Derivatives Use and Analysts' Earnings Forecast Accuracy

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Abstract

This paper examines whether the use of derivatives improves firms' information environment, which is a relatively under-investigated research area in risk management literature. Using a sample of French non-financial listed firms, we show that firms which use derivatives enjoy high levels of forecast accuracy relative to firms that do not. This result is in accord with the arguments developed by DeMarzo and Duffie (1995) and Breeden and Vishwanathan (1998) suggesting that hedging is an important means of reducing information asymmetry.

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1 – Introduction

Modigliani and Miller (1958, MM hereafter) show that in a world with perfect capital markets, the value of the firm is independent of its capital structure and depends only on investment decisions. In other words, financing decisions do not affect firm value. This theorem, originally applied to capital structure, can be extended to various other contexts, including risk management. A firm cannot create value by hedging its financial risks since individual investors can replicate the hedges. However, the oversimplifying nature of the MM (1958) hypothesis has led to the rejection of the irrelevance of financial decisions. Various researches have been carried out to explain rationales behind the corporate hedging behavior.[4] All of them are based on the violation of one or more of the assumptions underlying the MM (1958) model.

In an imperfect capital market -characterized by the presence of agency costs, transaction costs, and taxation- corporate financial risk management is a means to enhance shareholders' value. However, recent huge derivative's losses by Metallgesellschaft, Procter & Gamble, Orange, among others, beg the question of does the use of derivatives actually increase firm value?

There is a large volume of literature that deals with the effects of derivatives use decisions on firm value. In one side, there are many reasons to believe that using derivatives decreases firm value. First, Copeland and Joshi (1996) and Hagelin and Pramborg (2004) explain that risk management programs can be ineffective in reducing risk. If that is the case, hedging may decrease firm value. Second, the conception and implementation of risk management programs based on the use of derivatives can be costly for firms since they require important financial and human resources. Hence, if a hedging program does not generate enough value to offset the settled costs, it will negatively impact firm value. Finally, derivatives may decrease value if they are used for speculation, which, in principle, increases exposure and leads to loss of value.

[4] Various seminal papers have dealt with this issue including Stulz (1984; 1990), Smith and Stulz (1985), DeMarzo and Duffie (1991), Froot et al. (1993) and Breeden and Viswanathan (1998).

In the other side, hedging can increase shareholders' value. Indeed by hedging, companies can reduce various costs caused by highly volatile cash flows including financial distress costs (Mayer and Smith (1982), Smith and Stulz (1985)) and amounts of tax paid by corporations (Smith and Stulz (1985)). Ross (1997) and Leland (1998) show that through hedging; firms can reduce the likelihood of financial distress and hence increase their debt capacity and the associated tax advantages.

The above-mentioned arguments show that there is no unique effect of derivatives use on firm value, which is per se an important reason to study this relationship. In this paper we aim to empirically examine whether hedging is a value enhancing activity through the improvement of the firm's information environment as explained in the existing theoretical literature. Indeed, if hedging decreases noises in earnings it mitigates the adverse selection problem, which contributes to the costliness of external financing. Consequently, the reduction of asymmetric information -through the use of derivatives- would increase the likelihood that firms fund their projects at lower costs.

DeMarzo and Duffie (1991) argue that the use of derivatives for hedging can mitigate the agency problems between shareholders and managers when the former are uninformed about the risks of the firm's future cash flows. Specifically, hedging can be profitable for shareholders when the benefits of reducing information asymmetry about a firm's prospects exceed the costs of implementing a hedging strategy. DeMarzo and Duffie (1995) and Breeden and Viswanathan (1998) explore the relationship between hedging and asymmetric information using models in which shareholders learn about the quality of a firm's management by observing its operating performance. Through hedging, managers can reduce "noises" in earnings due to macroeconomic factors such as the fluctuations of exchange rates, interest rates and commodity prices. Noise in this context refers to factors contributing to earnings that are believed to be beyond managerial control. Thus, by reducing the impact of these factors, hedging can have two informational effects. Firstly, it better signals managerial capacities, which improves the quality of the information received by shareholders and hence the informativeness of corporate earnings. Secondly, the information revealed by profits, typically, affects managerial reputation and, thus, their current and future compensation.

In addition to high-quality managers, the reduction of information asymmetry, as a result of the implementation of a hedging program, benefits the firm, *per se*, because it has an indirect effect on the adopted investment and financing strategies. The presence of information asymmetry regarding a firm's earnings capacity leads to an adverse selection problem that makes external financing more costly than internally generated funds (see Myers and Majluf, 1984). Consequently, firms may have to give up some profitable projects. Froot et al. (1993) argue that both investment and financing decisions can be disrupted by an unfavorable cash flow variation because the lack of internal financing constrains firms to either give up positive NPV projects or to raise costly outside capital. They suggest that risk management may alleviate this under-investment problem. The importance of hedging, in this case, is to allow the redistribution of cash flows from states of cash surplus to states of cash shortfall. In addition, since hedging can alleviate the adverse selection problem, by reducing the information asymmetry between managers and shareholders, it can also decrease external fund costs.

Smith and Stulz (1985) prove, theoretically, that hedging may increase the expected firm value through the reduction of the probability that a firm faces financial distress costs. Smith and Stulz (1985) and Bessembinder (1991) show that hedging may also reduce the deadweight costs due to restrictive debt contract covenants that constrain the execution of the firm's plans. In this context, the improvement of earnings informativeness may reassure creditors about the actual financial situation of the firm. Consequently, the firm will benefit from an increase of debt capacity and tax shields.

Several empirical studies have investigated the rationale for hedging by examining the link between risk hedging and information asymmetry. Tufano (1996), Géczy et al. (1997), Haushalter (2000) and Graham and Rogers (2002), for example, find that firms' use of derivatives is positively associated with analyst coverage, institutional holdings, number of blockholders and market value of shares held by the largest outside blockholders. To the best to our knowledge, Dadalt et al. (2002) is the only study so far that investigates the effects of derivatives use on analysts' forecast quality proxied by analyst forecast accuracy and dispersion of analyst forecasts. They show that analysts' earnings forecasts are significantly more accurate and less dispersed for firms using currency derivatives.[5]

The contribution of this paper is threefold. First, this research sheds additional light on the effect of derivatives use on the quality of analysts' earnings forecasts. We provide support for the hypothesis that the use of derivatives improves the information environment of the firm proxied by the analysts' forecast errors. This theoretical hypothesis was examined only by Dadalt et al. (2002). Second, we use a sample of French non-financial listed firms for the years 1999 and 2000. The French data are suited for this study. France is one of the most important trading nations in the world (especially in the Eurozone), measured by the gross domestic product (GDP). France had the second-largest economy in the Eurozone and the 5th largest in the world.[6] It also has a large number of firms with substantial foreign operations. Thus, it will be important to study hedging decisions in France. Third, we make sure that our results are not plagued by endogeneity problems and are robust to the control for self-selection bias.

