another month.

7. Conclusion

As mentioned in the paper, analysts forecasts have an importance effect on stock prices. For this reason, many authors have studied the different factors that influence the accuracy of analysts' forecasts. However, no research has studied the possible effect of a firms' hedging policies on the accuracy of analysts' forecasts. This study examines the earnings forecasts of financial analysts in light of the hedging policies of the S&P 500 non-financial companies, for the 1994 - 1997 period. We test for the possible relationship between hedging activities and forecasts accuracy, using univariate and multivariate tests. Although, the nature of hedging would lead to an expectation of higher accuracy for firms that are actively involved in hedging policies, and an increasing accuracy with a greater degree of involvement, the results of this study show that the relationship is not as expected. Empirical results show that neither the involvement nor the degree of involvement in hedging activities of a firm results in more accurate forecasts, when considering the 1-year forecasts. Interest rate hedging and overall hedging do not affect the accuracy of forecasts in a statistically significant way. However, surprisingly, the results show an increase in the forecast error when a company is involved in higher levels of foreign exchange hedging. Interestingly enough, the results show evidence that the further away in time the forecast is made, the more relevant the hedging policies of a company are to the analyst who is making the forecast. Further research is necessary in order to explain some of the unexpected results obtained in this study.

8. Further Research

This study brings some new evidence on analysts' forecast accuracy, with respect to the involvement, as well as the degree of involvement, in hedging activities. We propose some ideas for future research on the impact of hedging activities on the forecast accuracy.

First, using the same methodology, analyst specific information can be included in the empirical model as independent variables. As mentioned before, many human factors affect the forecast decisions of analysts. The firm-specific experience of analysts is measured by the number of quarters the same analyst provides forecasts for a specific company. This measure of experience should be included in our model. Difference in the experience between analysts giving forecasts for hedging companies and non-hedging companies should be investigated to determine if varying levels of experience between analysts offsets the effect of hedging on the forecast accuracy.

Second, the effect of hedging on forecast accuracy could be tested using the same methodology, without taking the absolute value of the difference between the forecast and the actual earnings. This could test for the influence of hedging on the optimism bias of analysts, and might explain the results in Panel C of Table 4, which show that currency hedging increases the forecast error.

Third, the sample firms could be separated into quartiles by size. Regressions could be run for each quartile separately, in order to determine whether hedging activities have a greater effect on the accuracy of forecasts for smaller firms than for larger firms. This study will be interesting given that diversification is expected to reduce the volatility of future cash flows, and that larger firms are assumed to be more diversified.

Another approach to studying the impact of hedging on the accuracy of analysts' forecasts is to find what proportion of total earnings comes from the foreign operations of the firm. The foreign operation portion should be taken as a percentage of total earnings, and then this same percentage should be calculated for the total forecast earnings. The forecast error in this case should be computed as the difference between the numerical values of the percentage discussed above. This forecast error would relate only to the foreign position of the total forecast error. Thus, currency hedging should have a greater impact on this portion of the forecast error, while an insignificant impact on the remaining portion of the forecast error. Once this study would be performed we will have a more accurate picture of the influence of hedging on forecast accuracy.

Another suggestion would be to collect data reporting whether or not the company uses immunization as an alternative to derivative hedging. In the case where immunization is heavily used, while little or no derivative hedging is performed, the accuracy of forecasts should be relatively similar to the case where the firm is involved in interest rate hedging.

Also, it is possible that a more accurate picture of the relationship between hedging and forecasts accuracy may be obtained using a Tobit regression instead of the OLS regression.

Finally, future research could attempt to determine whether the higher error of the first 1-year forecasts for firms with higher levels of foreign exchange risk hedging drives the higher number of revisions for these firms. OLS regressions should be run using the number of total revisions as the dependent variable, and the forecast accuracy measure for the first forecast of the 1-year period, as an independent variable.

References:

Anderson, M. J. "A Comparative Analysis Of Information And Evaluation Behavior Of Professional And Non-Professional Financial Analysts," Accounting Organizations and Society, 1988, v13(5), 431-44.

Bailey, Charles D. and Sanjay Gupta. "Judgement in learning-curve forecasting: A Laboratory Study," Journal of Forecasting, 1999, v18, 39-57.

Berkman, Henk and Michael E. Bradbury. "Empirical Evidence On The Corporate Use Of Derivatives," Financial Management, 1996, v25(2,Summer), 5-13.

Bodnar, Gordon M. and Gunther Gebhardt. "Derivatives Usage In Risk Management By US And German Non-Financial Firms: A Comparative Study," Journal of International Financial Management and Accounting, 1999, v10(3,Autumn), 153-187.

Bodnar, Gordon M., Gregory S. Hayt and Richard C. Marston. "1995 Wharton Survey Of Derivatives Usage By US Non-Financial Firms," Financial Management, 1996, v25(4,Winter), 113-133.

Bodnar, Gordon M., Gregory S. Hayt and Richard C. Marston. "1998 Wharton Survey Of Financial Risk Management By US Non-Financial Firms," Financial Management, 1998, v27(4,Winter), 70-91.

Brown, P., G. Foster and E. Noreen. "Security Analysts' Multi-Year Earnings Forecasts and the Capital Market," In Studies in Accounting Research, 1985, #21, Sarasota, FL: American Accounting Association.

Brown, Lawrence D. and Kwon-Jung Kim. "Timely Aggregate Analyst Forecasts As Better Proxies For Market Earnings Expectations," Journal of Accounting Research, 1991, v29(2), 382-385.

Butler, Kirt C. and Larry H. P. Lang. "The Forecast Accuracy Of Individual Analysts: Evidence Of Systematic Optimism And Pessimism," Journal of Accounting Research, 1991, v29(1), 150-156.

Chopra, Vijay Kumar. "Why So Much Error In Analysts' Earnings Forecasts?," Financial Analyst Journal, 1998, v54(6,Nov-Dec), 35-42.

Clement, M. "Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter?," Working Paper, University of Texas at Austin, 1997.

Conroy, R. and R. Harris. "Consensus Forecasts of Corporate Earnings: Analysts' Forecasts and Time-Series Methods," Management Science, 1987, v33(6,June), 725-738.

DeBondt, Werner F. M. and Richard M. Thaler. "Do Security Analysts Overreact?," American Economic Review, 1990, v80(2), 52-57.

Dreman, David N. and Michael A. Berry. "Analyst Forecasting Errors And Their Implications For Security Analysis," Financial Analyst Journal, 1995, v51(3), 30-41.

Eastwood, John C. and Stacey R. Nutt. "Inefficiency in Analysts' Earnings Forecasts: Systematic Misreaction or Systematic Optimism?," Journal of Finance, 1999, v54, 1777-1797.

Francis, Jennifer and Donna Philbrick. "Analysts' Decisions As Products Of A Multi-Task Environment," Journal of Accounting Research, 1993, v31(2), 216-230.

Fried, Dov and Dan Givoly. "Financial Analysts' Forecasts Of Earnings: A Better Surrogate For Market Expectations," Journal of Accounting and Economics, 1982, v4(2), 85-107.

Froot, Kenneth A., David S. Scharfstein and Jeremy C. Stein. "Risk Management: Coordinating Corporate Investment And Financing Policies," Journal of Finance, 1993, v48(5), 1629-1658.

