Corporate Hedging Policy and Equity Mispricing

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ABSTRACT

We document that firms' use of derivatives is negatively associated with mispricing of their stock. This result remains robust after controlling for the endogenous nature of hedging and for self-selection bias associated with firms' decision to hedge. Our findings are consistent with the notion that hedging improves the transparency and predictability of firms' cash flows resulting in less misvaluation. Furthermore, we document that the negative relationship between mispricing and hedging is particularly strong when market value is below fundamental value, which is consistent with prior evidence that hedging has a positive impact on firm valuation. Finally, we provide evidence that a "spread-out" hedging policy that entails the use of a variety of derivative contracts can be more effective in reducing mispricing.

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I. INTRODUCTION

According to the proponents of the efficient markets hypothesis and rational asset pricing, stock mispricing, i.e., the deviation from intrinsic (fundamental) value can be either a short-term temporary phenomenon quickly exploitable by arbitrageurs or a rational compensation for risks that are not accounted for in asset pricing models (see, for example, Fama and French (1993, 1996)). On the other hand, advocates of behavioral finance regard persistent mispricing as the result of either the existence of an irrational (behavioral) component to asset prices, or the asymmetry of information between informed insiders and the rest of the market. Regardless of why misvaluation occurs, empirical evidence supports the notion that it has an impact on managers' investment and financing decisions[1], and therefore it warrants special attention.

In this paper we examine the relationship between mispricing and corporate hedging policy. We start by assuming that a sizeable component of stock misvaluation is due to the lack of transparency (i.e., opacity) at the corporate level. We use the term transparency to indicate the availability and quality of information about firms' future cash flows. The more opaque the information available to investors about a firm's true, but unobservable distribution of future cash flows, the greater the degree of deviation of market value from intrinsic value. In this context, lack of transparency is manifested in greater information uncertainty[2] about the firm's future cash flows and/or agency problems arising from asymmetric information between managers and outside

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[1] For example, Rhodes-Kropf *et al* (2004) and Dong *et al* (2003) provide evidence that irrational misvaluation affects firms' takeover behavior. Polk and Sapienza (2003) and Baker, Stein and Wurgler (2003) provide evidence in support of the notion that the levels of investment are affected by inefficient market valuations. Furthermore, several studies found that firms try to time equity issues to take advantage of misvaluation (for example, see Ritter (1991), Loughran and Ritter (1995), Rajan and Servaes (1997) and Baker and Wurgler (2002)).

[2] Francis, LaFond Olsson and Schipper (2003) find that information uncertainty plays an important role in explaining accounting-based anomalies, such as post-earnings announcement drift, value-glamour, and accruals strategies. Recently, Zhang (2005) finds that information uncertainty exacerbates underreaction to public information and contributes to the phenomenon of post-earnings announcement drift. He finds that greater information uncertainty about the impact of news on stock value leads to higher expected stock returns following good news and lower expected stock returns following bad news relative to stocks about which there is less information uncertainty. Pastor and Veronesi (2003) in an efficient market setting show that uncertainty about a firm's profitability results in temporary overvaluation because firm value is a convex function of the firm's expected growth rate. In their model, an increase in uncertainty about the firm's expected growth rate leads to lower future stock returns because of Jensen's inequality.

investors regarding future cash flows.[3] Hedging can improve firm transparency for the following two reasons. First, hedging has a direct mitigating effect on information uncertainty, because it reduces noise. According to a broad survey of financial executives (see Graham, Harvey and Rajgopal (2005)) managers believe that less predictable earnings can lead to low stock prices because investors and analysts dislike uncertainty. The notion that hedging reduces information uncertainty is also supported by recent empirical evidence (see, Barton (2001), Brown (2001), DaDalt, Gay and Nam (2002), and Pincus and Rajgopal (2002), among others) that shows corporations' derivatives use is associated with lower earnings volatility, greater number of analysts following the firm, and greater accuracy of analysts forecasts. Second, according to theoretical models developed by DeMarzo and Duffie (1995) and Breeden and Viswanathan (1996) and supporting empirical evidence (see Guay, Haushalter, and Minton (2002), Dolde and Mishra (2002) and Dadalt, Gay, and Nam (2002)),[4] hedging can reduce information asymmetries between managers and markets.[5] Thus, firms that hedge have lower agency costs [6], which may

[3] Healey and Palepu (2001) argue that misvaluation arises when there is information asymmetry between managers and investors that is not fully resolved. Another example of a study showing the link between misvaluation and information asymmetry is Nanda and Narayanan (1999). They formally develop an information related argument in the context of divestitures through a model of asymmetric information about firm value between the managers and the market. They assume that the market can observe the aggregate cash flows of the firm but not the individual divisional cash flows, which results in misvaluation of the firm's securities.

[4] Guay, Haushalter, and Minton (2002) present evidence that the errors in analysts' forecasts and the dispersion in analysts' forecasts are significantly correlated with unexpected shocks which are not transparent to investors or analysts, and that firms' hedging strategies are related to this earnings uncertainty. Their findings provide empirical support for the DeMarzo and Duffie (1995) assumption that outsiders encounter difficulty interpreting the impact of risks, which corporations can hedge away. Dolde and Mishra (2002) show that more complex firms (i.e. geographically diversified firms) use substantially greater amounts of foreign exchange derivatives than purely domestic firms. DaDalt *et al* (2002) present evidence that the use of derivatives is associated with lower asymmetric information.

[5] Rangel (2003) argued that given a linear incentive schedule the moral hazard problem could not be solved by any incentive, which explains the reluctance of some firms to hedge even though there are benefits associated with hedging. In addition, managers pursuing speculative investments may misuse derivatives. In these cases firm transparency would deteriorate with the use of derivatives. Allayannis and Ofek (2001), however, suggest that firms usually use foreign exchange derivatives as a means to hedge rather than to speculate in the foreign exchange markets.

[6] For example, consider the agency costs of underinvestment and the agency costs of overvalued equity. The former arises from the adverse selection problem, where external financing becomes more costly than internally generated funds (see Myers and Majluf (1984)) in the presence of asymmetric information about firms' earnings capacity. Froot, Scharfstein and Stein (1993) show that firms, that might otherwise fail to invest in valuable growth opportunities, have an incentive to hedge so as to ensure there are enough internal funds to undertake attractive investment opportunities. In addition, as argued in Geczy, Minton and Schrand (1997) and DaDalt *et al* (2002), in cases where there are insufficient internal funds to take on all positive-NPV projects, hedging can provide the additional benefit of lowering external financing costs because by

enable the market to assign prices closer to intrinsic value for their stocks. Consequently, we hypothesize that because hedging results in greater transparency of information related to future cash flows (i.e., lower levels of both information uncertainty and information asymmetry between managers and shareholders about firm's future earnings), it should be negatively related to mispricing.

Many theoretical studies (see, Stulz (1984), Shapiro and Titman (1985), Smith and Stulz (1985), Froot, Scharfstein and Stein (1993), and De Marzo and Duffie (1995)) have shown that, in the presence of market imperfections such as taxes, financial distress costs and agency conflicts, corporate hedging policy becomes relevant, i.e. hedging decisions have an impact on firm valuation. The empirical literature on corporate hedging policy is also quite extensive.[7] However, to our knowledge, there is a complete lack of empirical evidence regarding the nature of the relationship between hedging policy and misvaluation.

We provide an empirical test of the hypothesis that the relationship between mispricing and hedging is negative. We utilize five different misvaluation measures, which we combine into a mipricing index and we define hedging as the corporate use of derivatives. In our test methodology we recognize that the relationship between mispricing and the decision to hedge may be endogenous. In order to fully account for the potential problem arising from endogeneity, our empirical tests utilize a combination of panel data, instrumental variables', and treatment effects (specifically, the Heckman (1979) two-step procedure) regression models. [8]

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increasing the informativeness of earnings it alleviates the adverse selection problem. In addition, hedging may also contribute to the reduction of the agency costs of overvalued equity (Jensen (2004)), because by improving the predictability of future cash flows it allows for a greater possibility that overpricing can be improved by better-informed short-sellers. In particular, Jensen (2004) argues that the only private solution to the problem of overvalued equity would be to allow corporate boards to protect themselves by establishing a regular practice of communicating with short-sellers of their stocks. We argue that, since hedging makes earnings more informative, it should also ease the difficulty of communicating information to short-sellers in the spirit of Jensen.

[7] The majority of past empirical studies examining corporate hedging policy have focused on the determinants of hedging (see Bodnar, Hayt, Marston and Smithson (1996), Bodnar, Hayt, and Marston (1998), Phillips (1995), Dolde (1996)) and Géczy, Minton, and Schrand (1997)), the effectiveness of hedging in reducing exposure to risk (see Allayannis and Ofek (2001)) and on the relationship between hedging and firm value (see Allayannis and Weston (2001), Carter, Rodgers and Simkins (2003), Graham and Rogers (2002) and Bartram (2004)).

[8] Campa and Kedia (2002) used the three aforementioned techniques in the context of an examination of the endogenous nature of the relationship between industrial diversification and value discount.

We find support for the hypothesis that hedging is negatively associated with mispricing and confirm that the nature of the relationship is endogenous. Our results remain robust even after controlling for endogeneity and self-selection bias. Consistent with previous evidence that hedging has a positive effect on valuation (see Allayannis and Weston (2001)), we also document that the negative association between hedging and mispricing is particularly strong when firm value is below fundamental value. The relationship is insignificant for firms with high excess values. Furthermore, we show that the effectiveness of hedging in reducing mispricing is increasing with the number of different derivative contracts used and inversely related to the concentration of the amount of dollars invested across different types of derivative contracts.

The rest of the paper is organized as follows. In the next section, we describe the data sources and the sample selection. Section III introduces the mispricing, hedging and transparency variables, and describes the different models we use to account for endogeneity. Section IV reports correlations, univariate, and multivariate results. Section V provides a summary and concluding remarks.

II. DATA

We collect hedging data for all non-financial corporations listed in the Database of Users of Derivatives published by Swaps Monitor Publications, Inc. over the 1992 – 1996 period.[9] The database compiles information that firms are required to report according to SFAS 105. SFAS 105 requires firms to report information about financial instruments, such as forwards, futures, options, swaps etc., which have off-balance sheet risk. The database's contract spreadsheets contain information for 1698 firms that list notional amounts of over-the-counter and exchange-traded interest rate and currency derivatives outstanding at period-end. Our initial sample consists of 1,045 firms (and 5,225 observations over 5 years) for which we could access information in Compustat and CRSP. In the majority of our tests we use an indicator variable that

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[9] Swaps Monitor ceased compiling this database in the third quarter of 1997. Thus, our sample is restricted to the five-year period where complete annual derivatives use data are available. The Database of Users of Derivatives was compiled from annual reports and filings with regulatory agencies. It therefore, does not contain information on firms that used derivatives but made no disclosure of that fact.

takes the value of one if the firm used derivatives and zero otherwise. In our tests of hedging policy characteristics, we also use the number of different derivatives contracts the firms used and the notional amount of derivatives contracts. Swap Monitor lists the notional hedging amounts for seven different contracts spanning two general types of derivatives: interest rate (*IR*) derivatives and foreign exchange (*FX*) derivatives. The seven different contracts are: IR-options, IR-swaps, IR-forwards/futures, FX-options, FX-swaps, FX-futures, and FX- forwards.