The remainder of the paper proceeds as follows. Section 2 provides the theoretical framework and develops the hypotheses. Section 3 describes the sample and discusses the variables used in the study. Section 4 reports the empirical analysis. Section 5 checks the robustness of the results. Section 6 concludes the paper.

2 - Hypothesis development and literature review

DeMarzo and Duffie (1991) show that, in the presence of information asymmetry, a hedging strategy, even when it is costly, can be profitable for both firms and shareholders.[7] The main assumption of their model is that a

[5] Contrariwise, Nguyen et al. (2010) use a sample of Australian firms covered over a four-year period 2002–2005 to examine the returns following insiders' transactions. They find that insiders in firms using derivatives make larger gains than insiders in non-user firms, which means that financial derivatives' use is associated with higher levels of information asymmetry.
[6] See United Nations Statistics Division http:/ /unstats.un.org.
[7] DeMarzo and Duffie (1991) assume in their model that there are no agency problems between managers and shareholders.

firm communicates only a small portion of the information to its shareholders to preserve the value of proprietary information. They argue that if shareholders are fully and perfectly informed about risk exposure of the firm, they will take appropriate decisions to manage their own portfolio risk. Consequently, there will be no additional value of the firm's hedging policy.

Another motivation for hedging, based on managerial career concerns, is described by DeMarzo and Duffie (1995). Their model stresses the informational effect of hedging on managers' reputation. It is built in an environment in which uncertainty regarding managerial skills makes it difficult for outsiders to disentangle profits due to managerial ability from those due to exogenous market factors. Consequently, high-quality managers will be motivated to hedge to allow the labor market to discover their superior abilities. Indeed, through hedging, managers can reduce the "noise" in earnings. Noise, in this context, refers to factors contributing to earnings that are deemed to be beyond managerial control such as macroeconomic factors (exchange rates, interest rates, commodity prices and so on). Thus, by reducing the impact of these factors, hedging can improve the quality of information received by outsiders and increase the informativeness of earnings as an indicator of management quality. The information effect of hedging has two natural consequences. First, it affects the value of the shareholders' option to continue or abandon the investment project (DeMarzo and Duffie, 1995). Second, it affects the reputation and the future compensation of incumbent managers.

Breeden and Viswanathan (1998) draw upon similar reasoning to explain the information benefits of hedging. They provide a theoretical model where the rationale for hedging stems from managerial responses to asymmetric information. In their model, firm profits result from two elements namely managerial skills and factors beyond managerial control. In order to eliminate the "noise" in profits stemming from uncontrollable risks, high-quality managers resort to hedging activities. They are more inclined to use hedging to "lock-in" their superior ability. Breeden and Viswanathan (1998) demonstrate the existence of a separating equilibrium where a firm's decision to hedge or not depends on the differences in abilities between high- and low-quality managers. The equilibrium implies that high-quality managers hedge only when there is a sufficient difference in abilities and hedging costs are high. However, when the abilities of both kinds of managers are not sufficiently different, the equilibrium involves no hedging. Authors clarify that the separation occurs notably when the costs of hedging are sufficiently high.[8]

Derivatives use may increase firm value as a result of the mitigation of information asymmetry. This was extensively analyzed in the finance literature. Seminal papers by Grossman and Hart (1981), Myers and Majluf (1984) and Fazzari et al. (1988) postulate that information asymmetry between firms and outsiders can lead to costly external finance. Flannery (1986) and Diamond (1991) explore how asymmetric information affects lenders in their choice of financial conditions imposed on borrowers. They show that when outside investors are imperfectly informed about a firm's actual situation, they cannot differentiate risky firms from safer ones. Consequently, they will ask for default-risk premiums on long-run debt that may seem excessive to safe borrowers. Contrariwise, managers of firms with high risk levels recognize the existence of a high probability that firm's financial conditions will deteriorate, which may explain their preference for long-run debt over short-run debt.

The empirical framework of Dadalt et al. (2002) supports the conjectures of DeMarzo and Duffie (1995) and Breeden and Viswanathan (1998). It reports improvements in analysts' forecast accuracy and consensus for firms using derivatives, especially currency derivatives. The above-mentioned theoretical and empirical arguments lead to the testable hypothesis that the use of derivatives reduces information asymmetry.

H – The magnitude of analysts' forecast errors decreases with the use of derivatives.

[8] The hedging costs in the model of Breeden and Viswanathan (1998) represent the risk reduction induced by the decrease of the "equity option" value arising from the existence of debt or loan guarantees.

3 - Data and empirical design

3.1 - Sample description

We analyze hedging practices of French non-financial listed firms belonging to the SBF 250 index covered over the 1999–2000 period.[9] This period is well suited to study the effect of derivatives use on the quality of information conveyed to the financial market. Indeed, the beginning of 1999 marks transition to euro, which dramatically reduced foreign exchange currency rate exposure within Europe making our sampled firms more homogenous with respect to risk management activities.

The choice of the SBF 250 index firms is motivated by the fact that these firms are large and used to provide more detailed and comprehensive financial information in their annual reports. This is important because French firms are not compelled to disclose information on risk management practices in the notes to the financial statements.[10] We start from a sample of French firms belonging to the SBF250 covered over the 1999-2000 period. Consistent with extant researches in the field, we discard financial firms (SIC 6000–6999) since they use derivatives for both hedging and trading purposes. Foreign companies were also excluded because they are subjected to different regulations and use different accounting principles. We also remove firms that do not report information on financial risk exposure and risk management policy (operational hedging or derivatives uses). Following this procedure, we end up with 262 observations from 1999 and 2000.

Data used to compute analysts' earnings forecast accuracy is retrieved from the Institutional Brokers Estimate System (I/B/E/S) international

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[9] Information on derivatives' use was manually collected from firms' annual reports due to the absence of any readily available database.