Geczy, Christopher, Bernadette A. Minton and Catherine Schrand. "Why Firms Use Currency Derivatives," Journal of Finance, 1997, v52(4,Sep), 1323-1354.

Goldberg, R. Stephen, Joseph H. Godwin, Myung-Sun Kim and Charles A. Tritschler. "On the Determinants of Corporate Usage of Financial Derivatives," Journal of International Financial Management and Accounting, 1998, v9, 132-166.

Graham, John R. and Daniel A. Rogers "Is Corporate Hedging Consistent with Value Maximization? An Empirical Analysis," Working Paper, Northeastern University, 1999, (25, June).

Graham, John R. and Clifford W. Smith, Jr. "Tax Incentives To Hedge," Journal of Finance, 1999, v54(6,Dec), 2241-2262.

Jalilvand, Abolhassan. "Why Firms Use Derivatives: Evidence from Canada", Canadian Journal of Administrative Sciences, 1999, v16, 213-228.

Haushalter, G. David. "Financing Policy, Basis Risk, And Corporate Hedging: Evidence From Oil And Gas Producers," Journal of Finance, 2000, v55(1,Feb), 107-152.

Hayes, Rachel M. "The Impact Of Trading Commission Incentives On Analysts' Stock Coverage Decisions And Earnings Forecasts," Journal of Accounting Research, 1998, v36(2,Autumn), 299-320.

He, Jia and Lilian K. Ng. "The Foreign Exchange Exposure Of Japanese Multinational Corporations," Journal of Finance, 1998, v53(2,Apr), 733-753.

Higgins, Huong Ngo. "Analyst Forecasting Performance In Seven Countries," Financial Analyst Journal, 1998, v54(3,May/Jun), 58-62.

Ho, Thomas S. Y. and Roni Michaley. " Information Quality and Market Efficiency," Journal of Financial and Quantitative Analysis, 1988, v23, 53-70.

Howton, Shawn D. and Steven B. Perfect. "Currency And Interest-Rate Derivatives Use In US Firms," Financial Management, 1998, v27(4,Winter), 111-120.

Hunton, James E. and Ruth Ann McEwen. "An Assessment Of The Relation Between Analysts' Earnings Forecast Accuracy, Motivational Incentives And Cognitive Information Search Strategy," Accounting Review, 1997, v72(4,Oct), 497-515.

Lang, Mark H. and Russell J. Lundholm. "Corporate Disclosure Policy And Analyst Behavior," Accounting Review, 1996, v71(4,Oct), 467-492.

Lim, Terence. "Rationality and Analysts' Forecast Bias," Journal of Finance, 2001, v56(1,Feb), 369-385.

Lin, Hsiou-wei and Maureen F. McNichols. "Underwriting Relationships, Analysts' Earnings Forecasts And Investment Recommendations," Journal of Accounting and Economics, 1998, v25(1,Feb), 101-127.

Lys, Thomas and Sungkyu Sohn. "The Association Between Revisions Of Financial Analysts' Earnings Forecasts And Security-Price Changes," Journal of Accounting and Economics, 1990, v13(4), 341-363.

McEwen, R. A. and J. E. Hunton. "Is Analyst Forecast Accuracy Associated With Accounting Information Use?," Accounting Horizons, 1999, v13(1,Mar), 1-16.

Mian, Shehzad L. "Evidence On Corporate Hedging Policy," Journal of Financial and Quantitative Analysis, 1996, v31(3,Sep), 419-437.

Miller, Merton H. "Financial Innovation: The Last Twenty Years And The Next," Journal of Financial and Quantitative Analysis, 1986, v21(4), 459-471.

Mikhail, Michael B., Beverly R. Walther and Richard H. Willis. "Do Security Analysts Improve Their Performance With Experience?," Journal of Accounting Research, 1997, v35(Supp), 131-157.

Modigliani, Franco and Merton Miller. "Corporate Income Taxes And The Cost Of Capital: A Correction," American Economic Review, 1963, v53(3), 433-442.

Myers, Stewart C. "Determinants Of Corporate Borrowing," Journal of Financial Economics, 1977, v5(2), 147-175.

Nance, Deana R., Clifford W. Smith, Jr. and Charles W. Smithson. "On The Determinants Of Corporate Hedging," Journal of Finance, 1993, v48(1), 267-284.

O'Brien, Patricia C. "Forecast Accuracy Of Individual Analysts In Nine Industries," Journal of Accounting Research, 1990, v28(2), 286-304.

O'Brien, Patricia C. and Ravi Bhushan. "Analyst following and institutional ownership," Journal of Accounting Research, 1990, v28, 55-76.

Olsen, Robert A. "Implications Of Herding Behavior For Earnings Estimation, Risk Assessment, And Stock Returns," Financial Analyst Journal, 1996, v52(4,Jul-Aug), 37-41.

Samant, Ajay. "An Empirical Study Of Interest Rate Swap Usage By Nonfinancial Corporate Business," Journal of Financial Services Research, 1996, v10(1,Mar), 43-57.

Schrand, Catherine and Haluk Unal. "Hedging And Coordinated Risk Management: Evidence From Thrift Conversions," Journal of Finance, 1998, v53(3,Jun), 979-1013.

Smith, Clifford W. and Rene M. Stulz. "The Determinants Of Firms' Hedging Policies," Journal of Financial and Quantitative Analysis, 1985, v20(4), 391-406.

Stickel, Scott E. "Reputation and Performance Among Security Analysts," Journal of Finance, 1992, v47(5,Dec), 1811-1836.

Stulz, Rene M. "Managerial Discretion And Optimal Financing Policies," Journal of Financial Economics, 1990, v26(1), 3-28.

Tufano, Peter. "Who Manages Risk? An Empirical Examination Of Risk Management Practices In The Gold Mining Industry," Journal of Finance, 1996, v51(4,Sep), 1097-1137.

Wiedman, Christine I. "The Relevance Of Characteristics Of The Information Environment In The Selection Of A Proxy For The Market's Expectations For Earnings: An Extension Of Brown, Richardson, And Schwager [1987]," Journal of Accounting Research, 1996, v34(2,Autumn), 313-324.

Table 1: Descriptive Statistics of the Hedging Data

This table describes the hedging data for the companies of S&P 500 as of January 1995, for each of the years considered in the study and for the total of companies. The values of hedging activities are given in millions of dollars.

	1994	1995	1996	1997	Total
Panel (a): Currency Hedging					
Number of Hedgers	231	231	227	216	905
Number of Non-Hedgers	220	202	202	181	805
Number of Missing Observations	49	67	71	103	290
Notional Amount					
Mean	1466.18	1820.67	2069.37	2451.46	1951.92
Median	238.11	219.00	264.00	358.96	251.06
Panel (b): Interest rate Hedging					
Number of Hedgers	237	231	220	204	892
Number of Non-Hedgers	216	209	210	201	836
Number of Missing Observations	47	60	70	95	272
Notional Amount					
Mean	5250.76	7405.50	9637.05	11245.78	8384.773
Median	334.84	350.00	452.50	473.50	401.25
Panel (c): Total Hedging					
Number of Hedgers	299	297	294	273	1163
Number of Non-Hedgers	144	121	119	111	495
Number of Missing Observations	57	82	87	116	342
Notional Amount					
Mean	5246.56	7018.46	8685.04	10221.625	7792.921
Median	415.00	441.00	465.85	514.2	453.43