We extract financial data and stock returns for the sample firms from COMPUSTAT and CRSP, respectively. We use analyst forecasts information included in the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail History dataset.[10] We use individual analysts' forecasts issued in June or, if not available in June, forecasts issued in May, or April and last confirmed as "recent" in June. For example, if the forecast was made in April or May and was last confirmed as recent in June, it will be used in our computation of averages and standard deviations for June. If an analyst makes more than one forecast from April to June, only the last forecast is used in our calculations. Each stock must be covered by at least two analysts, since we define dispersion as the standard deviation of earnings forecasts scaled by the absolute mean forecast. All valuation and analyst coverage measures used in the study are aligned on the month of June (as in Fama and French (1992, 1993)).

III. VARIABLES' MEASUREMENT AND EMPIRICAL METHODOLOGY

III. A. Measures of Mispricing

Firm mispricing is measured as the deviation of a firm's equity value from its intrinsic or fundamental value. We employ six alternative mispricing measures. The first five measures employ alternative techniques in estimating intrinsic value benchmarks, while the last one is an index that combines all measures. The mispricing measures are:

1.) $|ARET_{it}|$, the absolute value of a firm's average monthly abnormal return for each year. The expected return of month t is computed using benchmarks from the Fama/French three-factor model estimated over the five-year period immediately preceding month t. For example, the 60-

[10] The use of the Detail History I/B/E/S data allows us to exclude outdated forecasts.

month period from January 1987 to December 1991 is used to estimate the parameters used to compute the expected return for January 1992. The estimation of the parameters is based on the following model:

$$E(R_{it}) - R_{ft} = \beta_0 + \beta_M (R_{ft} - R_{mt}) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \psi_{it} \tag{1}$$

where $E(R_{it})$ is the rate of return on the *i*th company's common stock in month *t*, R_{ft} is risk-free rate, R_{mt} is the value-weighted market portfolio return, and SMB_t and HML_t are the size and book-to-market factors as in Fama and French (1993, 1996). Abnormal returns, $ARET_{it}$, are computed as differences of actual returns, R_{it}, from the expected returns derived from the parameters of model (1).

$$|ARET_{it}| = |R_{it} - E(R_{it})| \tag{2}$$

2.) | $EXVRI_{it}$ |, the absolute value of excess value computed at the end of June of each year as the natural logarithm of the ratio between the stock price and its intrinsic value from Ohlson's (1995) residual income value approach.

$$EXVRI_{it} = \text{LN}\left[\frac{PRICE_{it}}{I(V)_{it}}\right], \tag{3}$$

where $PRICE_{it}$ is the stock price at the end of June of each year from CRSP, and $I(V)_{it}$ is intrinsic value using the residual income model (Ohlson (1995)) methodology and median values of analysts' forecasts issued in June, as in Frankel and Lee (1998). There is strong empirical evidence in support of the residual income valuation, V/P, as an indicator of mispricing.[11]

3.) $|EXVIA_{it}|$, the absolute value of excess value computed at the end of June of each year as the natural logarithm of the ratio between a firm's capital and its imputed value.

$$EXVIA_{it} = \text{LN}\left[\frac{CPTL_{it}}{I(CPTL)_{it}}\right] \tag{4}$$

where $CPTL_{it}$ is total capital, which is market value of equity plus book value of debt, $I(CPTL_{it})$ is the imputed value derived as the product of firm size (market value of common equity) and the

[11] Lee, Myers and Swaminathan (1999) report that V/P predicts one-month-ahead returns on the Dow 30 stocks better than aggregate book-to-market. Frankel and Lee (1998) also show that the residual income value is a better predictor than book value of the cross-section of contemporaneous stock prices, and that V/P is a predictor of the one-year-ahead cross-section of returns. In addition, Ali, Hwang, and Trombley (2003) show that after controlling for several possible risk factors, V/P continues to significantly predict future returns. D'Mello and Shroff (2000) apply V/P to measure mispricing of equity repurchases, and Dong, Hirshleifer, Richardson and Teoh (2003) to takeovers.

median capital to size ratio in the firm's industry. The industry classification here is based on the Fama-French 48 sectors. The third measure of mispricing is constructed in a similar fashion as the second one ($EXVRI_{it}$), but uses firm's total capital instead of price and computes imputed value based on Fama/French 48 industry classification. Thus the intrinsic value here is a size and industry benchmark.

4.) $|EXVRK_{it}|$, the absolute value of the firm-specific component of the difference between market value and fundamental value, based on Model III of Rhodes-Kropf, Robinson and Viswanathan (2004). This procedure differs from the residual income valuation approach in the sense that it does not rely on analysts' earnings forecasts. According to Rhodes-Kropf *et al*. (2004), fundamental value, V is estimated by decomposing the market-to-book into two components: a measure of price to fundamentals (ln(M/V)), and a measure of fundamentals to book value (ln(V/B)). The first component captures the part of book-to-market associated with mispricing. In extreme cases where markets perfectly anticipate, this component would be equal to zero, otherwise positive (over-valuation) or negative (under-valuation). This component is further decomposed into firm-specific and industry-specific misprising. In our tests, we use the firm-specific mispricing component based on Model III of Rhodes-Kropf *et al*. (2004) that also accounts for net income and leverage effects.

$$lnM_{it} = \alpha_{0it} + \alpha_{1it}\, lnB_{it} + \alpha_{2it}\, ln(NI)^{+}_{it} + \alpha_{3it}\, I_{(<0)} ln(NI)^{+}_{it} + \alpha_{4it}\, lnLEV_{it} + \zeta_{it} \quad (5)$$

where M is firm value, B is book value, NI^{+} is absolute value of net income, $I_{(<0)}ln(NI)^{+}$ is an indicator function for negative net income observations, and LEV is the leverage ratio.

5.) $|MBIA_{it}|$, the absolute value of the industry-adjusted market-to-book ratio.

$$|MBIA_{it}| = |MB_{it} - \text{Med}(MB_{jt})| \quad (6)$$

where, MB_{it} is the natural logarithm of the market to book ratio for firm i at time t, and Med(MB_{jt}) is the jth industry median of MB_t. Several empirical studies have utilized MB as a mispricing measure (see, among others, Walking and Edmister (1985), Rau and Vermaelen (1998) and Ikenberry, Lakonishok and Vermaelen (1995)). However, as Rhodes *et al* (2004) point out, the market to book ratio can be viewed as not only a proxy for misvaluation but also as a measure of future growth opportunities and managerial ability.

6.) MI_{it}, a mispricing index (MI) that combines all five mispricing measures described above.[12] The mispricing index (MI) is constructed each year for each observation $i = 1,\ldots,N$ as:

$$MI_i = \frac{1}{N}\frac{1}{K}\sum_{k}^{K} Rank_k(|EXV_{ik}|) \tag{7}$$

where $Rank_k(|EXV_{ik}|)$ is the rank function which assigns a rank for each observation from least misvalued (rank of one) to most misvalued (rank of N). $|EXV_{ik}|$ is the k^{th} measure of mispricing for firm i in our sample, and K represents the dimensions of mispricing measures. The denominator, K, averages the ranks by the number of mispricing values available for each firm in the sample in a particular year. For example, the sum of the $Rank_k(|EXV_{ik}|)$ values of a firm that has only 3 mispricing measures is divided by K=3. Finally, dividing by N, we scale the MI from 0 (least mispriced) to 1 (most mispriced). By computing average of all ranks from five different mispricing measures, MI has the advantage that it balances out the effects and shortcomings of all other mispricing measures while aggregating their informativeness, and thereby provides a more complete picture of mispricing.

III. B. Hedging Policy Characteristics

In our analysis, we use four measures that describe the firm's hedging policy. The main variable in our analysis is a hedging indicator variable, H, that takes the value of one if the firm uses derivatives and zero otherwise. *NTYPE* is a variable that counts the number of types of derivatives used by the firm. Since in Swap Monitor there are two broad types of derivative contracts, interest rate- and currency derivatives, *NTYPE* takes values from zero to two. *NCONTR* measures the total number of different interest rate and currency derivatives' contracts used by the firm, and takes values from zero to seven. *HERF* is a Herfindahl index that measures the concentration of notional dollar amounts invested across different derivative contracts. *HERF* is calculated as follows:

$$HERF = \sum_i \frac{(AMT_i)^2}{[\sum_i (AMT_i)]^2} \tag{8}$$

[12] In constructing MI, we employ the methodology outlined in Butler, Grullon, and Weston (2004). In their paper, they create a liquidity index that comprises the effects of ranking on 6 different liquidity measures.

where AMT_i is the annual notional amount of type i^{th} derivative contract. In our dataset we can distinguish two general categories of derivatives: foreign exchange (*FX*) and interest rate (*IR*) derivatives. We can also distinguish up to four different types of derivative contracts (forwards, futures, options and swaps) within each category. Since our data source does not separate *IR*-Forwards and *IR*-Futures, our Herfindahl index thus measures concentration over seven sub-types of derivative contracts. A higher value for *HERF* indicates a more highly concentrated corporate hedging policy. The greater the distribution of the firm's hedging efforts across multiple types of contracts, the lower the value of *HERF*.[13] A lower Herfindahl index thus indicates a more extensive, and possibly, sophisticated hedging program. We hypothesize that lower *HERF* is associated with reduced misvaluation.

III. C. Information Transparency Measures

In our tests we use several measures of transparency that have been used in previous studies as proxies for uncertainty, information asymmetry, or both. The first transparency measure is size, measured by the firm's total assets. In a recent study, Zhang (2005) used the reciprocal of size as an information uncertainty proxy, while several studies have used the percent of common shares owned by institutional investors (*INSTP*) as a measure of informational asymmetry (see Best, Hodges and Lin (2004), among others). We also use two variables constructed from security analyst' one fiscal year-ahead forecasts collected every June from *I/B/E/S* Detail History Database. These are the absolute forecast error (*AFE*) and the dispersion (*DISP*) of analyst forecasts.[14] Barron, Kim, Lim and Stevens (1998) show that *DISP* reflects both diversity of analyst beliefs and the uncertainty (lack of precision) in analyst forecasts. The forecast error captures forecasting ability of security analysts covering the firm, which we use

[13] For example, if a firm's total notional derivatives value reported is allocated to a single type of derivative contract, e.g. foreign exchange forwards, then this firm's *HERF* would be 1 [i.e. $1^2/1^2 = 1$]. On the other hand, If the firm allocates a third of its total reported notional derivative value equally across foreign exchange options, forwards and swaps, then its *HERF* would be 0.3333, i.e. $(1/3)^2/((1/3)^2+(1/3)^2+(1/3)^2) = 0.3333$.

[14] Some studies (e.g. Atiase (1985)) have used the number of analyst forecasts as an information asymmetry measure. This measure though is highly correlated with size. Therefore, in our regression models we control for analyst following by using the residual analyst following measure as in Hong, Lim and Stein (2000).

here as a proxy for the predictability of future earnings. Prior studies have used the dispersion of analyst forecasts as an information uncertainty proxy (e.g., see Zhang (2005)), as well as an information asymmetry proxy (e.g., see Krisnhnaswami and Subramaniam (1999)). The absolute forecast error has been used by several studies as a proxy of information asymmetry (e.g., see Atiase and Barber (1994), and Christie (1987)). *AFE* and *DISP* are computed as follows:

$$AFE=\frac{|FMD-A|}{|FMD|} \tag{9}$$

$$DISP=\frac{FSD}{|FMD|} \tag{10}$$

where $|FMD - A|$ is the absolute value of the difference between the median forecast (*FMD*) and the actual earnings per share (*A*), while *FSD* is standard deviation of one year ahead forecasts.