[10] SFAS 105 requires all US listed firms to report information about financial instruments with off-balance sheet risk (e.g. futures, forwards, options and swaps) for fiscal years ending after 15 June 1990. In particular, firms must report the face, contract or notional amount of the financial instrument together with information on the credit and market risk of those instruments and the related accounting policy.

database. Only four firms are not covered by I/B/E/S. Consequently, our final sample contains 258 firm-year observations (124 firms for 1999 and 134 firms

for 2000). Accounting and financial data were retrieved from the Worldscope database. All data are as of fiscal year-end. Table 1 provides summary statistics for the sample. Panel A presents the industry classification of the sampled firms using Campbell's (1996) classification. It is clear that the sample

spreads across 11 industries and firms belonging mainly to services (17.44%), consumer durable (16.67%), basic industry (13.95%) and textiles and trade (13.57%) sectors.

Panel B in Table 1 portrays descriptive statistics of some characteristics of the firms in the sample. The average firm market value is about €7,794 million. Book value of total debt averages €2,492 million and ranges from zero to €63,254 million. Firms have average total assets of €8,115 million, ranging from €20 million to €150,737 million. Capital expenditures are on average equal to €596 million and vary from zero to €36,005 million. Finally, the firms have an average turnover of €6,129 million with a minimum equal to €5,61 million and a maximum of €114,556 million.

Table 2 describes the extent of derivatives use. As shown in Panel A of this table, about 87% of total sampled firms use some kind of derivatives.

Table 1: Sample description

<u>Panel A: Descriptive statistics of the sample</u>

Values in millions of euros

Panel A: Industry classification of the sample firms using Campbell (1996) classification

Industry	SIC codes	Number of observations	Percentage of total
Petroleum	13, 29	6	2.33
Consumer durables	25, 30, 36, 37, 50, 55, 57	43	16.67
Basic industry	10, 12, 14, 24, 26, 28, 33	36	13.95
Food and tobacco	1, 2, 9, 20, 21, 54	15	5.81
Construction	15, 16, 17, 32, 52	16	6.20
Capital goods	34, 35, 38	16	6.20
Transportation	40, 41, 42, 44, 45, 47	9	3.49
Utilities	46, 48, 49	12	4.65
Textiles and trade	22, 23, 31, 51, 53, 56, 59	35	13.57
Services	72, 73, 75, 76, 80, 82, 87, 89	45	17.44
Leisure	27, 58, 70, 78, 79	25	9.69
Total		258	100.00

This Panel displays the distribution for sample firms using Campbell's (1996) classification. The sample consists of 258 firm-year observations belonging to the French SBF 250 index over the 1999-2000 period (124 firms for 1999 and 134 firms for 2000). Financial data is for consolidated firms, obtained from Worldscope and firms' annual reports. All data are as of the end of fiscal year.

Salma Mefteh-Wali, Sabri Boubaker, Florence Labégorre –
Derivatives Use and Analysts' Earnings Forecast Accuracy –
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Panel B: Descriptive statistics of the sample

Variable	Min	Q1	Median	Mean	Q3	Max
Market value of shares (M€)	45.043	347.965	1,023.753	7,793.682	5,229.931	134,514.449
Total debt(M€)	0.000	65.902	283.531	2,492.362	1,453.182	63,253.791
Total assets(M€)	20.146	408.967	1,327.908	8,114.640	7,147.001	150,737.402
Capital expenditures(M€)	0.000	17.123	74.530	596.546	310.957	36,005.876
Sales revenue(M€)	5.610	379.140	1,162.205	6,129.026	6,920.385	114,556.622
ERROR	0.000	0.002	0.009	0.023	0.013	0.889
LDEBT	0.000	0.036	0.156	0.338	0.410	4.874
MB	0.474	1.469	2.819	5.073	6.077	82.553
SIZE	16.818	19.818	21.029	21.189	22.703	25.739
DIVERS	1.000	2.000	3.000	3.609	5.000	8.000
SURPRISE	0.000	0.005	0.016	0.028	0.0332	0.281
XLIST	0.000	0.000	0.000	0.271	1.000	1.000
VOL	0.000	0.0005	0.0006	0.001	0.0007	0.005
CORR	0.019	1.223	5.312	7.100	8.006	43.377

This Panel reports summary statistics for firm characteristics for a sample of 258 firm-year observations. ERROR is the absolute difference between the median of forecasted earnings and actual earnings deflated by the stock price. LDEBT is the ratio of book value of long term debts over market value of equities. MB is the market value of equity plus the book value of debt all divided by the book value of total assets. DIVERS is the number of business segments in which the firm operates at the two-digit Standard Industrial Classification level. SURPRISE is the absolute difference between current earnings per share and earnings per share from the precedent year, divided by the mean of firm's stock price over the current fiscal year. XLIST is a dummy variable that takes on the value 1 if the firm is cross-listed on another stock exchange and 0 otherwise. VOL is the standard deviation of stock returns over the last three fiscal years. CORR is the correlation between earnings and returns over the last three fiscal years.

Table 2: Exposure and derivatives use

Panel A: Number of derivatives users and non-users

	Total		1999		2000	
	Number of firms	Percentage of total	Number of firms	Percentage of total	Number of firms	Percentage of total
Total sample	258	100	124	100	134	100
Derivatives users	225	87.21	109	87.9	117	87.31
Non users	33	12.79	15	12.1	17	12.69

Panel B: Extent of derivatives use

	All Firms	1999	2000
Number of observations	258	124	134
Minimum	0	0.0000	0.0000
Q1	0.0141	0.0181	0.0162
Mean	0.2277	0.2021	0.2159
Median	0.0962	0.1067	0.0952
Q3	0.2869	0.2534	0.3105
Maximum	2.2649	2.1205	1.8878
Standard deviation	0.3377	0.2904	0.2955

Table 2 describes the exposure (Panel A) and the extent of derivatives use (Panel B) by year for the sample firms. The extent of derivatives use is calculated as the total derivative notional value deflated by firm value.
The minimum value of 0 percent is applicable to derivatives' users indicates that firms use derivatives to hedge their exposures but at the end of fiscal year there are no outstanding contracts.

3.2 - Empirical design and control variables

If financial risk management has information effects, we expect to see a significant relationship between derivatives use and the characteristics of the information environment of the firm. More precisely, lower derivatives use would be associated with large forecast errors and more analyst disagreements. To examine the relation between derivatives use and information asymmetry, we regress analysts' forecast errors on the use of derivatives. The hypothesis predicts that the use of derivatives decreases information asymmetry. The relationship between derivatives use ratios and information asymmetry measure (FOR-ERROR) would be negative.