Table 2: Descriptive Statistics for the Control Variables

This table provides the descriptive statistics for the control variables used in the multivariate tests for the 1-year forecast period. These variables are collected from Compustat for the companies on the S&P 500 as of January 1995, for the 1994-1997 period.

numbesti: the number of estimates at the time the forecast is collected for the 1-year forecast period. The forecasts used in this study are the means of these estimates.

stdratiq: the standard deviation of quarterly earnings is calculated after actual quarterly earnings are deflated by the actual price at the end of the fiscal year for the company.

pb: the price-to-book ratio, as given in Compustat.

sales: gross sales reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers. This item is scaled in millions.

tanratio: the tangibility ratio measured as the ratio of tangible assets over total assets. Tangible assets are calculated as the difference between total assets and current assets, less intangible assets. All items involved in the computation of the tangibility ratio are scaled in millions.

leverage: leverage ratio is calculated as total debt divided by total assets. Total debt is calculated as the sum of long term debt and short term debt, and total assets are given in Compustat. All items involved in the computation of the leverage ratio are scaled in millions.

profit: the profitability ratio is calculated as the ratio of operation income before depreciation-to-total assets. The two components of this ratio are scaled in millions.

prefequi: is the ratio of preferred equity to the total value of the company.

Variable	Mean	Median	Std. Deviation	Minimum	Maximum
numbesti	18.72775	18.00000	8.69130	1.00000	46.00000
stdratiq	0.05110	0.00522	0.69425	0.00098	14.83327
pb	2.85621	2.45300	10.63586	-324.56100	58.02700
sales	9410.00000	4640.05000	17464.00000	181.46800	168738.00000
tanratio	0.53765	0.50621	0.21346	0.11446	0.97632
leverage	0.43820	0.43647	0.13132	0.07474	1.33488
profit	0.15688	0.15338	0.07931	-0.66965	0.49611
prefequi	0.00667	0.00000	0.02173	0.00000	0.26538

TABLE 3: Evolution of the Data Set:

This table describes the steps followed in order to achieve the final data set, which is used in running the statistical tests. The number of observations resulting as of each step is provided for each one of the three forecasting periods we are interested in. Steps 1 to 5 and 7 show the process followed to obtain the data set used in the OLS regressions and the univariate results involving the control variables. Steps 1 to 3, 6 and 8 are used to obtain the data set for the univariate tests involving only the dependent variables.

	Number of Observations		
Data step	**1-year forecasts**	**2-year forecasts**	**1-month forecast**
1. Reading IBES tapes for the 1 year and 2 year forecasts	18,788	18,788	18,788
2. Keep only one forecast for the period	1,843	1,849	1,820
3. Assign an indentification number for each company for the forecast data	1,707	1,588	1,721
4. Merging IBES data with the Compustat Data	1,410	1,415	1,358
5. Merging IBES, Compustat and Hedging Data	1,323	1,267	1,333
6. Merging IBES and Hedging Data	1,645	1,492	1,575
7. Final data set used in OLS regressions	1,135	955	1,227
8. Final data set used in univariate tests	1,344	1,133	1,338

TABLE 4: Univariate and OLS Results for the 1-year Forecasts

This table reports the results from the univariate tests and the OLS regressions for the influence of hedging on analysts' forecast accuracy. Our sample consists of S&P 500 non-financial firms as of January 1995.The same firms are tracked during the sample period, even if any one of them is subsequently removed from the S&P 500 index. The data are obtained from three main data bases: Edgar, I/B/E/S, and Compustat. Panel A shows the results of the univariate tests, investigating the difference between the means of the different proxies for forecast accuracy[24] for the 1-year forecasts. Faccu1 is the difference between forecast and actual earnings, deflated by the closing price at the fiscal year end. Faccu2 is the difference between forecast and actual earnings, deflated by the actual earnings. Fstddev is the standard deviation of forecasts among analysts at the time the forecasts are made, as given in I/B/E/S. Uprevi is the sum of upward revisions over the forecast period divided by the total number of estimates over the time frame of the forecast. Downrevi is the sum of downward revisions over the forecast period divided by the total number of estimates over the time frame of the forecast. Allrevi is the sum of total revisions over the forecast period divided by the total number of estimates over the time frame of the forecast. Panel B shows the results of the OLS regressions, testing Hypothesis 1a, which posits that analysts' forecasts for companies that are using derivative products for hedging purposes are more accurate than for companies that are not using derivative products. The results in Panel B are obtained using binary variables for hedging. Hedging variables are equal to 1 if there is any evidence that the company is engaging in that kind of hedging activities, and 0 otherwise. Negative coefficient estimates for the hedging variables would support this hypothesis. Panel C shows the results of the OLS regression, testing Hypothesis 1b, which posits that the degree of accuracy of analysts' forecasts is increasing with an increase in the level of hedging activities. Negative coefficient estimates for the hedging variables would support this hypothesis. The hedging variables in this panel are given as the ratios of the notional amounts of hedging to the total value of the company. All other independent variables are described in Table 2, with the exception of the size of the firm which is given by the natural logarithm of sales. The dependent variable in these results is given by the difference between the forecast and the actual earnings divided by the closing price at the end of the fiscal year. The first hypothesis is also tested, using the difference between the forecast and actual earnings divided by the actual earnings, as the dependent variables. However, the results are quite similar to those reported here, and hence not reported. They are available from the author upon request.

[24] See section 4.4. for a detail description of the different dependent variables.

Panel A: Results for the univariate tests on the dependent variables for the 1-year forecasts

	Interest Rate			Currency			Total Hedge		
Variable	Hedgers	Non-Hedgers	t-statistic	Hedgers	Non-Hedgers	t-statistic	Hedgers	Non-Hedgers	t-statistic
Faccu1	0.0083	0.0083	0.04	0.0089	0.008	-0.98	0.0095	0.0086	-1.27
Faccu2	0.162	0.1608	-0.11	0.1587	0.1653	0.58	0.1625	0.1607	-0.14
Fstddev	13.219	11.447	-1.98**	13.675	11.089	-2.85***	13.342	10.344	-3.25***
Uprevi	0.1279	0.1295	0.32	0.1349	0.1215	-2.70***	0.131	0.1234	-1.38
Dwnrevi	0.125	0.131	1.09	0.1283	0.1271	-0.21	0.1287	0.1246	-0.66
Allrevi	0.2561	0.2657	1.83*	0.2657	0.2549	-2.02**	0.2629	0.2549	-1.34

Panel B: Results from the OLS regressions, using binary variables for the hedging variables, for the 1-year forecasts, when the dependent variable is faccu1 = |forecasted earnings - actual earnings| / closing stock price.