III. D. Accounting for Endogeneity

We expect that the use of derivatives is negatively associated with stock misvaluation. Our hypothesis relies on the premise that firm transparency would be improved by the decision to hedge, i.e. hedging should be associated with lower uncertainty and informational asymmetry regarding firms' future cash flows. An empirical investigation of the relationship between mispricing and the decision to hedge has to account for the possibility of endogeneity. To illustrate the potential effect of endogeneity on the relationship between hedging and mispricing, consider, for example, the firms that depend highly on foreign markets or have extensive operations in foreign countries. These firms would have higher exposure to foreign exchange risk than purely domestic firms and, consequently, greater incentives to use foreign exchange derivatives. If the model fails to control for the impact of variables capturing dependence on foreign markets (or exposure to foreign exchange risk) on the decision to hedge, the empirical results on mispricing could be mistakenly attributed simply to hedging itself rather than to the real reason, which in this case would be the exposure to foreign exchange risk.

We investigate the effect of the firm's hedging decision on stock mispricing using the following model that controls for firm characteristics:

$$M_{it} = \beta_0 + \beta_1 H_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{11}$$

where, M_{it} is the stock misvaluation measure, H_{it} is an indicator variable that is set equal to one for firms that use derivatives (i.e. a hedging indicator) and equal to zero otherwise, X_{it} is a vector of exogenous observable firm characteristics, and ε_{it} is an error term. A typical OLS estimation of the above model may produce biased *β's* because some variables, related to the firms' hedging decision, may not have been included in equation (11). If a firm's decision to hedge is endogenous, it should be estimated by some important characteristics that are known to affect the decision to hedge. Therefore, the hedging indicator (*H*) is estimated as:

$$\hat{H}_{it} = \delta Z_{it} + \mu_{it} \qquad (12)$$

where $\hat{H}_{it}$ is an unobserved latent variable, Z_{it} is a set of firm characteristics, some of which are excluded from equation (11) but affect the hedging decision (*H*), and μ_{it} is an error term. H_{it} is then identified as equal to one *if* $\hat{H}_{it} > 0$, or equal to zero *if* $\hat{H}_{it} < 0$. In order to properly control for endogeneity, we need to identify variables that are correlated with the decision to hedge but uncorrelated with mispricing.[15] Our endogeneity tests are based on a methodology that is similar to the one used by Campa and Kedia (2002). Specifically, we use three techniques to capture the effects of possible correlation between H_{it} and ε_{it} : a) panel data regression models where equation (11) is estimated using fixed-effects and random-effects estimators, b) a simultaneous equation model where equations (11) and (12) are jointly estimated, and c) a treatment effects model based on Heckman's (1979) two-step procedure to control for the self-selection of firms that hedge.

Since our dataset is composed of a panel of several hundred firms spanning five years, we use the following fixed-effects model that controls for time-invariant unobservable firm characteristics affecting the hedging decision:

$$M_{it} = \beta_0 + \beta_1 H_{it} + \beta_2 X_{it} + c_i + u_{it} \qquad (13)$$

where c_i is unobserved heterogeneity, assumed constant over time, and u_{it} is the time-varying error. One of the reasons why the OLS procedure may produce inconsistent estimators is that β's

[15] Simple separate OLS regressions for hedging firms and non-hedging firms are not a good way to solve the endogeneity problem because this method would lead to inconsistent estimates of both sets of parameters.

and c_i could be correlated. If this indeed were the case, the pooled OLS model would cause heterogeneity bias.[16] Greene (1993) indicates that the fixed effects model is a reasonable approach when the researcher is confident that differences between units (in our case, firms) can be regarded as parametric shifts of the regression function, which is a reasonable assumption when the sample represents the full set of units. If this is not the case, i.e. when the sample is drawn from a large population as in our study, then it might be more appropriate to view individual specific constant terms as randomly distributed across cross-sectional units. Therefore, we also estimate the random effects version of model (13).

An alternative way to solve the problem of endogenous explanatory variables in multiple regression models is to use a two stage least squares (2SLS) model. 2SLS involves the simultaneous estimation of the two models, (11) and (12). Based on previous studies that have examined the determinants of derivatives' use, we have identified the following set of variables, which we include in our first stage equation (i.e., the probit model with the hedging indicator as dependent variable) of the 2SLS model. Size (Nance et. al. (1993), Block and Gallagher (1986) and Booth, Smith, and Stolz (1984)), geographic diversification (Geczy *et al* (1997) and Dolde and Mishra (2002)), analyst coverage (Dadalt *et al*. (2002)), dividend payout ratio (Nance *et al.* (1993)), free cash flow ((Mian (1996), Howton and Perfect (1998), and Gay and Nam (1998))[17], taxes paid (Howton and Perfect (1998)), book to market ratio (Froot *et al* (1993) and Gay and Nam (1998)), and profitability (Berkman and Bradbury (1996))[18]. The 2SLS procedure requires that the first stage equation contain at least one instrumental variable that is unrelated to mispricing and therefore is not included in the second stage model. Thus, our full 2SLS model is structured as:

[16] This is the same bias caused by omitting a time constant variable.

[17] Free cash flow proxies for financial constraints. Using various measures of liquidity, Mian (1996), Howton and Perfect (1998), and Gay and Nam (1998), among others, provide evidence of a negative relationship between liquidity and use of derivatives. Geczy *et al* (1997) find that firms with high growth and low accessibility to financing are more likely to hedge.

[18] Berkman and Bradbury (1996) find that derivative usage is strongly negatively related to earnings before interest and taxes scaled by interest expense.

$$H_{it} = \delta_0 + \delta_1\, TFSALEP_{it} + \delta_2\, SIZE_{it} + \delta_3\, PROF_{it} + \delta_4\, DVPOR_{it} + \delta_5\, NAFR_{it} + \delta_6\, RBM_{it} + \delta_7\, TXPD_{it} + \delta_8\, FREECFL_{it} + \mu_{it} \tag{14 a}$$

$$M_{it} = \beta_0 + \beta_1\, \hat{H}_{it} + \beta_2\, AFE_{it} + \beta_3\, DISP_{it} + \beta_4\, SIZE_{it} + \beta_5\, INSTP_{it} + \beta_6\, RBM_{it} + \beta_7\, DAT_{it} + \beta_8\, NAFR_{it} + \varepsilon_{it} \tag{14 b}$$

Our first stage probit model estimates the hedging decision, *H*, as a function of the foreign sales ratio (*TFSALEP*), size (*SIZE*, measured as the book value of total assets), profitability (*PROF*, computed as EBIT divided by sales), dividend payout ratio (*DVPOR*), residual analyst coverage (*NAFR*, the residual from the regression of log analyst coverage on log firm size as in Hong *et al* (2001)), book-to-market ratio (*RBM*), taxes paid (*TXPD*, measured as income taxes paid over EBIT) and free cash flow-to-total assets ratio (*FREECFL*). Year indicator variables are also included in the regression. The second stage model estimates the mispricing index, *MI*, as a function of the fitted value of *H* from the first stage equation, $\hat{H}_{it}$, and several firm characteristic and transparency variables. *AFE* and *DISP* are the absolute forecast error and the dispersion of analyst forecasts. *INSTP* is the percentage of institutional ownership. The expected relationship between the transparency variables and *MI* is negative, i.e. we expect *MI* to be lower when *INSTP* increases and *AFE* and *DISP* decrease. The *MI* model also controls for possible leverage effects on misvaluation. Leverage is measured by *DAT*, the debt ratio computed as total debt over total assets. In addition the second stage model's list of independent variables includes *SIZE*, *RBM* and the residual analyst coverage, *NAFR*. We expect smaller, growth firms to be more mispriced. The residual analyst coverage, *NAFR*, is computed as the residual from a regression of analyst following on firm size. The expected sign of *NAFR* in the *MI* regression model is uncertain. On the one hand, if *NAFR* is capturing the speed of information diffusion (see Hong, Lim and Stein (2001)), then higher levels of residual analyst coverage should be associated with lower levels of mispricing. On the other hand, if excessive coverage is indicative of information friction problems (see Doukas, Kim and Pantzalis (2005)) then high levels of *NAFR* would be associated with overvaluation.

Finally, we employ a treatment effects model based on Heckman's (1979) two-step procedure that corrects for self-selection bias. This bias is introduced if firms are selected into the sample on the basis of "hedging criteria," which might be correlated with mispricing. We expect that firm specific characteristics which cause firms to hedge also cause them to be less transparent and more mispriced by the market. Therefore a treatment effects model allows us to estimate firm mispricing conditional on whether or not the firm hedges. For the hedging firms,

$$E(M_{it} \mid H_{it} = 1) = \beta_0 + \beta_1 + \beta_2 X_{it} + E(\varepsilon_{it} \mid H_{it} = 1)$$

$$= \beta_0 + \beta_1 + \beta_2 X_{it} + \rho\sigma_e\lambda\,(-\delta Z_{it}) \qquad (15)$$

and for the non-hedging firms,

$$E(M_{it} \mid H_{it} = 0) = \beta_0 + \beta_1 + \beta_2 X_{it} + E(\varepsilon_{it} \mid H_{it} = 0)$$

$$= \beta_0 + \beta_2 X_{it} + \rho\sigma_e\left[\frac{-\varphi(\delta Z_{it})}{1-\Phi(\delta Z_{it})}\right] \qquad (16)$$

where σ_e is standard deviation, ρ is correlation between error terms in equations (11) and (12). φ and Φ are the density and distribution functions for a standard normal variable. Therefore, the difference in the mispricing of hedging and non-hedging firms, is given by

$$E(\varepsilon_{it} \mid H_{it} = 1) - E(\varepsilon_{it} \mid H_{it} = 0) = \beta_1 + \rho\sigma_e\left[\frac{\varphi_i}{\Phi_i(1-\Phi_i)}\right] \qquad (17)$$

If the selectivity correction λ_i (lambda) is omitted from the least squares regression, the right-hand side of equation (17) is what is estimated by the OLS coefficient on the treatment dummy variable H_{it} as in equation (11).

IV. EMPIRICAL RESULTS

IV. A. Hedging and Mispricing: Univariate and endogeneity Tests

Table I reports descriptive statistics for the pooled sample. Our pooled sample data show that about half of the firms in our sample use some type of derivative contract. The percentage of firms using currency and interest rate derivatives is about thirty and thirty-one, respectively. Interestingly, in our sample most firms use less than two different derivative contracts; the 90th percentile for both *NTYPE* and *NCONTR* is 2. On average, firms in our sample are covered by eleven analysts, have 48.4% institutional ownership, have a foreign sales' ratio of seventeen percent and report about 7.5% profit before interest and tax. Finally, the sample has a mean debt ratio value of twenty-two percent.

[Insert Table I About Here]

Table II shows the coefficients of correlations between the different mispricing measures, introduced in section III.A. As expected, most measures are significantly positively correlated, except for two cases. |*EXVRI*| is not significantly correlated with |*EXVRK*|. Moreover, |*EXVRI*| is significantly negatively related with |*ARET*|. As these valuation measures are based on widely different theoretical concepts, measurement constructions and accounting/financial variables, it is not surprising that there are some differences among these measures. We find that all individual mispricing measures are significantly and positively correlated with the mispricing index, *MI*. This suggests that *MI* balances out the effects and shortcomings of the individual mispricing measures, while aggregating their informativeness. To the degree that some small amount of difference exists among two of the excess valuation measures, the effectiveness of *MI* might be biased downward. Thus, if our empirical results still obtain using *MI*, the true underlying relationship might be even stronger than is captured by this measure. We conclude that *MI* is an appropriate aggregate measure of mispricing for use in our tests.