In order to draw appropriate inferences regarding the effect of derivatives use on the analysts' earnings forecast quality, we have to control for other factors that may impact forecast characteristics. As such, we follow the models used in Lang and Lundholm (1993, 1996), Lang et al. (2003), Thomas (2002) and Dadalt et al. (2002) and estimate OLS regression models of the following forms:

$$ERROR = \beta_0 + \beta_1\, DERIV + \beta_2\, (Control\ variables) + \beta_3\, (Year\ dummy) + \beta_4\, (Industry\ dummies) + \varepsilon_i \quad (1)$$

$$ERROR = \beta_0 + \beta_1\, NOTION + \beta_2\, (Control\ variables) + \beta_3\, (Year\ dummy) + \beta_4\, (Industry\ dummies) + \varepsilon_i \quad (2)$$

where DERIV is a dummy variable that takes the value of one if the firm uses derivatives and zero otherwise. NOTION is defined as the notional amount of derivatives outstanding at fiscal year-end deflated by the market value of the firm.

To be in the spirit of DeMarzo and Duffie (1995) and Breeden and Vishwanathan (1998), we use analysts' earnings forecasts to proxy for information asymmetry[11]. As previously advanced, the direct link between information asymmetry and derivatives use has not been extensively examined. In this paper, we study this relation with one measure of information asymmetry as in Krishnaswami and Subramaniam (1999): the analysts' forecast error. Firms with high information asymmetry between managers and outsiders concerning earnings should exhibit larger analysts' forecast errors.

Our proxy for the degree of information asymmetry, the analysts' forecast errors (ERROR), is defined as the absolute difference between the median of forecasted earnings ($EPS_{FORECAST}$) and actual earnings (EPS_{ACT}) deflated by the stock price (winsorized at the 98th percentile):

$$ERROR = \left| \frac{EPS_{FORECAST} - EPS_{ACT}}{Stock\ \mathrm{Pr}ice} \right|$$

3.3 - Control Variables

Firm Size

Prior research argues that the availability of information increases with firm size. Larger firms have generally more analysts following them (Bhushan, 1989, Brennan and Hughes, 1991) and more detailed disclosure policies (Lang and Lundholm, 1996). More information should lead to a convergence of opinions. Consequently, we expect lower forecast errors for large-sized firms. On the other hand, firm size may be correlated to the use of derivatives. Indeed, empirical evidence has frequently reported that larger firms are those that hedge. This is due to high start-up costs necessary to set up hedging programs (Nance et al., 1993, Mian, 1996 and Géczy et al., 1997). To control for size effects, we include the natural logarithm of the firm market value as a proxy for firm size.

[11] The forecast error is used as a proxy to capture information asymmetry. This is justified by the findings of Blackwell and Dubins (1962) who demonstrate that when the amount of available information about an unknown event decreases, public opinion tends to diverge.

Volatility

Lang and Lundholm (1996) show that high return variance discourages analysts from following firms. The advanced explanation of this result is that analysts prefer avoiding firms where it is difficult to make precise forecasts. Alford and Berger (1999) argue that the volatility of stock prices signals new information about the firm. They argue that when volatility increases, the quantity of information that analysts must process increases too. Thus, it will be more difficult for analysts to forecast earnings. We can expect that high earnings variance is associated with larger forecast errors. To control for this volatility effect, we include VOL, the standard deviation of daily returns over the last three fiscal years in all our regressions.

Return-earnings correlation

Literature dealing with analysts' forecasts quality uses, as a determinant, the return-earnings correlation. Lang et al. (2003) find that return-earnings correlation positively affects the number of analysts following a firm and the accuracy of their forecasts. They conclude that analysts are less motivated to follow firms with low return-earnings correlation because this low correlation reduces the potential returns to forecasting earnings. To control for return-earnings correlation, we use the correlation between earnings and returns over the last three fiscal years (CORR).

Diversification

Following diversified firms constrains analysts to spend more time and resources to learn about industries that may be outside their area of expertise. Dunn and Nathan (1998) report that earnings forecasts of an individual analyst are less accurate when the number of diversified firms he or she follows increases. They conclude that due to limited time and resources, the effectiveness of individual analysts in processing and understanding large amounts of complex information about diversified firms is reduced. Hence, diversification seems to reduce the accuracy of analyst forecasts. To control for this effect, we include the variable DIVERS in all regressions which equals the number of business segments in which the firm operates at the two-digit SIC level. We expect that analyst forecast errors increase with the number of industry segments in which firms operate.

Earnings surprise

As in previous studies, we include earnings surprise in all our regressions since it captures analysts' willingness to gather information and their difficulty to correctly forecast earnings. Its inclusion should mitigate the effect of a substantial deviation of the earnings report from the consensus forecast. Lang and Lundholm (1996) argue that forecast characteristics may be influenced by the magnitude of the new earnings information to be disclosed. For instance, when a firm experiences an important unexpected event, actual earnings may largely depart from those forecasted which worsens the quality of the estimates. We compute earnings surprise, SURPRISE, as the absolute value of the difference between the current earnings per share and the lagged earnings per share, scaled by the firm stock price at the beginning of the fiscal year.

Cross-listing

For a host of reasons, firms that cross-list in the US are believed to have a richer information environment than those that are listed only domestically. Firstly, cross-listed firms need to comply with a bundle of additional disclosure obligations, including the conformance with US generally accepted accounting principles (US GAAP). Secondly, they are subject to the active supervision of the Securities and Exchange Commission (SEC) and are also under high scrutiny from auditors and regulatory watchdogs to deliver timely, accurate and fair data. Furthermore, they are under shareholders' persistent pressure to keep abreast of the firm's actions and activities. This better disclosure policy increases the likelihood of high earnings forecast quality.

Previous empirical findings agree, showing a positive effect of cross-listing on analysts' forecast accuracy. For instance, Baker et al. (2002) and Lang et al. (2003) find that firms that cross-list on the US exchanges have greater analyst coverage and more accurate earnings forecasts. Accordingly, we control for cross-listing by introducing in all regressions a dummy variable XLIST that takes on the value one if the firm is cross-listed on another stock exchange and zero otherwise; and we expect a negative influence of cross-listing on the extent of analyst forecast errors.