	Full Sample		
Variables	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.00627 (1.43)	0.00610 (1.38)	0.00595 (1.36)
Interest Rate Hedging	-0.00005867 (-0.06)	- -	- -
Currency Hedging	- -	0.00013059 (0.13)	- -
Total Hedging	- -	- -	0.00083579 (0.83)
lnsales	-0.00080828 (-1.52)	-0.00077556 (-1.44)	-0.00072799 (-1.34)
tanratio	0.01413 (5.37)***	0.01543 (5.81)***	0.01459 (5.54)***
stdratiq	0.00026587 (0.40)	0.00025527 (0.38)	0.00023567 (0.35)
d96	-0.00099418 (-0.87)	-0.00089707 (-0.77)	-0.00097984 (-0.85)
d97	-0.00167 (-1.45)	-0.00150 (-1.31)	-0.00149 (-1.30)
d98	0.00463 (3.61)***	0.00513 (3.98)***	0.00493 (3.86)***
dindser	0.00556 (3.34)***	0.00532 (3.17)***	0.00519 (3.14)***
dindmauf	0.00912 (6.34)***	0.00923 (6.19)***	0.00866 (5.96)***
leverage	0.00293 (0.79)	0.00107 (0.30)	0.00115 (0.32)
profit	-0.03614 (-5.77)***	-0.03790 (-6.10)***	-0.03562 (-5.72)***
pb	-0.00009391 (-1.03)	-0.00008971 (-1.03)	-0.00009323 (-1.03)
prefequi	0.05073 (1.99)**	0.01903 (0.91)	0.02609 (1.25)
numbesti	0.00000333 (0.05)	0.00002386 (0.35)	-0.00000138 (-0.02)
R^2	0.1588	0.1620	0.1544
Sample Size	734	730	738

Panel C: Results from the OLS regressions, using continuous variables for the hedging variables, for the 1-year forecasts, when the dependent variable is faccu1 = |forecasted earnings - actual earnings| / closing stock price.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.00645 (1.49)	0.00655 (1.50)	0.00631 (1.43)
Interest Rate Hedging	-0.00042394 (-1.09)	- -	- -
Currency Hedging	- -	0.00703 (1.69)*	- -
Total Hedging	- -	- -	-0.00036789 (-0.95)
lnsales	-0.00078352 (-1.48)	-0.00090828 (-1.69)*	-0.00083849 (-1.54)
tanratio	0.01402 (5.33)***	0.01554 (5.87)***	0.01505 (5.59)***
stdratiq	0.00025927 (0.39)	0.00026294 (0.39)	0.00026147 (0.39)
d96	-0.00095930 (-0.84)	-0.00092241 (-0.80)	-0.0009885 (-0.85)
d97	-0.00164 (-1.43)	-0.00149 (-1.30)	-0.00181 (-1.56)
d98	0.00466 (3.63)***	0.00516 (4.01)***	0.00471 (3.60)***
dindser	0.00552 (3.32)***	0.00552 (3.29)***	0.00577 (3.36)***
dindmauf	0.00911 (6.35)***	0.00923 (6.44)***	0.00949 (6.48)***
leverage	0.00248 (0.68)	0.00115 (0.32)	0.00209 (0.57)
profit	-0.03610 (-5.77)***	-0.03663 (-5.87)***	-0.03601 (-5.70)***
pb	-0.00009566 (-1.05)	-0.00008608 (-0.99)	-0.00009554 (-1.04)
prefequi	0.05114 (2.01)**	0.02054 (0.98)	0.04542 (1.76)*
numbesti	-0.00000407 (-0.06)	0.00003095 (0.45)	0.00000186 (0.03)
R^2	0.1602	0.1653	0.1632
Sample Size	734	730	709

TABLE 5: Results of OLS Regressions for Three Forecast Horizons

This table reports the results from the multivariate tests, inquiring the influence of hedging on analysts' forecast accuracy. Our sample consists of S&P 500 non-financial firms as of January 1995.The same firms are tracked during the sample period, even if any one of them is subsequently removed from the S&P 500 index. The data are obtained from three main data bases: Edgar, I/B/E/S, and Compustat. Panel A shows the results of the multivariate tests, investigating the impact of the level of involvement in hedging activities on the accuracy of analysts' forecasts for the 1-month forecast revisions for the originally 1-year forecasts. Panel B gives the same results for the 1-year prior to the announcement of actual earnings. Panel C gives the univariate results for the 2-year forecasts. The results of these three panels would either support or reject the second hypothesis that states that the longer the forecast horizons are, the greater the impact of the derivative usage on the forecast accuracy will be. For a description of hedging variables please refer to Table 4, and for a description of the other independent variables, please refer to Table 2.

Panel A: OLS regression test results for the 1-month forecast revisions for the 1-year forecasts.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.00041853 (0.15)	0.00126 (0.44)	0.00148 (0.52)
Interest Rate Hedging	-0.00017892 (-0.67)	- -	- -
Currency Hedging	- -	0.00106 (0.38)	- -
Total Hedging	- -	- -	-0.00016505 (-0.62)
lnsales	0.00006977 (0.20)	-0.000000566557 (-0.00)	-0.00009672 (-0.28)
tanratio	0.00343 (2.04)**	0.00419 (2.44)**	0.00365 (2.14)**
stdratiq	0.00063707 (1.39)	0.00066049 (1.42)	0.00065754 (1.43)
d96	-0.0021644 (-0.29)	-0.00035394 (-0.46)	-0.00022686 (-0.29)
d97	-0.00051727 (-0.67)	-0.00066942 (-0.90)	-0.00060068 (-0.77)
d98	0.00683 (8.06)***	0.00680 (7.90)***	0.00661 (7.67)***
dindser	0.00348 (3.19)***	0.00290 (2.60)***	0.00336 (3.00)***
dindmauf	0.00305 (3.23)***	0.00291 (3.04)***	0.00325 (3.38)***
leverage	0.00362 (1.53)	0.00301 (1.28)	0.00354 (1.48)
profit	-0.01256 (-3.21)***	-0.01401 (-3.52)***	-0.01248 (-3.17)***
pb	-0.00006650 (-1.06)	-0.00005829 (-0.97)	-0.00006549 (-1.04)
prefequi	0.03498 (2.56)**	0.00855 (0.74)	0.03066 (2.15)**
numbesti	-0.00009574 (-2.13)**	-0.00008185 (-1.79)*	-0.00008573 (-1.86)*
R^2	0.1684	0.1591	0.1594
Sample Size	797	793	769

Panel B: Multivariate test results for the 1-year forecasts.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.00645 (1.49)	0.00655 (1.50)	0.00631 (1.43)
Interest Rate Hedging	-0.00042394 (-1.09)	- -	- -
Currency Hedging	- -	0.00703 (1.69)*	- -
Total Hedging	- -	- -	-0.00036789 (-0.95)
lnsales	-0.00078352 (-1.48)	-0.00090828 (-1.69)*	-0.00083849 (-1.54)
tanratio	0.01402 (5.33)***	0.01554 (5.87)***	0.01505 (5.59)***
stdratiq	0.00025927 (0.39)	0.00026294 (0.39)	0.00026147 (0.39)
d96	-0.00095930 (-0.84)	-0.00092241 (-0.80)	-0.0009885 (-0.85)
d97	-0.00164 (-1.43)	-0.00149 (-1.30)	-0.00181 (-1.56)
d98	0.00466 (3.63)***	0.00516 (4.01)***	0.00471 (3.60)***
dindser	0.00552 (3.32)***	0.00552 (3.29)***	0.00577 (3.36)***
dindmauf	0.00911 (6.35)***	0.00923 (6.44)***	0.00949 (6.48)***
leverage	0.00248 (0.68)	0.00115 (0.32)	0.00209 (0.57)
profit	-0.03610 (-5.77)***	-0.03663 (-5.87)***	-0.03601 (-5.70)***
pb	-0.00009566 (-1.05)	-0.00008608 (-0.99)	-0.00009554 (-1.04)
prefequi	0.05114 (2.01)**	0.02054 (0.98)	0.04542 (1.76)*
numbesti	-0.00000407 (-0.06)	0.00003095 (0.45)	0.00000186 (0.03)
R^2	0.1602	0.1653	0.1632
Sample Size	734	730	709