[Insert Table II About Here]

Table III reports mean values of all variables used in the study for the sub-samples of firms using derivatives and firms not using derivatives. Also reported are the mean differences across the two groups and the corresponding t-statistics for the mean difference test. On average, users of derivatives are significantly less misvalued than firms that do not use derivatives. This is a first, albeit incomplete, indication of support for our hypothesis that hedging is negatively related to mispicing. Furthermore, the subsample of firms that hedge consists of, on average, larger firms, with greater institutional shareholdings and more accurate earnings forecasts produced by analysts following them, than the firms that do not hedge. This evidence is consistent with the findings of Dadalt *et al* (2002) and in support of the notion that firm transparency is improved by hedging. Our findings from the remaining variables (firm characteristics) are also consistent with prior studies examining the relationship of firm characteristics and the use of derivatives (see, among others, Geczy, Minton, and Schrand (1997)). In particular, we find that users of derivatives have, on average, greater growth opportunities, higher dividend payout ratios, larger free cash flow, higher foreign sales ratios, and lower level of *NAFR* than the non-users group.

[Insert Table III About Here]

Next, we investigate whether, on average, characteristics of firms that are more mispriced differ from those of firms that are less mispriced. We divide firms into three subsamples after ranking firms on their mispricing index (*MI*). Firms belonging to the lowest (highest) 30^{th} percentile of *MI* are classified into the *low* (*high*) *MI* group, while the remaining firms are classified into the *medium MI* group. Table IV presents means for all variables for these three groups of firms sorted on the degree of misvaluation (*MI*). It also presents the difference in means between the *low MI* and *high MI* groups and the corresponding t-statistics. The evidence indicates that hedging is associated with less misvaluation. In addition, less mispriced firms are more likely to use both interest rate and currency types of derivatives and to allocate their investment across a greater number of different derivative contracts, as evidenced by the significantly lower Herfindahl index. This is consistent with the notion that more diversified hedging policies are associated with lower levels of mispricing. As the level of mispricing decreases, all transparency measures improve; low *MI* firms are associated with higher forecast accuracy, less dispersion of forecasts, larger size, and greater institutional shareholdings. Overall, taken together, the univariate evidence from Tables III and IV provides preliminary support in line with the notion that hedging improves firm transparency and reduces mispricing. However, the issue of causality and the possibility of endogeneity in the relationship between mispricing and hedging remain to be analyzed. This will be addressed in a series of multivariate tests included in the next sub-section.

[Insert Table IV About Here]

Our multivariate tests of the hypothesis that the degree of misvaluation, measured by the mispricing index (*MI*), is related to hedging are conducted via OLS, fixed- and random-effects, instrumental variables (2SLS), and treatment-effects (using Heckman's (1979) two-step procedure) regression models.[19] Table V reports the regression results. The OLS model shows that hedging (*H*) is significantly and negatively related to mispricing. However, as discussed earlier, there is a possibility that the OLS model coefficients are biased due to the possibility that the relationship is endogenous.

The random effects, 2SLS and treatment effects models yield a significant negative relationship between the use of derivatives and mispricing. The 2SLS model controls for not only time consistent variables but also for time varying variables. Here, the inclusion of valid instruments in the first stage regression (the probit model with *H* as a dependent variable) generates second stage regression results that show a significant negative relationship between *H* and *MI*. For the 2SLS model, we also report the Hausman test results. Under the null hypothesis the two estimators, β_{OLS} and β_{2SLS}, are consistent, while under the alternative hypothesis only β_{2SLS} is consistent. The Hausman test results indicate that the null is rejected in favor of the alternative hypothesis, i.e. that the coefficient of OLS model is inconsistent and that the relationship is endogenous.

The treatment effects model results show a significant positive coefficient for lambda (the inverse of Mill's ratio, i.e. the correction for self-selection), indicating that characteristics that make firms choose to hedge are positively correlated with mispricing. This important result indicates that the true relationship between hedging and mispricing is more negative than was initially revealed in the OLS model. In other words, hedging is a more effective strategy for reducing mispricing for firms that actually pursue the objective of reducing mispricing by hedging. For firms which hedge due to other reasons, such as the need to manage high exposure to foreign exchange risk (i.e. when there is self-selection bias), the reduction in mispricing is mitigated because the characteristics that make firms choose to hedge also have a positive effect on mispricing. The coefficients of the control variables show, in most cases, the expected signs. Forecast error and dispersion of forecasts are significantly positively related to mispricing, while size and institutional shareholdings are insignificantly but negatively related. The *RBM* coefficient

[19] It should be noted that the results we obtained using the individual mispricing measures compiled in *MI* are qualitatively similar to the ones reported here. They are left out of the paper for the sake of brevity, but are available upon request.

is negative and significant (except for the fixed effects model), indicating that growth stocks tend to be more mispriced. The leverage effects are mostly insignificant, except for the 2SLS and treatment effects models.

Overall, the results from Table V show a strong negative association between use of derivatives and misvaluation. This relationship remains robust even after controlling for endogeneity and self-selection bias. In fact, the underlying relationship is much stronger after endogeneity and self-selection bias are controlled for.

[Insert Table V About Here]

One interesting observation from Table V is that the fixed effects model's results are not in line with the ones obtained from all the other models. The fact that the negative relationship between use of derivatives and mispricing is not captured by the fixed effects model suggests either that the use of derivatives is very persistent over time or, alternatively, that the decision to start (or quit) using derivatives does not affect mispricing. In order to identify the reason for the weak fixed effects results, we provide some additional univariate results in Table VI. In Panel A, we sort firms based on how many years they used derivatives and on how many times during the sample period they changed their status from user to non-user and vice versa. The median firm in the sample uses derivatives in two out of five years. Thirty-eight percent of firms did not use derivatives at all, or only used them in one year, while thirty-two percent used derivatives either four or five years. This indicates that firms in our sample did not change hedging policy from a user to a non-user and vice versa many times during the 1992-1996 period. The third and fourth columns in Panel A directly show that firms were reluctant to change hedging policy. Eighty-two percent of firms just changed their policy only once or kept the same policy over the five years.

Panel B of Table VI uncovers important evidence related to how responsive is the degree of misprcing to a change in hedging policy. Sample firms that use derivatives every year consistently during the five-year period covered in the study display an average mispricing index of 0.4792. In contrast, firms that never used derivatives over the sample period display an average mispricing index of 0.5650, which is significantly higher than that of the consistent users. The third and fourth rows show how the level of mispricing changes when a firm changes hedging policy. When a firm starts using derivatives, its level of mispricing computed during the following year is reduced significantly at the ten percent level. However, firms that stop using derivatives do not display a significant increase in mispricing. These asymmetric results indicate that while hedging is associated with an increase in informativeness and reduced mispricing, a discontinuation of the use of derivatives does not immediately lead to increased mispricing. These results also seem to imply that changes of hedging policy do not immediately affect firm's cash flow informativeness and therefore do not result in rapid shifts of market valuation toward (or away from) fundamental value. The apparent asymmetry in market mispricing in response to changes in firms' hedging policy implies that on average managers choose to use or not to use derivatives based on value maximizing principles. In other words, managers decide to adopt (or abandon) the use of derivatives if the impact on firm value is positive or non-negative. We provide further empirical evidence on this issue in a later section.

Overall, the evidence from Table VI indicates that the weak fixed effects results can be attributed to the "stickiness" of hedging policies and to the slow response of valuation to hedging policy changes. In addition, the stronger results obtained from the random effects model is a manifestation of its better fit to our data, which only cover a relatively short (five year) period.

[Insert Table VI About Here]

As we saw in Table V, the 2SLS and the treatment effects models revealed the existence of significant endogeneity and self-selection bias. Table VII reports the results of the probit model with the derivatives dummy (*H*) as dependent variable, which was estimated in the first stage of the 2SLS and treatment models. Due to difficulty in interpretation, for each variable we report the marginal effect in addition to its coefficient. The marginal effect allows us to interpret the coefficient effects easily as in a typical regression model. The result of the probit model indicates that the larger, more profitable firms, which are more exposed to foreign exchange risk and pay a greater proportion of profits as dividends, are more likely to hedge.

[Insert Table VII About Here]

Thus far we have established that the relationship between use of derivatives and mispricing is negative and endogenous. Next, we address the question as to whether and how hedging policy characteristics affect mispricing. We substitute several variables describing hedging policy characteristics for the use of derivatives dummy in the 2SLS and treatment effects models described previously. The hedging policy characteristics variables are: a) *NTYPE*, which takes the value of zero if the firm does not use derivatives, the value of one when the firm uses only foreign exchange derivatives or only interest rate derivatives, and the value of two if the firm uses both types of derivatives; b) *NCONTR*, which measures the number of different derivative contracts the firm is using and takes values from zero to seven; and c) *HERF*, a Herfindahl index of the notional amount of dollars across different derivatives contracts. *NTYPE* and *NCONTR* are used as proxies for the sophistication and extensiveness of the firm's hedging program. *HERF* is a measure of how concentrated the firm's hedging efforts are across different derivatives' contracts. Because *NTYPE* and *NCONTR* are not binary, Heckman's (1979) two-stage procedure is used in regression (1) and (2). In addition, since *HERF* is always positive, it cannot be used in a Heckman two-stage procedure. We therefore create a Herfinahl index indicator variable (*HERFD*), which takes the value of one if the *HERF* is higher than the sample median, and zero otherwise and use it in estimating a treatment effects model. The results in Table VIII indicate that the coefficients of *NTYPE* and *NCONTR* are negative and significant, consistent with the notion that the more sophisticated and/or extensive the hedging policy is, the lower the misvaluation. The coefficients of *HERFD* are positive and significant[20], implying that lower levels of mispricing are associated with hedging efforts that are more "spread-out". [21]

[Insert Table VIII About Here]

IV. B. Examining the Impact of Hedging on Mispricing Separately for High and Low Excess Value Firms

[20] We also used the original Herfindahl index (*HERF*) in a 2SLS model. The coefficient of *HERF* is positive and significant, consistent with the results displayed in Table VIII based on *HERFD*.

[21] We also estimated a model accounting for potential curvi-linear effects of the notional dollar amount of derivatives on mispricing. The coefficients of the notional dollar amount invested in derivatives (*AMT*) and its square term (AMT^2) are negative and positive, respectively. Thus, misvaluation is reduced initially as the notional amount of derivatives increases, however, beyond a certain range, a further increase in derivatives' notional amount has an inverse (positive) effect on *MI*. This finding is consistent with the notion that excessive use of derivatives can exacerbate mispricing. These results are not reported for the sake of brevity, but are available from the authors upon request.

Our evidence thus far provides strong support for the notion that the use of derivatives is associated with lower levels of misvaluation. This may be interpreted as an indication that hedging can increase value for undervalued firms, but it may also imply that hedging can decrease the value of overvalued firms. If the latter were the case, then the question that arises is why would an overvalued firm's manager decide to hedge. Moreover, Allayannis and Weston (2001) report that the use of currency derivatives positively affects valuation. The evidence from our results thus far and from the Allayannis and Weston study can be potentially reconciled if we can demonstrate that the value increase from hedging is primarily occurring in the case of firms that are undervalued. On the other hand, if we find evidence that use of derivatives reduces mispricing in the case of both undervalued and overvalued firms then our evidence would be in direct conflict with that of Allayannis and Weston (2001).