Leverage

Since leverage increases earnings volatility, it may imply less forecast accuracy. Alternatively, leverage can also be correlated with derivatives use. As leverage increases the probability of financial distress increases, too. Smith and Stulz (1985) and Bessembinder (1991) argue that heavily indebted firms are motivated to hedge financial risks to reduce the costs of such a distress. To control for the effect of leverage, we include the ratio of book value of long-term debts to the market value of the firm (LDEBT).

Growth opportunities

Thomas (2002) conjectures that it is more difficult for analysts to make forecasts for firms with many future growth opportunities compared to firms with more assets-in-place. Alternatively, Froot et al. (1993) state that high-growth firms are more inclined to hedge financial exposures because they are more likely to suffer from a greater extent of under-investment. We include Market-to-Book ratio (MB) in our regressions because it may affect the level of information asymmetry and it may be correlated with derivatives use. MB ratio is defined as the market value of equity plus the book value of debt all divided by the book value of total assets. [12]

Year and industry dummies

All our regressions include a year-indicator variable to control for additional unobserved heterogeneity. It equals one if the observation is from 1999 and zero otherwise. To control for industry effects, we include industry dummies in all regressions. We classify sampled firms into 11 non-financial separate industries based on Campbell (1996) classification. The leisure industry is considered as the reference industry in our regressions.

4 – The relation between derivatives use and analysts'forecasts error

There are two levels of decisions when considering derivatives use. First, there is a qualitative decision about whether or not to use derivatives.

[12] All continuous control variables are winsorized at the 98th percentile to mitigate the effects of outlier observations.

For hedgers, there is a quantitative second decision regarding the level of hedging. To examine the relationship between the decision to use derivatives and the quality of analysts' earnings forecasts, we first run regressions with a dummy variable (DERIV) that takes the value of one if the firm uses derivatives and zero otherwise. Results of these regressions are reported in the first part of this section. In the second part, we report the regression results of hedging levels using the continuous variable (NOTION), defined as the notional amount of derivatives outstanding at fiscal year-end deflated by the market value of the firm.

The OLS estimates are provided along with significance levels calculated using White (1980) heteroskedasticity-consistent standard errors. The correlations between independent variables are rather weak and do not seem to be at the origin of multicollinearity.[13] For all regressions, we have computed the variance inflation factors (VIF) to test for possible multicollinearity. The VIFs values range between 1.066 and 3.130 by far below the critical value of 10, which indicates the absence of harmful collinearity (Neter et al., 1989).

[13] Table 3 reports the Pearson correlation coefficients among the variables used in the analysis.

Table 3: Correlation matrix

	DERIV	SIZE	LDEBT	DIVERS	SURPRISE	XLIST	MB	VOL	CORR	YEAR
DERIV	1.0000									
SIZE	0.4934 [a]	1.0000								
LDEBT	0.1661 [a]	0.1933 [a]	1.0000							
DIVERS	0.2663 [a]	0.4319 [a]	0.0772	1.0000						
SURPRISE	0.1347 [b]	0.0883 [c]	0.1120 [b]	-0.0261	1.0000					
XLIST	0.0771	0.3159	0.0208	0.1617 [b]	-0.1182 [b]	1.0000				
MB	-0.4121 [a]	-0.3284 [a]	-0.2454 [a]	-0.1903 [a]	-0.1485 [b]	0.0931 [c]	1.0000			
VOL	-0.4443 [a]	-0.2924 [a]	-0.1181 [b]	-0.1942 [a]	-0.0448	0.1827 [b]	0.5689 [a]	1.0000		
CORR	0.0815 [c]	0.5095 [a]	-0.1489 [b]	0.2252 [a]	-0.0759	0.4137 [a]	0.0781	0.1732 [b]	1.0000	
YEAR	-0.0373	0.0195	0.0283	-0.0256	0.0070	0.0018	0.0143	0.1689 [b]	0.0039	1.0000

Table 3 portrays Pearson correlation coefficients between independent variables. DERIV is defined as a dummy variable that equals 1 if the firm uses derivatives and 0 otherwise SIZE is the natural logarithm of the market value of the firm. LDEBT is the ratio of book value of long term debts over market value of equities. DIVERS is the number of business segments in which the firm operates at the two-digit SIC level. SURPRISE is equal to the absolute difference between current earnings per share and earnings per share from the precedent year, divided by the mean of firm's stock price computed over the current fiscal year. XLIST is a dummy variable that takes one the value 1 if the firm is cross-listed on another stock exchange and 0 otherwise. MB is defined as the market value of equity plus the book value of debt all divided by the book value of total assets. VOL is calculated as the standard deviation of returns over the last three fiscal years. CORR is the correlation between earnings and returns over the last three fiscal years. YEAR is a dummy variable that equals to 1 if the observation is from 1999 and 0 otherwise. a, b and c indicate significance at the 1, 5 and 10% levels, respectively.

4.1 - The effect of the decision to use derivatives on analysts' forecasts errors

The key explanatory variable in this model is an indicator variable for the use of derivatives. The regression results are reported in Table 4. They show a statistically significant relationship between the analysts' forecasts errors and five independent variables namely DERIV, SIZE, SURP, XLIST and LDEBT. The adjusted R^2 for the regression model is around 19%, suggesting that the regression explains a significant proportion of the variation in the forecasts errors.

Consistent with evidence reported by Dadalt et al. (2002), the coefficient on the focus dummy variable, DERIV, is negative and statistically significant at 1% level. This finding is consistent with the hypothesis that analysts' forecasts for firms using derivatives are more accurate. It empirically supports the theoretical analysis of DeMarzo and Duffie (1995) and Breeden and Vishwanathan (1998); namely, hedging instruments allow managers to eliminate the "noise" in profits caused by uncontrollable factors which decreases the level of asymmetric information proxied by forecast errors.