Panel C: Multivariate test results for the 2-year forecasts.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.00429 (0.84)	0.00725 (1.40)	0.00638 (1.23)
Interest Rate Hedging	-0.00070469 (-1.71)*	- -	- -
Currency Hedging	- -	0.01088 (2.34)**	- -
Total Hedging	- -	- -	-0.00063808 (-1.55)
lnsales	-0.00056043 (-0.99)	-0.00108 (-1.86)*	-0.00087483 (-1.51)
tanratio	0.01341 (4.30)***	0.01690 (5.36)***	0.01555 (4.83)***
stdratiq	-0.00015862 (-0.19)	-0.00001728 (-0.02)	-0.00006855 (-0.08)
d97	0.00042592 (0.34)	0.00012864 (0.10)	0.00033433 (0.26)
d98	0.00628 (4.58)***	0.00676 (4.93)***	0.00649 (4.67)***
d99	0.00593 (4.14)***	0.00663 (4.63)***	0.00629 (4.29)***
dindser	0.00385 (1.99)**	0.00416 (2.11)**	0.00385 (1.91)*
dindmauf	0.00872 (5.10)***	0.00911 (5.29)***	0.00929 (5.25)***
leverage	0.00687 (1.66)*	0.00464 (1.13)	0.00545 (1.29)
profit	-0.01975 (-2.35)**	-0.02496 (-2.97)***	-0.02298 (-2.67)***
pb	-0.00026265 (-1.89)*	-0.00027179 (-2.01)**	-0.00027356 (-1.96)*
prefequi	0.03399 (1.14)	-0.00377 (-0.15)	0.01338 (0.41)
numbesti	-0.00025316 (-2.02)**	-0.00007895 (-0.62)	-0.00018114 (-1.38)
R^2	0.1364	0.1617	0.1486
Sample Size	619	613	596

TABLE 6: OLS Results to Standard Deviation of Forecasts Among Analysts

This table reports the results from the OLS regressions, for the influence of hedging on the standard deviation of forecasts among analysts. Our sample consists of S&P 500 non-financial firms as of January 1995.The same firms are tracked during the sample period, even if any one of them is subsequently removed from the S&P 500 index. The data are obtained from three main data bases: Edgar, I/B/E/S, and Compustat. Panel A and B, show the results of the OLS regressions, testing Hypothesis 3, which posits that the higher the involvement of the company in hedging activities is, the lower the standard deviation of forecasts among analysts will be. The results in Panel A are obtained using binary variables for hedging. Hedging variables are equal to 1 if there is any evidence that the company is engaging in that kind of hedging activities, and 0 otherwise. Panel B shows the results of the OLS regressions, using continuous variables for the hedging variables. Negative coefficient estimates for the hedging variables in either of the two panels would support this hypothesis. The dependent variable for these results is the standard deviation of forecasts among analysts at the time the forecasts are made, as given in the I/B/E/S database. For a description of hedging variables please refer to Table 4, and for a description of the other independent variables, please refer to Table 2.

Panel A: Results from OLS regressions, using binary variables for hedging variables, where the standard deviation of forecasts among analysts for the 1-year forecasts is the dependent variable.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	-17.35427 (-3.18)***	-15.88487 (-2.85)***	-16.81832 (-3.04)***
Interest Rate Hedging	-0.28579 (-0.25)	- -	- -
Currency Hedging	- -	0.61355 (0.49)	- -
Total Hedging	- -	- -	0.76683 (0.60)
lnsales	2.30134 (3.48)***	1.98839 (2.93)***	2.20199 (3.22)***
tanratio	22.85102 (6.96)***	25.50413 (7.61)***	24.67885 (7.42)***
stdratiq	0.44158 (0.53)	0.41886 (0.49)	0.42646 (0.50)
d96	-1.78364 (-1.24)	-1.82769 (-1.24)	-1.96647 (-1.35)
d97	-1.01996 (-0.71)	-1.34838 (-0.92)	-1.16962 (-0.80)
d98	-3.13974 (-1.96)*	-3.11005 (-1.91)*	-2.97058 (-1.84)*
dindser	7.15397 (3.47)***	7.30730 (3.46)***	6.84172 (3.28)***
dindmauf	12.15598 (6.81)***	12.73259 (6.80)***	12.30839 (6.74)***
leverage	-4.43283 (-0.95)	-5.61356 (-1.23)	-6.40377 (-1.38)
profit	-30.23896 (-3.89)***	-35.25871 (-4.51)***	-33.00589 (-4.21)***
pb	-0.27527 (-2.41)**	-0.22905 (-2.09)**	-0.27647 (-2.42)**
prefequi	117.63078 (3.88)***	75.49467 (2.94)***	79.24293 (3.10)***
numbesti	-0.15240 (-1.81)*	-0.11222 (-1.30)	-0.12957 (-1.51)
R^2	0.1737	0.1806	0.1767
Sample Size	731	726	734

Panel B: Results from OLS regressions, using continuous variables for hedging variables, where the standard deviation of forecasts among analysts for the 1-year forecasts is the dependent variable.

Variables	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	-17.03702 (-3.17)***	-14.65600 (-2.70)***	-16.24340 (-2.93)***
Interest Rate Hedging	-0.25214 (-0.52)	- -	- -
Currency Hedging	- -	24.42606 (4.69)***	- -
Total Hedging	- -	- -	-0.05169 (-0.11)
lnsales	2.29382 (3.51)***	1.56632 (2.35)**	2.04702 (3.01)***
tanratio	22.76243 (6.94)***	25.86522 (7.84)***	24.37934 (7.19)***
stdratiq	0.42921 (0.51)	0.45343 (0.54)	0.45106 (0.54)
d96	-1.75159 (-1.22)	-1.90063 (-1.31)	-1.84492 (-1.25)
d97	-0.98808 (-0.69)	-1.26300 (-0.88)	-1.16434 (-0.79)
d98	-3.10907 (-1.94)*	-3.02712 (-1.89)*	-3.09246 (-1.88)*
dindser	7.15491 (3.47)***	7.98469 (3.84)***	7.38029 (3.44)***
dindmauf	12.12283 (6.81)***	12.78511 (7.17)***	12.67829 (6.91)***
leverage	-4.93553 (-1.08)	-5.35247 (-1.19)	-5.14368 (-1.10)
profit	-30.14831 (-3.88)***	-30.47585 (-3.93)***	-30.79738 (-3.89)***
pb	-0.27731 (-2.43)**	-0.21731 (-2.01)**	-0.27092 (-2.35)**
prefequi	118.21111 (3.90)***	81.08594 (3.21)***	112.08203 (3.63)***
numbesti	-0.15837 (-1.88)*	-0.08709 (-1.02)	-0.13644 (-1.55)
R^2	0.1740	0.2049	0.1788
Sample Size	731	726	706

TABLE 7: OLS Results Using the Number of Total Revisions as the Dependent Variable

This table reports the results from the OLS regressions, testing for the influence of hedging on the number of total revisions for the 1-year forecasts. Our sample consists of S&P 500 non-financial firms as of January 1995.The same firms are tracked during the sample period, even if any one of them is subsequently removed from the S&P 500 index. The data are obtained from three main data bases: Edgar, I/B/E/S, and Compustat. Panel A and B, show the results of the OLS regressions, testing Hypothesis 4a, which posits that there will be fewer revisions for the firms with higher levels of hedging than for those with lower levels (Panel B), or those that do not hedge (Panel A). The results in Panel A are obtained using binary variables for hedging variables. Hedging variables are equal to 1 if there is any evidence that the company is engaging in that kind of hedging activities, and 0 otherwise. Panel B shows the results of the OLS regressions, using continuous variables for the hedging variables. Negative coefficient estimates for the hedging variables in either of the two panels would support this hypothesis. The dependent variable for these results is the number of total revisions over the 1-year period as a percentage of the number of total forecasts over the year. For a description of hedging variables please refer to Table 4, and for a description of the other independent variables, please refer to Table 2.