To examine whether the impact of hedging on mispricing is different for overvalued and undervalued firms, we start by using the five alternative excess value variables described in Table I to create an excess valuation index (*EXVI*) following the method used to create *MI*. We define an indicator variable, *HEXVI*, which takes the value of one if the firm belongs to the top 30th percentlile of firms after sorting on *EXVI*. We then include in our model the interaction terms of the hedging indicator *H* with *HEXVI* and (1 – *HEXVI*) respectively, which allows us to capture the two separate effects of derivatives use on *MI* for the top 30th percentile (high *EXVI*) and the bottom 30th percentile (low *EXVI*) groups.[22] The 2SLS results shown in Table IX indicate that the effect of hedging on mispricing is particularly strong for undervalued firms only. The coefficient of undervalued firms is -0.1899 (t-stat of -3.73), while that of overvalued firms is 0.0075 (t-stat of 0.20). These coefficients are statistically different at the five percent level. This implies that hedging increases value of undervalued firms substantially but does not affect value of overvalued firms. The results obtained from using the hedging policy characteristics variables in

[22] These tests are performed on the subsample that consists of undervalued and overvalued firms only, i.e. the sample includes the top and bottom 30th percentile after sorting on EXVI. Alternatively, we also used the sample median *EXVI* as our cutoff point to define over- and undervalued firms. In these tests, not reported here but available upon request, the full sample is used. The results remain qualitatively similar to the ones reported here.

place of the derivatives use indicator (see columns (2) to (4)) reveal a similar story.[23] These results also imply that managerial hedging decisions are made based on the value maximization principle.

[Insert Table IX About Here]

IV. C. Robustness Tests: Controlling for Future Cash Flow Volatility

Thus far we provided evidence that hedging is associated with high transparency and low mispricing. However, this result does not clearly show the cause-and-effect relation of our story. We have argued that hedging improves the informativeness of cash flows because it improves transparency, and therefore, it should be negatively related to mispricing. However, it is difficult to make inferences regarding hedging's impact on mispricing based on past measures of transparency, because these are already reflected in today's valuation. What matters for the relationship between the use of derivatives and mispricing at time t is the impact of the decision to hedge on future cash flow uncertainty. As a result, we follow Allayannis and Weston (2004) and Shin and Stulz (2000), and adopt a "perfect foresight" approach by using the time *t+1* (i.e. future) earnings and cash flow volatilities as our measure of the time *t* (current) expectations about future volatility. If our argument that hedging improves transparency is correct, then we should find that the decision to hedge is negatively related to future volatility. We measure volatility in future cash flows in two ways, using the rank of the variation in earnings per share (*RVEPS*) and the rank in variation of cash flow (*RVCFO*).

$$RVEPS = Rank\left(\frac{EPSSD}{EPSMD}\right) \tag{18}$$

$$RVCFO = Rank\left(\frac{CFOSD}{CFOMD}\right) \tag{19}$$

where *EPSSD* and *EPSMD* are standard deviation and median value of quarterly earnings per share (EPS) in the five years ahead, respectively. We rank based on deciles of variation, where the variation is computed as the ratio of *EPSSD* to *EPSMD*. The rank of future cash flow volatility

[23] We do not report treatment effect models because it is not technically proper to use interaction terms in treatment effects models that control for self-selection bias.

is computed in a similar fashion. The variation of future cash flows is measured as the ratio of the standard deviation (*CFOSD*) and the median (*CFOMD*) of quarterly cash flows over the next five years. We use cash flows from operations, which is earnings before extraordinary items minus total accruals (Δ current assets – Δ cash – Δ current liabilities – Δ depreciation expense + Δ short-term debt), scaled by average total assets.

In Table X we observe that non-user low excess value firms have the highest mean *RVEPS*, while non-user high excess value firms have the highest mean *RVCFO*. Oppositely, high excess value user firms have the lowest mean value for both measures of future cash flow volatility. Table X also reports that overvalued firms as well as undervalued firms reduce future cash flow and earnings volatility by using derivatives. In light of the evidence in the previous table that hedging does not have a significant impact on valuation for overvalued firms, this result can provide a rationale for the use of derivatives by high excess value firms. In other words, hedging does not destroy values of overvalued firms but instead it substantially improves transparency by reducing uncertainty as defined by future earnings and cash flow volatility. For undervalued firms, hedging provides dual benefit in terms of both lower mispricing and greater transparency. These results also are clearly shown in Figure I, which compares the mean values of mispricing and future EPS volatility between high excess value firms and all other firms, and between low excess value firms and all other firms.

[Insert Table X About Here]

[Insert Figure I About Here]

In Table XI, we re-examine future earnings (*RVEPS*) and cash flow (*RVCFO*) volatilities for portfolios of firms formed after sorting on different contemporaneous measures of transparency and on use of derivatives. As before, we use the absolute value of the error in mean analyst forecast (*AFE*), the dispersion in analysts forecasts (*DISP*), the institutional shareholdings (*INST*) and size as alternative transparency measures. Generally, mean levels of *RVEPS* and *RVCFO* are lower for firms that hedge. However the mitigating effect of the use of derivatives on future uncertainty is much stronger for currently more transparent firms than for the other firms. If one also considers the fact that more (less) transparent firms are more likely to have high (low) excess values, the results obtained in Table XI are consistent with the evidence from Figure I. A small reduction of future uncertainty in less transparent firms is paralleled by a similar effect observed in low *EXVI* (undervalued) firms in Figure I. Similarly, the strong mitigating effect of hedging on future uncertainty reported in Table XI is also evident in firms with high *EXVI* (overvalued firms) in Figure I.

Overall, the results from Table X, Figure I, and Table XI, draw the following big picture about the association between misvaluation, use of derivatives and contemporaneous and expected transparency. Firms that are currently less transparent tend to be undervalued. If they adopt a hedging policy (i.e. they start using derivatives) they will enjoy, on average, a large increase in value but only a small reduction in future uncertainty. On the other hand, firms that are currently more transparent tend to be overvalued. If they hedge they would not experience a significant change in their valuation. However, they would achieve a sizeable reduction in future uncertainty.

[Insert Table XI About Here]

In Table XII we extend the univariate analysis based on the future uncertainty measures, and presented in tables X and XI, into a multivariate setting. Specifically, we examine whether our results remain robust to the inclusion of an expected (future) uncertainty measure in the first stage of our 2SLS and treatment effects models. We re-estimate the probit model from table VII by adding the future earnings volatility (*RVEPS*) as an independent variable in order to see how much expected uncertainty about future earnings affects manager's decision to use derivatives.[24] The coefficient of *RVEPS* is negative and significant suggesting that the use of derivatives is motivated by the desire to reduce the uncertainty in future cash flows. Using the predicted use of derivatives indicator from the first stage probit model, we estimate the 2SLS and treatment effects models. The results are in line with our previous evidence. Self-selection bias and endogeneity still exist, as evidenced by the significant lambda coefficient and the Hausman test statistic. The results of both the 2SLS and the treatment effects models show a significant negative association between derivatives use and mispricing. Moreover, in the 2SLS model, the effect of hedging is

[24] We also repeated the tests in Table XII using the future cash flow volatility (RVCFO) measure. The results, not shown here but available upon request, are similar to the ones reported here.

significant only for undervalued firms. Thus, our previous evidence is not changed after controlling for expected uncertainty measured by the volatility of future cash flows.

[Insert Table XII About Here]

V. CONCLUSIONS

We investigate the relationship between corporate hedging policy and misvaluation. We hypothesize that since hedging improves transparency, it should allow investors to assign market values of hedging firms closer to their true (fundamental) values. Thus, we expect a negative relationship between hedging and mispricing. Our tests use a mispricing index that combines annual rankings based on five different misvaluation measures and the use of derivatives as a proxy for hedging. In addition, we recognize that the relationship may be endogenous and we account for it by using both an instrumental variables and a self-selection model. The results show a strong and significant negative association between hedging and mispricing, and confirm that the decision to hedge is endogenous. We also show that corporate hedging policy characteristics are important in explaining the effect of hedging on misvaluation. In particular, we find that firms using a wider array of types of derivatives contracts and spreading out the dollar amount invested in derivatives across several different derivative contracts are less mispriced. This result is consistent with the view that firms using more extensive, spread out, and sophisticated hedging policies are less mispriced. Consistent with previous evidence by Allayannis and Weston (2001) that hedging increases firm value, our results suggest that the negative association between use of derivatives and mispricing is much stronger for undervalued firms. Overall, our evidence indicates that currently less transparent firms tend to be undervalued and experience large value increases but small reductions in future uncertainty when they hedge. On the other hand, currently more transparent firms tend to be overvalued. When they use derivatives they experience a large reduction in future uncertainty but no significant change in their valuation. Expectations about future uncertainty are an important factor in explaining manager’s decision to use derivatives. Our results show that hedging decisions are partly motivated by the desire to reduce future cash flow volatility.

Numerous prior studies have focused on the relationship between corporate hedging and firm valuation. We expand the literature by providing the first piece of evidence with regards to the relationship between hedging and misvaluation, and by presenting further illuminating evidence about the value-increasing effect of hedging as well as its connection to expected future volatility. This is an important contribution, in the presence of a growing interest in the effects of mispricing on corporate financing and investment policies.

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Table I
Descriptive Statistics for Pooled Sample

Reported are descriptive statistics for our sample firms. The sample contains 1,045 firms (5,225 observations) covered in the Swaps Monitor Publications' Database of Users of Derivatives over the period 1992-1996. The variables examined are defined as follows. |*ARET*|, |*EXVRI*|, |*EXVIA*|, |*EXVRK*|, and |*MBIA*| are mispricing measures computed as absolute values of deviations from five alternative fair value benchmarks. *ARET* is the average monthly abnormal return computed as the difference of the actual return from the expected return derived from the parameters of the Fama-french (1993, 1996) three-factor model. *EXVRI* is the excess value relative to a benchmark derived using Ohlson's (1995) residual income valuation approach. *EXVIA* is the excess value computed as a size- and industry-adjusted total capital using Fama and French's 48 industries classification. *EXVRK* is the excess value computed using the Rhodes-Kropf *et al*. (2004) approach. *MBIA* is the market to book ratio adjusted to the industry median. *MI* is the mispricing index created as the average, scaled cross-sectional ranking over the five aforementioned mispricing measures. *H, FX* and *IR* are dummy variables indicating the use of derivatives, foreign exchange derivatives and interest rate derivatives, respectively. *HERF* measures the concentration of hedging and is measured as a Herfindahl index of notional amounts invested in different derivatives contracts. *NTYPE* is the number of types of derivatives used, i.e. *FX* and/or *IR*, or none and thus takes values from zero to two. *NCONTR* is the number of different derivative contracts used by the firm and based on Swaps Monitor's database it can take values from zero to seven. *AFE* is the absolute value of the median forecast error, computed as the difference between the median one-year ahead EPS forecast and the actual EPS. *DISP*, the dispersion, is the standard deviation of the one-year ahead forecasts. *AFE* and *DISP* are measured in June of each year. *SIZE* is measured by the total assets. *INSTP* is the percentage of common shares outstanding owned by institutions. *DAT* is the debt ratio, measured as total debt over total assets. *RBM* is the book-to-market decile ranking, computed as using NYSE benchmarks for BM measured as in Fama and French (1993). *DVPOR* is the dividend payout ratio. *TXPD* is income taxes paid over earnings before interest and taxes (EBIT). *PROF* is EBIT divided by sales. *FREECFL* is the free cash flow divided by total assets. *TFSALEP* is the foreign sales ratio, computed as total foreign sales as percentage of total firm sales. *NAFR* is the residual from regression of *NAF* on *SIZE*, where *NAF* is the number of non-stale one-year ahead analyst EPS forecasts.