The coefficient on the natural logarithm of market value, a proxy for size, is positive and statistically significant at 5% or 10% level depending on the specification. This positive coefficient is not consistent with our prediction that larger firms have more accurate forecasts. This is in contrast with the empirical results of Lang and Lundholm (1996) and Dadalt et al. (2002), but in concordance with Hope (2003). The latter considers that the effect of firm size cannot be predicted clearly because size is also a proxy for many additional factors, including managers' incentives, whose effects on forecast accuracy are unclear. The coefficient of earnings surprise, SURP, is positive and statistically significant at 1% level, which means that analysts' forecasts are less accurate when earnings surprise is important. Dierkens (1991) considers that high earnings surprise exists when outsiders suffer from high levels of information asymmetry or when managers release substantial private information. The coefficient of XLIST is negative and statistically significant, which provides empirical support for Lang et al. (2003) who show that cross-listing improves the accuracy of analysts' forecasts. The coefficient on LDEBT is negative but statistically significant in only one specification indicating that heavily indebted firms are more likely to feature high forecasts quality. This result contrasts with our prediction and is inconsistent with the findings of Dadalt et al. (2002). The negative relationship may be due to the fact that highly leveraged firms are very often mature firms with more assets-in-place to be given as collaterals and thus more predictable earnings (Dadalt et al. (2002)).

Results in Table 4 also show that the signs on the other control variables (VOL, DIVERS, MB) are generally consistent with existing literature but insignificantly related to forecast earnings errors.

Table 4: The effect of derivatives use decision

Variable	Predicted sign	Regression 1	Regression 2	Regression 3	Regression 4
CONSTANT		-0.2016[c]	-0.2041[c]	-0.2057[b]	-0.2075[c]
		(0.0633)	(0.0628)	(0.0271)	(0.0626)
DERIV	-	-0.0353[a]	-0.0352[a]	-0.0346[a]	-0.0347[a]
		(0.0035)	(0.0031)	(0.0020)	(0.0035)
SIZE	-	0.0110[c]	0.0112[c]	0.0112[b]	0.0113[c]
		(0.0672)	(0.0670)	(0.0291)	(0.0662)
LDEBT	+	-0.0449	-0.0440	-0.0441[c]	-0.0441
		(0.1016)	(0.1042)	(0.0907)	(0.1039)
DIVERS	+	0.0018	0.0018	0.0018	0.0018
		(0.3289)	(0.3306)	(0.3232)	(0.3273)
SURPRISE	+	0.4033[a]	0.4096[a]	0.4084[a]	0.4081[a]
		(0.0031)	(0.0029)	(0.0032)	(0.0030)
XLIST	-	-0.0453[b]	-0.0455[b]	-0.0458[b]	-0.0458[b]
		(0.0138)	(0.0139)	(0.0164)	(0.0141)
MB	+		0.0005	0.0005	0.0005
			(0.1490)	(0.2001)	(0.2044)
VOL	+	5.2653		1.5239	1.6573
		(0.3582)		(0.8081)	(0.7905)
CORR	-	0.0000	0.0000		0.0000
		(0.9837)	(0.9892)		(0.9528)

YEAR	0.0054	0.0059	0.0057	0.0057
	(0.4989)	(0.4532)	(0.4872)	(0.4814)
Industry dummies	YES	YES	YES	YES
Adjusted R-squared	0.1969	0.1985	0.1986	0.1952
F-statistic	4.3159[a]	4.3498[a]	4.3511[a]	4.1163[a]
Prob (F-statistic)	0.0000	0.0000	0.0000	0.0000

The regressions are run using an ordinary least squares specification. The dependent variable is ERROR. It is defined the absolute difference between the median of forecasted earnings and actual earnings deflated by the stock price. DERIV is defined as a dummy variable that equals 1 if the firm uses derivatives and 0 otherwise. SIZE is the natural logarithm of the market value of the firm. LDEBT is the ratio of book value of long term debts over market value of equities. DIVERS is the number of business segments in which the firm operates at the two-digit SIC level. SURPRISE is equal to the absolute difference between current earnings per share and earnings per share from the precedent year, divided by the mean of firm's stock price computed over the current fiscal year. XLIST is a dummy variable that takes on the value 1 if the firm is cross-listed on another stock exchange and 0 otherwise. MB is defined as the market value of equity plus the book value of debt all divided by the book value of total assets. VOL is calculated as the standard deviation of returns over the last three fiscal years. CORR is the correlation between earnings and returns over the last three fiscal years. YEAR is equal to 1 if the observation is from 1999 and 0 otherwise. Industry dummies correspond to the industrial classifications as proposed by Campbell (1996). a, b and c indicate significance at the 1, 5 and 10% levels, respectively. The p-values, based on the White's *heteroscedasticity-consistent* robust standard errors, are between parentheses below the estimated coefficients.

4.2 - The effect of the extent of derivatives use on analysts' forecasts error

As noted earlier, a firm that decides to use derivatives has to make another decision on the level of that use. To examine the effect of the extent of derivatives use on analysts' forecasts errors, we focus on the sub-sample of firms that use derivatives. The size of this sub-sample is 225 firms. Our key variable is NOTION representing the ratio of notional amount of derivatives position at the fiscal year-end scaled by the market value of the firm. The other control variables remain unchanged. We expect that the level of derivatives use to be negatively related to information asymmetry proxy by analysts' forecast errors.

The regression results are reported in Table 5. Interestingly, the coefficient of NOTION is negative and statistically significant, which indicates that greater use of derivatives lowers prediction errors. This finding is in accord with the empirical results of Dadalt et al. (2002) and with the theoretical analysis of DeMarzo and Duffie (1995) and Breeden and Vishwanathan (1998). That is, it appears that not only the decision to use derivatives that affects analysts' forecast errors but also the level of derivatives use. In Table 5, the coefficients of the other control variables remain qualitatively similar to those in Table 4.

Table 5: The effect of the extent of derivatives use

Variable	Predicted sign	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
CONSTANT		-0.2886[b]	-0.2921[b]	-0.2906[a]	-0.2951[a]	-0.3032[b]
		(0.024)	(0.0326)	(0.0089)	(0.0087)	(0.0236)
NOTION	-	-0.0295[b]	-0.0278[c]	-0.0295[b]	-0.0280[c]	-0.0279[c]
		(0.0482)	(0.0606)	(0.0470)	(0.0562)	(0.0595)
SIZE	-	0.0136[b]	0.0138[b]	0.0137[b]	0.0138[b]	0.0142[b]
		(0.0395)	(0.0472)	(0.0178)	(0.0176)	(0.0378)
LDEBT	+	-0.0407	-0.0396	-0.0408	-0.0397	-0.0401
		(0.1240)	(0.1345)	(0.1087)	(0.1177)	(0.1279)
DIVERS	+	0.0018	0.0019	0.0018	0.0020	0.0021
		(0.3545)	(0.3345)	(0.3420)	(0.3106)	(0.3066)
SURPRISE	+	0.4227[a]	0.4328[a]	0.4225[a]	0.4317[a]	0.4313[a]
		(0.0016)	(0.0014)	(0.0016)	(0.0015)	(0.0015)
XLIST	-	-0.0477[b]	-0.0477[b]	-0.0477[b]	-0.0482[b]	-0.0480[b]
		(0.0178)	(0.0192)	(0.0199)	(0.0195)	(0.0178)
MB	+		0.0008		0.0007	0.0008
			(0.1876)		(0.1956)	(0.1895)
VOL	+	6.5404		6.8306	5.5967	6.6263
		(0.6488)		(0.6412)	(0.7006)	(0.6461)
CORR	-	0.0000	0.0000			-0.0001
		(0.9532)	(0.9512)			(0.8297)