Panel A: Results from OLS regressions, using binary variables for hedging, where the total revisions for the 1-year forecasts is the dependent variable.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.10228 (3.01)***	0.10147 (2.96)***	0.11347 (3.33)***
Interest Rate Hedging	-0.01762 (-2.47)**	- -	- -
Currency Hedging	- -	-0.01446 (-1.88)*	- -
Total Hedging	- -	- -	-0.00739 (-0.93)
lnsales	0.00652 (1.58)	0.00639 (1.52)	0.00556 (1.32)
tanratio	0.08745 (4.28)***	0.09913 (4.80)***	0.08855 (4.32)***
stdratiq	0.00140 (0.27)	0.00169 (0.32)	0.00113 (0.22)
d96	-0.00679 (-0.76)	-0.00468 (-0.52)	-0.00430 (-0.48)
d97	0.00600 (0.67)	0.00655 (0.73)	0.00873 (0.98)
d98	0.00496 (0.50)	0.00540 (0.54)	0.00700 (0.70)
dindser	0.06820 (5.30)***	0.06748 (5.17)***	0.06581 (5.11)***
dindmauf	0.07492 (6.73)***	0.08039 (6.95)***	0.07330 (6.50)***
leverage	-0.02060 (-0.71)	-0.04030 (-1.44)	-0.03618 (-1.27)
profit	-0.03986 (-0.82)	-0.03718 (-0.77)	-0.03421 (-0.71)
pb	-0.00165 (-2.32)**	-0.00153 (-2.26)**	-0.00170 (-2.40)**
prefequi	-0.01170 (-0.06)	-0.05485 (-0.35)	-0.03741 (-0.24)
numbesti	0.00150 (2.88)***	0.00150 (2.83)***	-0.00146 (2.78)***
R^2	0.1008	0.1057	0.0946
Sample Size	733	728	736

Panel B: Results from OLS regression, using continuous variables for hedging variables, where the total revisions for the 1-year forecasts is the dependent variable.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.11770 (3.51)***	0.11920 (3.53)***	0.12016 (3.49)***
Interest Rate Hedging	-0.00277 (-0.92)	- -	- -
Currency Hedging	- -	0.11421 (3.54)***	- -
Total Hedging	- -	- -	-0.00160 (-0.53)
lnsales	0.00522 (1.27)	0.00279 (0.67)	0.00361 (0.85)
tanratio	0.08494 (4.15)***	0.10232 (4.98)***	0.09640 (4.57)***
stdratiq	0.00078279 (0.15)	0.00098208 (0.19)	0.00086191 (0.16)
d96	-0.00580 (-0.65)	-0.00515 (-0.57)	-0.00613 (-0.67)
d97	0.00700 (0.78)	0.00667 (0.75)	0.00447 (0.49)
d98	0.00578 (0.58)	0.00565 (0.57)	0.00494 (0.48)
dindser	0.06951 (5.39)***	0.07276 (5.61)***	0.07398 (5.53)***
dindmauf	0.07273 (6.53)***	0.07377 (6.65)***	0.07727 (6.76)***
leverage	-0.03948 (-1.39)	-0.04349 (-1.57)	-0.03630 (-1.25)
profit	-0.03582 (-0.74)	-0.01763 (-0.37)	-0.04363 (-0.89)
pb	-0.00173 (-2.42)**	-0.00150 (-2.23)**	-0.00167 (-2.33)**
prefequi	0.01344 (0.07)	-0.01885 (-0.12)	-0.01705 (-0.09)
numbesti	0.00135 (2.57)**	0.00151 (2.86)***	0.00149 (2.74)***
R^2	0.0942	0.1168	0.0986
Sample Size	733	728	708

TABLE 8: OLS Results Using the Number of Upward Revisions as the Dependent Variable

This table reports the results from the OLS regressions, testing for the influence of hedging on the number of upward forecast revisions for the 1-year forecasts. Our sample consists of S&P 500 non-financial firms as of January 1995.The same firms are tracked during the sample period, even if any one of them is subsequently removed from the S&P 500 index. The data are obtained from three main data bases: Edgar, I/B/E/S, and Compustat. Panel A and B show the results of the OLS regressions, testing Hypothesis 4b, which posits that there will be fewer upward revisions for the firms with higher levels of hedging than for those with lower levels (Panel B), or those that do not hedge (Panel A). The results in Panel A are obtained using binary variables for hedging variables. Hedging variables are equal to 1 if there is any evidence that the company is engaging in that kind of hedging activities, and 0 otherwise. Panel B shows the results of the OLS regressions, using continuous variables for the hedging variables. Negative coefficient estimates for the hedging variables in either of the two panels would support this hypothesis. The dependent variable for these results is the number of upward revisions over the 1-year period as a percentage of the number of total forecasts over the year. For a description of hedging variables please refer to Table 4, and for a description of the other independent variables, please refer to Table 2.

Panel A: Results of OLS regressions, using binary variables for hedging variables, where the upward revisions for the 1-year forecasts is the dependent variable.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.09237 (2.77)***	0.09382 (2.78)***	0.09865 (2.94)***
Interest Rate Hedging	-0.01733 (-2.49)**	- -	- -
Currency Hedging	- -	-0.01638 (-2.17)**	- -
Total Hedging	- -	- -	-0.01223 (-1.57)
lnsales	0.00259 (0.64)	0.00228 (0.55)	0.00174 (0.42)
tanratio	0.00208 (0.10)	-0.00237 (-0.12)	-0.00058629 (-0.03)
stdratiq	-0.00036912 (-0.07)	-0.00012263 (-0.02)	-0.00057050 (-0.11)
d96	-0.02116 (-2.42)**	-0.01828 (-2.05)**	-0.01758 (-2.00)**
d97	-0.01057 (-1.21)	-0.01183 (-1.35)	-0.01013 (-1.16)
d98	-0.03478 (-3.57)***	-0.03369 (-3.43)***	-0.03375 (-3.47)***
dindser	0.00126 (0.10)	0.00170 (0.13)	0.00283 (0.22)
dindmauf	0.02386 (2.19)**	0.02927 (2.58)**	0.02594 (2.34)**
leverage	0.03344 (1.19)	0.02654 (0.97)	0.02845 (1.02)
profit	-0.06220 (-1.29)	-0.05404 (-1.13)	-0.05734 (-1.20)
pb	-0.00096474 (-1.38)	-0.00092198 (-1.39)	-0.00112 (-1.61)
prefequi	0.06696 (0.36)	0.15243 (0.98)	0.12611 (0.81)
numbesti	0.00114 (2.23)**	0.00119 (2.29)**	0.00120 (2.33)**
R^2	0.0550	0.0548	0.0515
Sample Size	734	730	738