Type of Variables	Variables	Number of Obs.	Mean	Median	Std. Dev.	10%	90%
Mispricing measures	|*ARET*|	3,729	0.0224	0.0152	0.0288	0.0026	0.0497
	|*EXVIA*|	3,627	0.3341	0.2328	0.3448	0.0395	0.7570
	|*EXVRI*|	2,740	0.6555	0.6415	0.3787	0.1566	1.1205
	|*EXVRK*|	3,389	0.2438	0.1890	0.2022	0.0314	0.5334
	|*MBIA*|	3,677	0.3405	0.2547	0.3337	0.0389	0.7385
	MI	4,268	0.5113	0.4964	0.1958	0.2697	0.7770
Firm excess valuation variables	*ARET*	3,729	-0.0013	-0.0015	0.0365	-0.0370	0.0323
	EXVIA	3,627	0.0539	0.0000	0.4771	-0.4323	0.6185
	EXVRI	2,740	0.5988	0.6215	0.4632	0.0357	1.1117
	EXVRK	3,389	0.0683	0.0606	0.3093	-0.3212	0.4559
	MBIA	3,677	0.0697	0.0000	0.4717	-0.4284	0.6527
Hedging variables	*H*	5,225	0.4967	0.0000	0.5000	0.0000	1.0000
	FX	5,225	0.3049	0.0000	0.4604	0.0000	1.0000
	IR	5,225	0.3100	0.0000	0.4626	0.0000	1.0000
	HERF †	2,216	0.8680	1.0000	0.2115	0.5073	1.0000
	NTYPE	5,225	0.6149	0.0000	0.6881	0.0000	2.0000
	NCONTR	5,255	0.7950	0.0000	1.0359	0.0000	2.0000
Transparency measures	*AFE*	3,397	0.4128	0.0857	1.6801	0.0071	0.6833
	DISP	3,169	0.1466	0.0429	0.5998	0.0114	0.2533
	SIZE	4,513	2768.3480	409.0600	11222.3700	43.7100	5403.1000
	INSTP	3,466	48.3970	50.6000	22.4370	17.4900	76.7500
Other firm characteristics	*DAT*	4,466	22.4284	20.0050	20.9160	0.0000	49.4700
	RBM	3,914	4.8235	4.0000	2.8509	1.0000	9.0000
	DVPOR	4,076	356.8576	18.2950	52.6585	0.0000	101.0100
	TXPD	4,025	0.4392	0.2443	0.9126	0.0204	0.7118
	PROF	4,567	0.0742	0.0756	0.6771	0.0062	0.2268
	FREECFL	4,414	0.0114	0.0130	0.1009	-0.0706	0.0977
	TFSALEP	3,490	16.6507	6.1930	21.5806	0.0000	48.6145
	NAFR	3,422	-0.0043	0.8006	6.4689	-8.5888	7.4221

† computed with sample of hedging firms

Table II
Correlations Coefficients between Mispricing Measures

This table shows the correlations coefficients between the mispricing measures, |*ARET*|, |*EXVRI*|, |*EXVIA*|, |*EXVRK*|, |*MBIA*|, and *MI*. The corresponding p-values are reported in brackets. *MI* is created as the average, scaled cross-sectional ranking over five different mispricing measures. The mispricing measures are computed as absolute values of deviations from five alternative fair value benchmarks. *ARET* is the average monthly abnormal return computed as the difference of the actual return from the expected return derived from the parameters of the Fama-french (1993, 1996) three-factor model. *EXVRI* is the excess value relative to a benchmark derived using Ohlson's (1995) residual income valuation approach. *EXVIA* is the excess value computed as a size- and industry-adjusted total capital using Fama and French's 48 industries classification. *EXVRK* is the excess value computed using the Rhodes-Kropf *et al*. (2004) approach. *MBIA* is the market to book ratio adjusted to the industry median. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	MI	|*ARET*|	|*EXVIA*|	|*EXVRI*|	|*EXVRK*|	|*MBIA*|
MI	1.0000					
|*ARET*|	0.4823 *** [0.0000]	1.0000				
|*EXVIA*|	0.6046 *** [0.0000]	0.2205 *** [0.0000]	1.0000			
|*EXVRI*|	0.3132 *** [0.0000]	-0.0490 ** [0.0116]	0.0533 *** [0.0055]	1.0000		
|*EXVRK*|	0.5607 *** [0.0000]	0.0751 *** [0.0000]	0.1902 *** [0.0000]	0.0049 [0.7982]	1.0000	
|*MBIA*|	0.6633 *** [0.0000]	0.1457 *** [0.0000]	0.3098 *** [0.0000]	0.0937 *** [0.0000]	0.3971 *** [0.0000]	1.0000

Table III
Users versus Non-users of Derivatives: Comparison of Mean Values of Mispricing Measures, Hedging Variables, and Other Firm Characteristics:

Reported are mean values of all variables used in the multivariate tests for the subsamples that consist of users and non-users of derivatives, respectively. Also reported are the difference in mean values between the two subsamples and the corresponding t-statistic. White's (1980) heteroskedasticity-consistent standard errors are used in t-tests. The variables examined are defined as follows. *MI* is the mispricing index created as the average, scaled cross-sectional ranking over the five mispricing measures defined in Table I. *H, FX* and *IR* are dummy variables indicating the use of derivatives, foreign exchange derivatives and interest rate derivatives, respectively. *HERF* measures the concentration of hedging and is measured as a Herfindahl index of notional amounts invested in different derivatives contracts. *NTYPE* is the number of types of derivatives used, i.e. *FX* and/or *IR*, or none and thus takes values from zero to two. *NCONTR* is the number of different derivative contracts used by the firm and based on Swaps Monitor's database it can take values from zero to seven. *AFE* is the absolute value of the median forecast error, computed as the difference between the median one-year ahead EPS forecast and the actual EPS. *DISP*, the dispersion, is the standard deviation of the one-year ahead forecasts. *AFE* and *DISP* are measured in June of each year. *SIZE* is measured by the total assets. *INSTP* is the percentage of common shares outstanding owned by institutions. *DAT* is the debt ratio, measured as total debt over total assets. *RBM* is the book-to-market decile ranking, computed as using NYSE benchmarks for BM measured as in Fama and French (1993). *DVPOR* is the dividend payout ratio. *TXPD* is income taxes paid over earnings before interest and taxes (EBIT). *PROF* is EBIT divided by sales. *FREECFL* is the free cash flow divided by total assets. *TFSALEP* is the foreign sales ratio, computed as total foreign sales as percentage of total firm sales. *NAFR* is the residual from regression of *NAF* on *SIZE*, where *NAF* is the number of non-stale one-year ahead analyst EPS forecasts. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Type of Variables	Variables	Users of derivatives (N of Obs. = 2,595)	Non-users of derivatives (N of Obs. = 2,630)	Mean difference: Users – Non-users	t-statistics: Users = Non-users
Mispricing index	*MI*	0.4965	0.5300	0.0335 ***	-5.49
Hedging variables	*FX*	0.6139	0.0000	0.6139 ***	64.22
	IR	0.6243	0.0000	0.6243 ***	65.65
	HERF	0.8680	N/A	N/A	N/A
	NTYPE	1.2382	0.0000	1.2382 ***	148.05
	NCONTR	1.6008	0.0000	1.6008 ***	87.39
Transparency measures	*AFE*	0.3419	0.5120	-0.1701 ***	-2.66
	DISP	0.1387	0.1583	-0.0196	-0.85
	SIZE	4311.0590	1105.6030	3205.4560 ***	10.00
	INSTP	51.6028	44.2975	7.3053 ***	9.53
Other firm characteristics	*DAT*	22.1512	22.7312	-0.5800	-0.92
	RBM	4.6996	4.9787	-0.2791 ***	-3.03
	DVPOR	41.4568	32.0508	9.4060 ***	5.73
	TXPD	0.4263	0.4538	-0.0275	-0.94
	PROF	0.0835	0.0639	0.0196	0.98
	FREECFL	0.0165	0.0059	0.0106 ***	3.49
	TFSALEP	20.6642	12.1232	8.5410 ***	11.98
	NAFR	-0.3057	0.4226	0.7283 ***	3.35

Table IV
Descriptive Statistics for Portfolios of Firms Classified Formed After Sorting on Mispricing Index (*MI*)

This table reports means values of the mispricing measure, the hedging variables, the security analysis variables, and other firm characteristics, for portfolios formed by sorting firms annually into groups based on the mispricing index (*MI*). *MI* is created as the average, scaled cross-sectional ranking over the following five mispricing measures: |*ARET*|, |*EXVRI*|, |*EXVIA*|, |*EXVRK*|, and |*MBIA*|. The mispricing measures are computed as absolute values of deviations from five alternative fair value benchmarks. *ARET* is the average monthly abnormal return computed as the difference of the actual return from the expected return derived from the parameters of the Fama-french (1993, 1996) three-factor model. *EXVRI* is the excess value relative to a benchmark derived using Ohlson's (1995) residual income valuation approach. *EXVIA* is the excess value computed as a size- and industry-adjusted total capital using Fama and French's 48 industries classification. *EXVRK* is the excess value computed using the Rhodes-Kropf *et al*. (2004) approach. *MBIA* is the market to book ratio adjusted to the industry median. Firms belonging to the lowest (highest) 30^{th} percentile of *MI* are classified in the *Low* (*High*) *MI* group, while the remaining firms are classified into the *Medium MI* group. Also reported are the difference in means between the *Low MI* and the *High MI* subsamples as well as the corresponding t-statistics. White's (1980) heteroskedasticity-consist standard errors are used in t-tests. The variables examined are defined as follows. *H, FX* and *IR* are dummy variables indicating the use of derivatives, foreign exchange derivatives and interest rate derivatives, respectively. *HERF* measures the concentration of hedging and is measured as a Herfindahl index of notional amounts invested in different derivatives contracts. *NTYPE* is the number of types of derivatives used, i.e. *FX* and/or *IR*, or none and thus takes values from zero to two. *NCONTR* is the number of different derivative contracts used by the firm and based on Swaps Monitor's database it can take values from zero to seven. *AFE* is the absolute value of the median forecast error, computed as the difference between the median one-year ahead EPS forecast and the actual EPS. *DISP*, the dispersion, is the standard deviation of the one-year ahead forecasts. *AFE* and *DISP* are measured in June of each year. *SIZE* is measured by the total assets. *INSTP* is the percentage of common shares outstanding owned by institutions. *DAT* is the debt ratio, measured as total debt over total assets. *RBM* is the book-to-market decile ranking, computed as using NYSE benchmarks for BM measured as in Fama and French (1993). *DVPOR* is the dividend payout ratio. *TXPD* is income taxes paid over earnings before interest and taxes (EBIT). *PROF* is EBIT divided by sales. *FREECFL* is the free cash flow divided by total assets. *TFSALEP* is the foreign sales ratio, computed as total foreign sales as percentage of total firm sales. *NAFR* is the residual from regression of *NAF* on *SIZE*, where *NAF* is the number of non-stale one-year ahead analyst EPS forecasts. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Type of Variables	Variables	*Low MI* Firms (N of Obs. = 1,281)	*Medium MI* Firms (N of Obs. = 1,706)	*High MI* Firms (N of Obs. = 1,281)	Mean Difference: Low – High	t-statistics: Low = High
Mispricing Measures	|*ARET*|	0.0094	0.0199	0.0395	-0.0301 ***	-22.29
	|*EXVIA*|	0.1284	0.2888	0.6386	-0.5102 ***	-34.63
	|*EXVRI*|	0.5514	0.6365	0.8309	-0.2795 ***	-14.36
	|*EXVRK*|	0.1253	0.2315	0.4010	-0.2758 ***	-32.46
	|*MBIA*|	0.1284	0.2971	0.6446	-0.5162 ***	-36.50
Hedging Variables	*H*	0.5909	0.5809	0.4965	0.0945 ***	4.82
	FX	0.3583	0.3880	0.3115	0.0468 **	2.51
	IR	0.4020	0.3476	0.2795	0.1226 ***	6.60
	HERF	0.8474	0.8520	0.8950	-0.0475 ***	-3.91
	NTYPE	0.7603	0.7356	0.5909	0.1694 ***	6.21
	NCONTR	0.9891	0.9701	0.7549	0.2342 ***	5.61
Transparency measures	*AFE*	0.1785	0.3676	0.7496	-0.5711 ***	-6.50
	DISP	0.0667	0.1522	0.2334	-0.1667 ***	-6.28
	SIZE	3923.8860	3165.1490	2103.8990	1819.9870 ***	3.88
	INSTP	51.1065	51.6134	43.9253	7.1811 ***	7.08
Other firm characteristics	*DAT*	21.2183	20.0811	21.6369	-0.4186	-0.50
	RBM	4.9356	4.8178	4.7649	0.1707	1.40
	DVPOR	52.2153	37.3066	21.5526	36.6504 ***	14.47
	TXPD	0.4628	0.4733	0.4786	-0.0158	-0.37
	PROF	0.1046	0.0524	0.0654	0.0392 ***	3.53
	FREECFL	0.0157	0.0141	0.0173	-0.0015	-0.42
	TFSALEP	16.9068	17.9221	17.2671	-0.3603	-0.35
	NAFR	-0.1009	0.0552	0.0086	-0.1095	-0.36