YEAR	0.00605	0.0063	0.0060	0.0059	0.0057
	(0.5280)	(0.4847)	(0.5388)	(0.5461)	(0.5463)
Industry dummies	YES	YES	YES	YES	YES
Adjusted R-squared	0.2095	0.2107	0.2133	0.2110	0.2780
F-statistic	4.1244[a]	4.1478[a]	4.3747[a]	4.1537[a]	3.9283[a]
Prob (F-statistic)	0.0000	0.0000	0.0000	0.0000	0.0000

The regressions are run using an OLS specification. The dependent variable is ERROR. It is defined as the absolute difference between the median of forecasted earnings and actual earnings deflated by the stock price. NOTION defined as the notional amount of derivatives outstanding at fiscal year-end deflated by the market value of the firm. SIZE is the natural logarithm of the market value of the firm. LDEBT is the ratio of book value of long term debts over market value of equities. DIVERS is the number of business segments in which the firm operates at the two-digit SIC level. SURPRISE is equal to the absolute difference between current earnings per share and earnings per share from the precedent year, divided by the mean of firm's stock price computed over the current fiscal year. XLIST is a dummy variable that takes on the value 1 if the firm is cross-listed on another stock exchange and 0 otherwise. MB is defined as the market value of equity plus the book value of debt all divided by the book value of total assets. VOL is calculated as the standard deviation of returns over the last three fiscal years. CORR is the correlation between earnings and returns over the last three fiscal years. YEAR is equal to 1 if the observation is from 1999 and 0 otherwise. Industry dummies correspond to the industrial classifications as proposed by Campbell (1996). a, b and c indicate significance at the 1, 5 and 10% levels, respectively. The p-values, based on the White's *heteroscedasticity-consistent* robust standard errors, are between parentheses below the estimated coefficients.

5 – Robustness checks

In this section, we conduct some sensitivity analyses to check the robustness of our findings to self-selection bias and endogeneity problems.[14]

5.1 - Controlling for self-selection bias

Our previous analysis establishes a link between the decision to use derivatives and the magnitude of analysts' forecast errors in predicting earnings of the firm. That is the use of derivatives by firms allows analysts to forecast earnings more accurately. However, it may be the case that firms with accurate forecasts choose to use derivatives for other reasons than reducing information asymmetry. In other words, firms with high forecast accuracy may use derivatives for reasons unrelated to their information environment, which are not captured by our controls. The above-tested models do not take into account that possibility and the relation may be driven by self-selection endogeneity. To mitigate this potential effect, we apply a self-selection model that controls for this bias. Specifically, we test the robustness of our results by using the two-step correction of Heckman (1979) to control for the self-selection bias induced by analysts' decision to select firms that use derivatives.

The above-estimated model can be written as follows:

$$\mathrm{ERROR}_i = \alpha_0 + \beta' \Delta_i + \varphi * \mathrm{DERIV}_i + \varepsilon_i \qquad (3)$$

where DERIV_i is a dummy variable that takes the value one if the firm uses derivatives. Δ_i is a set of firm specific control variables and ε_i is the error

[14] We have addressed the issue of within firm-dependencies in two additional ways. We have examined the relationship between changes in derivatives usage status and asymmetric information over time and we have rerun regressions after accounting for clustering at the firm level. The results remain qualitatively similar and support the hypothesis that the use of derivatives negatively affects the levels of information asymmetry. Conclusions remain also virtually unchanged when we lag the independent variables for one year.

component. As firms decide whether to use derivatives based on various factors, we can model this decision as:

$$DERIV_i^* = \xi' \Gamma_i + \eta_i \quad (4)$$

$$DERIV_i = 1 \text{ if } DERIV_i^* > 0$$

$$DERIV_i = 0 \text{ if } DERIV_i^* < 0$$

where Γ_i is the set of variables that affect the decision to use derivatives, $DERIV_i^*$ is an unobserved latent variable and η_i is the error component.

If firms make the decision on whether to use or not derivatives because of some expected benefit in ERROR, OLS estimates of φ will not correctly measure the effect of derivatives use. Namely, the correlation between $DERIV_i$ and ε_i will be different from zero if the exogenous set of variables Γ_i in (4) affect ERROR, but are not in (3), or if ε_i and η_i are correlated.

This problem of self-selection is often handled empirically with a treatment effect model (e.g., see Greene, 2002). Heckman (1979) explains that using non-randomly selected samples when estimating behavioral relations leads to an "omitted variables" bias and proposes a consistent two-stage method to estimate (3) and (4) at once. This method assumes that ε_i and η_i are bivariate normally and identically distributed with means zero, standard deviations σ_ε and σ_η, respectively, and correlation ρ. The expected analysts' forecast error (ERROR) of a firm i can be written as:

$E\left(ERROR|_{DERIV=1}\right) = \alpha_0 + \beta' \Delta_i + \varphi + \rho \sigma_\varepsilon \lambda_{i1}\left(\xi' \Gamma_i\right)$, if firm i uses derivatives (5.a)

$$E\left(ERROR\big|_{DERIV=0}\right)=\alpha_0+\beta'\Delta_i+\rho\sigma_\varepsilon\lambda_{i2}\left(\xi'\Gamma_i\right),\text{ if not} \quad (5.b)$$

where $\lambda_{i1}(\xi'\Gamma_i)$ and $\lambda_{i2}(\xi'\Gamma_i)$ are the "inverse Mills' ratios" computed as follows:

$$\lambda_{i1}(\xi'\Gamma_i) = \Phi(\xi'\Gamma_i)/\Psi(\xi'\Gamma_i) \quad (6.a)$$

$$\lambda_{i2}(\xi'\Gamma_i) = -\Phi(\xi'\Gamma_i)/[1-\Psi(\xi'\Gamma_i)] \quad (6.b)$$ [15]