Panel B: Results of OLS regressions, using continuous variables for hedging variables, where the upward revisions for the 1-year forecasts is the dependent variable.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.10638 (3.22)***	0.11092 (3.32)***	0.10627 (3.14)***
Interest Rate Hedging	0.00023927 (0.08)	- -	- -
Currency Hedging	- -	0.09186 (2.89)***	- -
Total Hedging	- -	- -	0.00121 (0.41)
lnsales	0.00110 (0.27)	-0.00100 (-0.25)	0.00065798 (0.16)
tanratio	0.00034284 (0.02)	0.00078374 (0.04)	0.00390 (0.19)
stdratiq	-0.00094285 (-0.18)	-0.00093303 (-0.18)	-0.00091564 (-0.18)
d96	-0.02054 (-2.34)**	-0.01850 (-2.08)**	-0.01981 (-2.20)**
d97	-0.00982 (-1.12)	-0.01170 (-1.34)	-0.01110 (-1.25)
d98	-0.03400 (-3.48)***	-0.03342 (-3.41)***	-0.03389 (-3.39)***
dindser	0.00271 (0.21)	0.00655 (0.51)	0.00408 (0.31)
dindmauf	0.02162 (1.98)**	0.02212 (2.02)**	0.02286 (2.04)**
leverage	0.01818 (0.66)	0.02274 (0.84)	0.01728 (0.61)
profit	-0.05812 (-1.21)	-0.04032 (-0.84)	-0.06486 (-1.33)
pb	-0.00102 (-1.46)	-0.00090313 (-1.36)	-0.00096897 (-1.38)
prefequi	0.08922 (0.48)	0.18382 (1.18)	0.09071 (0.48)
numbesti	0.00104 (2.03)**	0.00116 (2.25)**	0.00117 (2.20)**
R^2	0.0469	0.0595	0.0489
Sample Size	734	730	709

TABLE 9: OLS Results Using the Number of Downward Revisions as the Dependent Variable

This table reports the results from the OLS regressions, testing for the influence of hedging on the number of downward revisions for the 1-year forecasts. Our sample consists of S&P 500 non-financial firms as of January 1995.The same firms are tracked during the sample period, even if any one of them is subsequently removed from the S&P 500 index. The data are obtained from three main data bases: Edgar, I/B/E/S, and Compustat. Panel A and B, show the results of the OLS regressions, testing Hypothesis 4c, which posits that there will be fewer downward revisions for the firms with higher levels of hedging than for those with lower levels (Panel B), or those that do not hedge (Panel A). The results in Panel A are obtained using binary variables for hedging variables. Hedging variables are equal to 1 if there is any evidence that the company is engaging in that kind of hedging activities, and 0 otherwise. Panel B shows the results of the OLS regressions, using continuous variables for the hedging variables. Negative coefficient estimates for the hedging variables in either of the two panels would support this hypothesis. The dependent variable for these results is the number of downward revisions over the 1-year period as a percentage of the number of total forecasts over the year. For a description of hedging variables please refer to Table 4, and for a description of the other independent variables, please refer to Table 2.

Panel A: Results of OLS regressions, using binary variables for hedging variables, where downward revisions for the 1-year forecasts is the dependent variable.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.01617 (0.44)	0.01991 (0.54)	0.02279 (0.62)
Interest Rate Hedging	0.00052862 (0.07)	- -	- -
Currency Hedging	- -	0.01047 (1.26)	- -
Total Hedging	- -	- -	0.01006 (1.18)
lnsales	0.00407 (0.92)	0.00335 (0.74)	0.00349 (0.76)
tanratio	0.08923 (4.05)***	0.10631 (4.76)***	0.09399 (4.25)***
stdratiq	0.00228 (0.41)	0.00196 (0.35)	0.00207 (0.37)
d96	0.01515 (1.57)	0.01395 (1.42)	0.01393 (1.44)
d97	0.01890 (1.96)*	0.02065 (2.14)**	0.02115 (2.20)**
d98	0.04134 (3.86)***	0.04055 (3.75)***	0.04221 (3.94)***
dindser	0.06117 (4.39)***	0.06063 (4.29)***	0.05804 (4.16)***
dindmauf	0.05077 (4.24)***	0.04754 (3.83)***	0.04599 (3.79)***
leverage	-0.05924 (-1.90)*	-0.07203 (-2.39)**	-0.07128 (-2.33)**
profit	0.00218 (0.04)	-0.00253 (-0.05)	0.00608 (0.12)
pb	-0.00056722 (-0.74)	-0.00050528 (-0.69)	-0.00046733 (-0.61)
prefequi	-0.10864 (-0.53)	-0.21478 (-1.26)	-0.16827 (-0.99)
numbesti	-0.00005629 (-0.10)	-0.00018093 (-0.31)	-0.00019822 (-0.35)
R^2	0.0603	0.0684	0.0630
Sample Size	735	730	738

Panel B: Results of OLS regressions, using continuous variables for hedging variables, where the downward revisions for the 1-year forecasts is the dependent variable.

Variables	Full Sample		
	Interest Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.01675 (0.46)	0.01426 (0.39)	0.02027 (0.55)
Interest Rate Hedging	-0.00319 (-0.98)	- -	- -
Currency Hedging	- -	0.02167 (0.62)	- -
Total Hedging	- -	- -	-0.00302 (-0.93)
lnsales	0.00434 (0.99)	0.00392 (0.87)	0.00313 (0.69)
tanratio	0.08852 (4.02)***	0.10551 (4.73)***	0.09598 (4.24)***
stdratiq	0.00227 (0.40)	0.00249 (0.44)	0.00236 (0.42)
d96	0.01538 (1.60)	0.01392 (1.42)	0.01407 (1.43)
d97	0.01907 (1.98)**	0.02070 (2.14)**	0.01780 (1.82)*
d98	0.04151 (3.88)***	0.04054 (3.74)***	0.04053 (3.70)***
dindser	0.06079 (4.37)***	0.05996 (4.24)***	0.06301 (4.38)***
dindmauf	0.05082 (4.26)***	0.05132 (4.26)***	0.05384 (4.40)***
leverage	-0.06178 (-2.03)**	-0.06890 (2.29)**	-0.05713 (-1.84)*
profit	0.00221 (0.04)	0.00374 (0.07)	0.00158 (0.03)
pb	-0.00057699 (-0.75)	-0.00048236 (-0.66)	-0.00057555 (-0.75)
prefequi	-0.10637 (-0.52)	-0.21661 (-1.26)	-0.13858 (-0.67)
numbesti	-0.00010638 (-0.19)	-0.00009757 (-0.17)	-0.00011470 (-0.20)
R^2	0.0616	0.0668	0.0617
Sample Size	735	730	710

TABLE 10: OLS Results for the December and Non-December Samples

This table reports the results from the OLS regressions, testing for the influence of hedging on the analysts' forecast accuracy, using two different samples: one that consists of companies having fiscal years ending in December, and another that consists of companies having fiscal years ending in another month of the year. Our sample consists of S&P 500 non-financial firms as of January 1995.The same firms are tracked during the sample period, even if any one of them is subsequently removed from the S&P 500 index. The data are obtained from three main data bases: Edgar, I/B/E/S, and Compustat. Panel A and B, show the results of the OLS regressions, testing Hypothesis 5, which posits that analysts will provide more accurate forecasts for firms with December fiscal year end than for those with Non-December fiscal year end. Panel A provides the results for the 1-year forecasts, using the difference between forecast and actual earnings divided by the closing price at the end of the fiscal year. Panel B provides the same type of results, but using the difference between forecast and actual earnings divided by the actual earnings. For a description of hedging variables please refer to Table 4, and for a description of the other independent variables, please refer to Table 2.