Table V

Effect of Corporate Hedging on Misvaluation

This table reports coefficients for regressions of the mispricing index (*MI*) on the use of derivatives dummy (*H*) using the OLS, fixed effects, 2SLS and the treatment effects models. In the instrumental variables (2SLS) estimation and the treatment effects model, the first step involves a probit model wherein *H* is estimated. The probit estimation is shown in the Table VII and we only report the second stage regression results in this table. Treatment effects model uses Heckman (1979) two-step procedure and captures the effect of an endogenously chosen binary treatment (*H*, hedging decision) on another endogenous continuous variable (*MI*). To determine whether the relation between mispricng and hedging is endogenous, we use the Hausman test statistic in the 2SLS model, and the significance of the lamda (inverse of Mill's ratio) coefficient in the treatment effects model. The variables examined are defined as follows. Dependent variable is the mispricing index, *MI*, created as the average, scaled cross-sectional ranking over the following five mispricing measures: |*ARET*|, |*EXVRI*|, |*EXVIA*|, |*EXVRK*|, and |*MBIA*|. The mispricing measures are computed as absolute values of deviations from five alternative fair value benchmarks. The five aforementioned mispricing measures are defined in Table I. *H* is an indicator variable, which takes the value one if the firm used derivatives and zero otherwise. *AFE* is the absolute value of the median forecast error, computed as the difference between the median one-year ahead EPS forecast and the actual EPS. *DISP*, the dispersion, is the standard deviation of the one-year ahead forecasts. *AFE* and *DISP* are measured in June of each year. *INSTP* is the percentage of common shares outstanding owned by institutions. *SIZE* is measured by the firm's total assets. *RBM* is the book-to-market decile ranking, computed as using NYSE benchmarks for BM measured as in Fama and French (1993). *DAT* is the debt ratio, measured as total debt over total assets. *NAFR* is the residual from regression of *NAF* on *SIZE*, where *NAF* is the number of non-stale one-year ahead analyst EPS forecasts. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	OLS	Fixed Effects	Random Effects	2SLS	Treatment
Intercept	0.5865 *** (47.58)	0.4381 *** (22.64)	0.5267 *** (35.80)	0.6389 *** (29.94)	0.6363 *** (30.44)
H	-0.0370 *** (-5.33)	-0.0029 (-0.41)	-0.0137 ** (-2.12)	-0.1270 *** (-4.99)	-0.1302 *** (-5.26)
AFE	0.0096 *** (2.97)	0.0038 (1.25)	0.0066 ** (2.42)	0.0239 ** (2.16)	0.0225 ** (2.12)
DISP	0.0161 * (1.75)	0.0053 (0.66)	0.0054 (0.72)	0.1142 *** (4.16)	0.1145 *** (4.37)
INSTP	-0.0002 (-1.43)	0.0008 ** (2.58)	0.0001 (0.39)	-0.0001 (-0.35)	-2.55×10^{-5} (-0.12)
SIZE	-3.60×10^{-7} (-1.53)	-3.47×10^{-7} (-0.56)	-4.27×10^{-7} (-1.23)	2.50×10^{-7} (0.86)	2.59×10^{-7} (0.90)
RBM	-0.0116 *** (-8.62)	0.0037 ** (2.00)	-0.0043 *** (-2.88)	-0.0156 *** (-8.71)	-0.0155 *** (-8.67)
DAT	-0.0003 (-1.62)	0.0003 (1.41)	3.64×10^{-5} (0.21)	-0.0008 *** (-2.91)	-0.0007 *** (-2.71)
NAFR	0.0007 (1.35)	0.0036 *** (2.99)	0.0010 (1.33)	0.0011 (1.51)	0.0010 (1.46)
Lambda					0.0636 *** (4.00)
Hausman Test [p-value]				42.38 *** [0.0000]	
Number of obs.	2,447	2,447	2,447	1,505	1,505
R^2	0.0590	0.0161	0.0938	0.0983	
F (or χ^2) [Prob. > F (or χ^2)]	19.11 *** [0.0000]	3.64 *** [0.0003]	34.87 *** [0.0000]	20.39 *** [0.0000]	208.11 *** [0.0000]

Table VI
Changes in Hedging Corporate Policy and Mispricing

This table shows the relation between changes in corporate hedging policy and the level of mispricing. Changes in corporate hedging policy are defined as changes in the status of the firm from user of derivatives to non-user and vice versa. In Panel A, we sort firms based on the number of years they used derivatives over the 1992-1996 period and on the number of policy changes. Because the sample includes five years, the maximum number of policy changes a firm records is four. In Panel B, we report the change in the level of mispricing around the changes in hedging policy. The mispricing index, *MI*, is created as the average, scaled cross-sectional ranking over the following five mispricing measures: |*ARET*|, |*EXVRI*|, |*EXVIA*|, |*EXVRK*|, and |*MBIA*|. The mispricing measures are computed as absolute values of deviations from five alternative fair value benchmarks. The five aforementioned mispricing measures are defined in Table I. White's (1980) heteroskedasticity-consist standard errors are used in t-tests. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Panel A: Distribution of sample firms by number of years they used derivatives and by the number of hedging policy changes.

Number of years firms used derivatives over the sample period	Number of firms (%)	Number of policy changes over the sample period	Number of firms (%)
0 *NOT* used	157 (15)	0 *NOT* changed	388 (37)
1	241 (23)	1	475 (45)
2	151 (14)	2	157 (15)
3	163 (16)	3	24 (2)
4	102 (10)	4 Changed every year	1 (0)
5 Consistently used	231 (22)		
Mean	2.4833	Mean	0.8278
Median	2.0000	Median	1.0000
Total	1,045 (100)	Total	1,045 (100)

Panel B: Mean mispricing index before and after changes in corporate hedging policy.

	Number of firms (%)†	Before the policy change: mean and [median]	After the policy change: mean and [median]	Whole sample period: mean and [median]	Δ*MI*: After-Before mean diff. and [median diff.]
[1] firms that hedge throughout the sample period	231 (22)	N/A	N/A	0.4792 (0.4619)	N/A
[2] firms that do *NOT* hedge throughout the sample period	157 (15)	N/A	N/A	0.5650 (0.5512)	N/A
[3] firms that changed policy from non-hedger to hedger	511 (49)	0.5182 [0.5149]	0.4986 [0.4820]	N/A	-0.0196 * [-0.0329] *
[4] firms that changed policy from hedger to non-hedger	328 (31)	0.5082 [0.5080]	0.4979 [0.4975]	N/A	-0.0103 [-0.0105]
Difference of *MI* :[1] – [2]				-0.0857 *** [-0.0893] ***	

† Note that [3] and [4] are not exclusive. Some firms show both policy changes in the sample period.

Table VII
Probit Estimates for Users of Derivatives

This table reports coefficients, corresponding z-statistics in parentheses and marginal effects for a probit model using the use of derivatives dummy variable (*H*) as dependent variable. The estimates of this model were used to calculate the fitted probabilities and self-selectivity correction for the 2SLS and treatment effects models in Table V and VIII. *TFSALEP* is the foreign sales ratio, computed as total foreign sales as percentage of total firm sales. *SIZE* is measured by the total assets. *PROF* is EBIT divided by sales. *DVPOR* is the dividend payout ratio. *RBM* is the book-to-market decile ranking, computed as using NYSE benchmarks for BM measured as in Fama and French (1993). *NAFR* is the residual from regression of *NAF* on *SIZE*, where *NAF* is the number of non-stale one-year ahead analyst EPS forecasts. *TXPD* is income taxes paid over earnings before interest and taxes (EBIT). *FREECFL* is the free cash flow divided by total assets. Year dummies are included. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Variables	Coefficient	Marginal Effect
Intercept	-0.5820 *** (-4.38)	
TFSALEP	0.0159 *** (8.74)	0.0058
SIZE	0.0001 *** (7.11)	2.52×10^{-5}
PROF	1.7921 *** (3.29)	0.6557
DVPOR	0.0017 * (1.94)	0.0006
RBM	0.0167 (1.09)	0.0061
NAFR	0.0068 (1.05)	0.0025
TXPD	-0.0637 (-0.98)	-0.0233
FREECFL	0.3897 (0.77)	0.1426
Year Dummies	Yes	
Number of obs.	1,505	
Pseudo R^2	0.1249	
χ^2 [Prob. > χ^2]	251.99 *** [0.0000]	