We first estimate (ξ') in (4) using a probit model and compute λ_{i1} and λ_{i2}. Then, we estimate the ERROR equation (3) using OLS while adding the correction term λ_i, computed as follows:

$$\lambda_{i1}\left(\xi'\Gamma_i\right)*DERIV+\lambda_{i2}\left(\xi'\Gamma_i\right)*\left(1-DERIV\right) \quad (6.c)$$

The corrected ERROR equation can be written more parsimoniously as:

$$\text{ERROR}_i = \alpha_0 + \beta'\Delta_i + \varphi * \text{DERIV}_i + \varphi_\lambda\lambda_i + \varepsilon_i \quad (7)$$ [16]

More specifically, in the first-stage, we estimate a probit model of the determinants of the derivatives use, as follows:

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[15] $\Phi(\cdot)$ and $\Psi(\cdot)$ are the density function and cumulative distribution functions for the standard normal, respectively.

[16] φ_λ captures the sign of the correlation between error terms in (3) and (4).

$$DERIV_i = a0 + a1*QUICK + a2*DY + a3*LDEBT + a4*MB + a5*CAPEX + a6*TAILLE + a7*YEAR + \sum_{j=1}^{10} a_{(j+7)} * D_{ij} + \eta_i \qquad (8)$$

The estimation of a probit model allows to compute the Heckman *Lambda* (λ_i).

In the second stage, the Heckman *Lambda* is included in the estimation of determinants of ERROR as a variable to control for self-selection.

Table 6 reports the results of the Heckman test. The two-step estimation procedure produces similar results to those in Table 4. The negative relation between derivatives use and forecast error is robust to the self-selection bias.

Table 6: (Heckman two-step selection)

Heckman two-step selection (Correction for selection bias)			
Variable	**Predicted sign**	**Regression**	
CONSTANT		-0.2075[c]	(0.0626)
DERIV	-	-0.0347[a]	(0.0035)
SIZE	-	0.0113[c]	(0.0662)
LDEBT	+	-0.0441	(0.1039)
DIVERS	+	0.0018	(0.3273)
SURPRISE	+	0.4081[a]	(0.0030)
XLIST	-	-0.0458[b]	(0.0141)
MB	+	0.0005	(0.2044)
VOL	+	1.6573	(0.7905)
CORR	-	0.0000	(0.9528)
Self selectivity correction (Heckman *LAMBDA*)		-0 0281[b]	(0.0452)
YEAR		0.0057	(0.4814)
Industry dummies		YES	
Adjusted R-squared		0.1952	
F-statistic		4.1163 [a]	
Prob(F-statistic)		0.0000	

The equation is estimated using the Heckman-two step method. The dependent variable is ERROR. It is defined as the absolute difference between the median of forecasted earnings and actual earnings deflated by the stock price. DERIV is defined as a dummy variable that equals 1 if the firm uses derivatives and 0 otherwise. SIZE is the natural logarithm of the market value of the firm. LDEBT is the ratio of book value of long term debts over market value of equities. DIVERS is the number of business segments in which the firm operates at the two-digit SIC level. SURPRISE is equal to the absolute difference between current earnings per share and earnings per share from the precedent year, divided by the mean of firm's stock price computed over the current fiscal year. XLIST is a dummy variable that takes on the value 1 if the firm is cross-listed on another stock exchange and 0 otherwise. MB is defined as the market value of equity plus the book value of debt all divided by the book value of total assets. CORR is the correlation between earnings and returns over the last three fiscal years. a, b and c indicate significance at the 1, 5 and 10% levels, respectively. The p-values, based on the White's *heteroscedasticity-consistent* robust standard errors, are between parentheses next to the estimated coefficients.

5.2 - Endogeneity bias

Empirical results show that higher use of derivatives reduces analysts' forecast errors. Reverse causality may however be possible. CEOs of firms for which analysts make accurate forecasts may decide to continue using more derivatives as a signal of their higher quality. The ultimate objective to their behavior is hence to reduce information asymmetry with outside investors. When the relationship between analysts' forecast errors and the extent of derivatives use is endogenous, then the OLS regression method is inappropriate and its estimates are inconsistent. Thus, we conduct a Durbin-Wu-Hausman procedure to test whether our results are driven by this potential endogeneity. It consists of two steps. In the first step, we regress NOTION on all the exogenous variables ((SIZE, LDEBT, MB, DIVERS, SURPRISE, XLIST, VOL, and CORR) to obtain the residual $\hat{v}_i$. In the second step, we estimate equation (2) after adding $\hat{v}_i$ as an independent variable. A t-test on the coefficient of $\hat{v}_i$ is then performed. If the estimated coefficient of $\hat{v}_i$ is significant, we conclude that there is a significant endogeneity. The results show that the Student-t of the coefficient of $\hat{v}_i$ in step 2 is equal to 0.4197 (p-value = 0.6751), which rejects the presence of endogeneity.

6- Conclusion

In this paper, we examine the hedging effect on the accuracy of the analysts' forecasts. This subject is original because it relates to two research fields. The first one deals with the hedging effect on firm value while the second one concerns the study of the determinants of analysts' forecast quality. The theoretical framework of DeMarzo and Duffie (1995) and Breeden and Viswanathan (1998), states that, by hedging, managers can reduce the noisiness of earnings induced by fluctuations of exchange rates and interest rates. Using insights taken from this original framework, we put forth the hypothesis that analysts anticipate more easily the earnings of companies that hedge their financial risks. This hypothesis proposes a new determinant of the analysts' forecast errors and provides an additional benefit of hedging – its impact on asymmetric information regarding firms' earnings.

Using a sample of 258 firm-year observations, we obtain the following findings. First, results highlight a significant and negative relationship between analysts' forecast errors and the use of derivatives. Companies that use derivatives contribute to neutralizing the effect on earnings of macroeconomic fluctuations which are not under the managerial control. Consequently, firms hedging their financial exposure reduce the uncertainty on their earnings which improves the quality of analysts' forecasts. This improvement is also an increasing function of the hedging extent. Second, other factors affecting the analysts' forecast errors were identified. Some have a positive effect such as firm size and earnings fluctuations whereas others such as cross-listing and leverage have a negative effect.

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