Panel A: Results from OLS regressions, using continuous variables for hedging variables, and the forecast error for the 1-year forecasts divided by the closing price as the dependent variable.

Variables	December Fiscal Year End			Non-December Fiscal Year End		
	Int. Rate Hedging	Currency Hedging	Total Hedging	Int. Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.00551 (1.01)	0.00556 (1.01)	0.00545 (0.98)	0.00517 (0.68)	0.00715 (0.93)	0.00737 (0.96)
Interest Rate Hedging	0.00620 (0.78)	- -	- -	-0.00031374 (-0.84)	- -	- -
Currency Hedging	- -	0.00678 (1.49)	- -	- -	0.00294 (0.23)	- -
Total Hedging	- -	- -	0.00582 (1.56)	- -	- -	-0.00030436 (-0.81)
lnsales	-0.00054373 (-0.83)	-0.00063898 (-0.95)	-0.00070263 (-1.03)	-0.00154 (-1.57)	-0.00187 (-1.91)*	-0.00177 (-1.79)*
tanratio	0.01393 (4.31)***	0.01596 (4.95)***	0.01555 (4.70)***	0.02003 (3.95)***	0.01919 (3.72)***	0.01857 (3.64)***
stdratiq	0.00045745 (0.22)	0.00026256 (0.13)	0.00040326 (0.19)	0.00031228 (0.47)	0.00033196 (0.50)	0.00032059 (0.48)
d96	-0.00087042 (-0.62)	-0.00080861 (-0.57)	-0.00101 (-0.71)	-0.00010629 (-0.05)	-0.00011881 (-0.06)	-0.00008390 (-0.04)
d97	-0.00164 (-1.17)	-0.00131 (-0.94)	-0.00183 (-1.29)	-0.00125 (-0.62)	-0.00138 (-0.67)	-0.00133 (-0.65)
d98	0.00568 (3.55)***	0.00653 (4.10)***	0.00595 (3.64)***	0.00309 (1.43)	0.00276 (1.26)	0.00282 (1.29)
dindser	0.00429 (1.94)*	0.00464 (2.11)**	0.00508 (2.21)**	0.00480 (1.46)	0.00406 (1.20)	0.00382 (1.13)
dindmauf	0.00965 (5.80)***	0.01009 (6.09)***	0.01032 (6.07)***	0.00828 (2.59)**	0.00742 (2.27)**	0.00745 (2.30)**
leverage	0.00213 (0.47)	0.00047188 (0.11)	0.00152 (0.34)	0.00687 (0.88)	0.00899 (1.16)	0.00799 (1.02)
profit	-0.04106 (-5.40)***	-0.04334 (-5.78)***	-0.04032 (-5.24)***	-0.02388 (-1.93)*	-0.02128 (-1.71)*	-0.02178 (-1.76)*
pb	-0.00009055 (-0.82)	-0.00008278 (-0.81)	-0.00008735 (-0.79)	-0.00028162 (-1.47)	-0.00029484 (-1.54)	-0.00029071 (-1.52)
prefequi	0.05973 (2.19)**	0.02513 (1.14)	0.05874 (2.14)**	-0.00262 (-0.03)	-0.06220 (-0.53)	-0.06092 (-0.52)
numbesti	-0.00006565 (-0.77)	-0.00003600 (-0.41)	-0.00006099 (-0.68)	0.00020482 (1.69)*	0.00023516 (1.93)*	0.00022599 (1.86)*
R^2	0.1831	0.1927	0.1947	0.1553	0.1441	0.1467
Sample Size	513	515	494	220	214	214

Panel B: Results of OLS regressions, using continuous variables for hedging variables, and the forecast error for the 1-year forecasts divided by the actual earnings as the dependent variable.

Variables	December Fiscal Year End			Non-December Fiscal Year End		
	Int. Rate Hedging	Currency Hedging	Total Hedging	Int. Rate Hedging	Currency Hedging	Total Hedging
Intercept	0.11977 (1.34)	0.06584 (0.72)	0.10249 (1.12)	0.16212 (1.19)	0.16262 (1.19)	0.17243 (1.26)
Interest Rate Hedging	0.08156 (0.63)	- -	- -	-0.00860 (-1.28)	- -	- -
Currency Hedging	- -	0.01476 (0.19)	- -	- -	0.24543 (1.06)	- -
Total Hedging	- -	- -	0.03073 (0.50)	- -	- -	-0.00874 (-1.30)
lnsales	-0.01871 (-1.76)*	-0.01141 (-1.02)	-0.01763 (-1.58)	-0.01544 (-0.88)	-0.01764 (-1.01)	-0.01461 (-0.83)
tanratio	0.12545 (2.36)**	0.16817 (3.08)***	0.14474 (2.64)***	0.19257 (2.12)**	0.20865 (2.26)**	0.17985 (1.97)*
stdratiq	-0.00041439 (-0.01)	-0.00276 (-0.08)	-0.00077178 (-0.02)	0.00275 (0.23)	0.00278 (0.23)	0.00257 (0.21)
d96	0.02549 (1.11)	0.02707 (1.14)	0.02455 (1.04)	0.00632 (0.17)	0.00502 (0.14)	0.00575 (0.16)
d97	0.00970 (0.42)	0.01604 (0.69)	0.00698 (0.30)	0.03758 (1.03)	0.03032 (0.82)	0.03165 (0.86)
d98	0.13740 (5.24)***	0.15049 (5.62)***	0.14004 (5.21)***	0.14551 (3.75)***	0.14759 (3.77)***	0.14846 (3.80)***
dindser	0.12149 (3.37)***	0.11577 (3.13)***	0.13767 (3.65)***	0.04508 (0.78)	0.03687 (0.62)	0.02701 (0.46)
dindmauf	0.12961 (4.78)***	0.13728 (4.95)***	0.13657 (4.90)***	0.06862 (1.22)	0.05300 (0.92)	0.05861 (1.02)
leverage	0.08473 (1.16)	0.03320 (0.45)	0.08120 (1.09)	-0.07693 (-0.54)	-0.05852 (-0.42)	-0.07556 (-0.54)
profit	-0.51718 (-4.19)***	-0.56330 (-4.49)***	-0.52515 (-4.16)***	-0.40627 (-1.84)*	-0.35665 (-1.60)	-0.38759 (-1.75)*
pb	0.00106 (0.58)	0.00056464 (0.33)	0.00105 (0.57)	-0.00020381 (-0.06)	-0.00019060 (-0.06)	-0.00030514 (-0.09)
prefequi	1.02099 (2.39)**	0.45824 (1.26)	0.96749 (2.23)**	2.68072 (1.52)	1.35886 (0.64)	1.27298 (0.61)
numbesti	0.00154 (1.11)	0.00164 (1.13)	0.00142 (0.97)	0.00296 (1.36)	0.00302 (1.39)	0.00301 (1.39)
R^2	0.1473	0.1437	0.1513	0.1456	0.1369	0.1395
Sample Size	516	517	497	218	213	213