Table VIII
Effect of Corporate Hedging Policy Characteristics on Misvaluation

This table shows the impact of variables describing the breadth and variety of derivatives contracts use on mispricing. Reported are coefficients of 2SLS, Heckman, and treatment effects models. Dependent variable in the second stage model is the mispricing index, *MI*, created as the average, scaled cross-sectional ranking over the following five mispricing measures: |*ARET*|, |*EXVRI*|, |*EXVIA*|, |*EXVRK*|, and |*MBIA*|. The mispricing measures are computed as absolute values of deviations from five alternative fair value benchmarks. The five aforementioned mispricing measures are defined in Table I. Regression (1) and (2) use *NTYPE* and *NCONTR* as dependent variable in the first stage model. Because these are not binary, Heckman (1979) two-stage procedure is used. For Herfindahl index of the amount invested across different derivatives' contracts (*HERF*) to be used in the self-selection model, we create a dummy variable (*HERFD*), which takes one if it *HERF* higher than the sample median and zero otherwise. *NTYPE* is the number of types of derivatives used, i.e. *FX* and/or *IR*, or none and thus takes values from zero to two. *NCONTR* is the number of different derivative contracts used by the firm and based on Swaps Monitor's database it can take values from zero to seven. *HERF* measures the concentration of hedging and is measured as a Herfindahl index of notional amounts invested in different derivatives contracts. *AFE* is the absolute value of the median forecast error, computed as the difference between the median one-year ahead EPS forecast and the actual EPS. *DISP*, the dispersion, is the standard deviation of the one-year ahead forecasts. *AFE* and *DISP* are measured in June of each year. *INSTP* is the percentage of common shares outstanding owned by institutions. *SIZE* is measured by the firm's total assets. *RBM* is the book-to-market decile ranking, computed as using NYSE benchmarks for BM measured as in Fama and French (1993). *DAT* is the debt ratio, measured as total debt over total assets. *NAFR* is the residual from regression of *NAF* on *SIZE*, where *NAF* is the number of non-stale one-year ahead analyst EPS forecasts. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	(1) *NTYPE*		(2) *NCONTR*		(3) *HERFD*	
	2SLS	Heckman	2SLS	Heckman	2SLS	Treatment
Intercept	0.6164 *** (31.00)	0.5536 *** (19.47)	0.6017 *** (32.56)	0.5215 *** (19.58)	0.4866 *** (15.26)	0.4854 *** (16.63)
NTYPE	-0.0671 *** (-3.87)	-0.0280 ** (-2.42)				
NCONTR			-0.0343 *** (-3.35)	-0.0023 (-0.42)		
HERFD					0.0979 *** (2.75)	0.0883 *** (2.99)
AFE	0.0265 ** (2.46)	0.0641 *** (3.52)	0.0270 ** (2.51)	0.0643 *** (3.52)	0.0639 *** (3.29)	0.0613 *** (3.22)
DISP	0.1178 *** (4.39)	0.0883 *** (2.60)	0.1181 *** (4.40)	0.0878 ** (2.58)	0.0799 ** (2.09)	0.0769 ** (2.06)
INSTP	-0.0001 (1.08)	-3.18×10^{-5} (-0.12)	-0.0001 (-0.54)	-0.0001 (-0.41)	-0.0001 (-0.32)	-1.80×10^{-5} (-0.06)
SIZE	4.11×10^{-7} (1.28)	2.69×10^{-7} (0.95)	6.46×10^{-7} * (1.67)	2.36×10^{-7} (0.81)	6.67×10^{-7} (1.18)	5.55×10^{-7} (1.05)
RBM	-0.0158 *** (-8.91)	-0.0175 *** (-7.97)	-0.0161 *** (-9.11)	-0.0176 *** (-7.91)	-0.0201 *** (-8.08)	-0.0201 *** (-8.22)
DAT	-0.0009 *** (-3.28)	-0.0003 (-0.99)	-0.0008 *** (-3.22)	-0.0003 (-1.08)	-0.0002 (-0.57)	-2.96×10^{-5} (-0.09)
NAFR	0.0010 (1.46)	0.0018 ** (2.22)	0.0010 (1.42)	0.0018 ** (2.22)	0.0011 (1.26)	0.0012 (1.34)
Lambda		0.0376 * (1.77)		0.0473 ** (2.17)		-0.0323 * (-1.70)
Hausman Test [p-value]	51.15 *** [0.0000]		50.67 *** [0.0000]		22.66 *** [0.0009]	
Number of obs.	1,505	1,505	1,505	1,505	753	753
R^2	0.0914		0.0890		0.1064	
F (or χ^2) [Prob. > F (or χ^2)]	18.80 *** [0.0000]	148.94 *** [0.0000]	18.27 *** [0.0000]	142.17 *** [0.0000]	11.07 *** [0.0000]	138.61 *** [0.0000]

Table IX
Effect of Corporate Hedging Policy and Its Characteristics on Mispricing for High and Low Excess Value Firms

This table reports coefficients for regressions of the mispricing index (*MI*) on the use of derivatives dummy (*H*) using the 2SLS model. In order to test whether the effect is different for firms with high excess value than for firms with low excess value, we start by using the five alternative excess value variables described in Table I to create an excess valuation index (*EXVI*) following the method used to create *MI*. We define an indicator variable, *HEXVI*, which takes the value of one if the firm belongs to the top 30th percentlile of firms after sorting on *EXVI*. We then include in our model the interaction terms of the hedging indicator *H* with *HEXVI* and (1 – *HEXVI*) respectively, which allows us to capture the two separate effects of derivatives use on *MI* for the top 30th percentile (high *EXVI*) and the bottom 30th percentile (low *EXVI*) groups. In the instrumental variables (2SLS) estimation, the first step involves a probit model wherein *H* is estimated. The probit estimation is shown in the Table VII and we only report the second stage regression results in this table. To determine the endogenous relation between mispricng and hedging, we use the Hausman test statistic. The variables examined are defined as follows. Dependent variable is the mispricing index, *MI*, created as the average, scaled cross-sectional ranking over the following five mispricing measures: |*ARET*|, |*EXVRI*|, |*EXVIA*|, |*EXVRK*|, and |*MBIA*|. The mispricing measures are computed as absolute values of deviations from five alternative fair value benchmarks. The five aforementioned mispricing measures are defined in Table I. *H* is an indicator variable, which takes the value one if the firm used derivatives and zero otherwise. *NTYPE* is the number of different broadly defined types of derivatives used by the firm, i.e. *FX* and/or *IR*, or none, and thus takes values from zero to two. *NCONTR* is the number of different derivative contracts used by the firm as reported in Swaps Monitor's database. *NCONTR* can take values from zero to seven. Herfinahl index dummy (*HERFD*) takes one if it is higher than the median and zero otherwise, where *HERF* measures the concentration of the notional amounts invested across different types of derivatives' contracts. *AFE* is the absolute value of the median forecast error, computed as the difference between the median one-year ahead EPS forecast and the actual EPS. *DISP*, the dispersion, is the standard deviation of the one-year ahead forecasts. *AFE* and *DISP* are measured in June of each year. *INSTP* is the percentage of common shares outstanding owned by institutions. *SIZE* is measured by the firm's total assets. *RBM* is the book-to-market decile ranking, computed as using NYSE benchmarks for BM measured as in Fama and French (1993). *DAT* is the debt ratio, measured as total debt over total assets. *NAFR* is the residual from regression of *NAF* on *SIZE*, where *NAF* is the number of non-stale one-year ahead analyst EPS forecasts. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Table IX (cont'd)
Effect of Corporate Hedging Policy and Its Characteristics on Mispricing for High and Low Excess Value Firms

	(1) *H*	(2) *NTYPE*	(3) *NCONTR*	(4) *HERFD*
Intercept	0.7159 *** (24.73)	0.6701 *** (23.40)	0.6615 *** (25.56)	0.5345 *** (13.12)
*H*HEXVI*	0.0075 (0.20)			
*H**(1 – *HEXVI*)	-0.1899 *** (-3.73)			
*NTYPE*HEXVI*		-0.0084 (-0.35)		
*NTYPE**(1 – *HEXVI*)		-0.0780 ** (-2.26)		
*NCONTR*HEXVI*			0.0067 (0.50)	
*NCONTR**(1 – *HEXVI*)			-0.0701 *** (-2.84)	
*HERFD*HEXVI*				0.1127 * (1.67)
*HERFD**(1 – *HEXVI*)				-0.0120 (-0.36)
AFE	0.0160 (1.08)	0.0227 (1.53)	0.0230 (1.56)	0.0289 (1.30)
DISP	0.1339 *** (3.70)	0.1439 *** (3.94)	0.1437 *** (3.94)	0.1664 *** (2.86)
INSTP	-0.0004 (-1.50)	-0.0005 * (-1.66)	-0.0004 * (-1.67)	-0.0005 (-1.22)
SIZE	2.61×10^{-7} (0.83)	2.50×10^{-6} ** (2.10)	2.71×10^{-6} *** (2.61)	4.92×10^{-7} (0.62)
RBM	-0.0196 *** (-8.59)	-0.0192 *** (-7.86)	-0.0193 *** (-8.23)	-0.0227 *** (-6.63)
DAT	-0.0003 (-0.84)	-0.0004 (-1.11)	-0.0004 (-1.20)	0.0002 (0.45)
NAFR	0.0004 (0.43)	0.0006 (0.56)	0.0005 (0.51)	-0.0005 (-0.38)
Test: *H*HEXVI* = *H**(1 – *HEXVI*) [p-value]	5.83 ** [0.0160]			
Test: *NTYPE*HEXVI* = *NTYPE**(1 – *HEXVI*) [p-value]		1.80 [0.1795]		
Test: *NCONTR*HEXVI* = *NCONTR**(1 – *HEXVI*) [p-value]			4.99 ** [0.0257]	
Test: *HERFD*HEXVI* = *HERFD**(1 – *HEXVI*) [p-value]				1.29 [0.2569]
Hausman Test [p-value]	55.46 *** [0.0000]	30.71 *** [0.0000]	29.28 *** [0.0001]	32.03 *** [0.0000]
Number of obs.	815	815	815	390
R^2	0.1211	0.1464	0.1045	0.1445
F [Prob. > F]	12.32 *** [0.0000]	10.24 *** [0.0000]	10.44 *** [0.0000]	7.13 *** [0.0000]

Table X
Future Earnings and Cash Flow Volatilities for Portfolios of Firms Formed After Sorting on Excess Value Index and Use of Derivatives

This table reports future earnings volatility which is computed as two variables: 1) rank of EPS variation (*RVEPS*) and 2) rank of CFO variation (RVCFO) in brackets. Portfolios are formed by excess value (*EXVI*) and use of derivatives (*H*). Firms belonging to the lowest and highest 30th percentile are classified in the *Low* and *High* excess value group, respectively. Also reported are the difference in means between the *Low* and the *High* portfolios as well as the corresponding t-statistics in parenthesis. White's (1980) heteroskedasticity-consist standard errors are used in t-tests. The variables examined are defined as follows. The excess value index, *EXVI*, is created as the average, scaled cross-sectional ranking over the following five excess value measures: *ARET*, *EXVRI*, *EXVIA*, *EXVRK*, and *MBIA*| The five aforementioned excess value measures are defined in Table I. *RVEPS* and *RVCFO* are the decile ranks of the variation in EPS and CFO (cash flow from operations), respectively. EPS and CFO variation are computed as the ratio of the standard deviation to the mean EPS and CFO, respectively, over twenty-quarters (five-years) ahead. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

	Low excess value firms (*Low EXVI*)	*High* excess value firms (*High EXVI*)	All firms	*RVEPS* mean diff.: *Low – High* (t-statistics)	[*RVCFO*] mean diff.: *Low – High* (t-statistics)
Users of derivatives	5.5261 [5.3957]	5.3014 [5.3239]	5.4043 [5.3572]	0.2248 (1.36)	[0.0717] (0.39)
Non-users of derivatives	6.1935 [5.8574]	5.9371 [6.0446]	6.0775 [5.9412]	0.2565 (1.46)	[-0.1872] (-0.96)
All firms	5.8607 [5.6290]	5.5635 [5.6250]	5.7118 [5.6270]	0.2972 ** (2.46)	0.0040 (0.03)
RVEPS mean diff.: *Users – Non-users* (t-statistics)	-0.6674 *** (-3.93)	-0.6357 *** (-3.69)	-0.6732 *** (-5.59)		
[*RVCFO*] mean diff.: *Users – Non-users* (t-statistics)	[-0.4618 **] (-2.46)	[-0.7207 ***] (-3.71)	[-0.5840 ***] (-4.34)		

Table XI
Future Earnings and Cash Flow Volatilities for Portfolios Formed After Sorting on Alternative Measures of Transparency and Use of Derivatives

This table reports future earnings volatility (measured by the decile rank of EPS variation (*RVEPS*)) and, in brackets, future cash flow volatility (measured by the decile rank of CFO variation (*RVCFO*)). Portfolios are formed after sorting on transparency (*AFE*, *DISP*, *INSTP*, or *SIZE*) and use of derivatives (*H*). Firms belonging to the lowest (or smallest) and highest (or largest) 30th percentile are classified in the *Low* (or *Small*) and *High* (or *Large*) group, respectively, while the remaining firms are classified into the *Medium* group. Also reported are the differences in means between the *Low* (or *Small*) and the *High* (or *Large*) portfolios as well as the corresponding t-statistics in parentheses. White's (1980) heteroskedasticity-consist standard errors are used in t-tests. The variables examined are defined as follows. *RVEPS* and *RVCFO* are decile ranks of EPS and CFO (cash flow from operation) variation, computed as the ratio of standard deviation to the mean of the EPS and CFO, respectively, over twenty-quarters (five-years) ahead. *AFE* is the absolute value of the median forecast error, computed as the difference between the median one-year ahead EPS forecast and the actual EPS. *DISP*, the dispersion, is the standard deviation of the one-year ahead forecasts. *INSTP* is the percentage of institutional ownership. *SIZE* is measured by the firm's total assets. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Panel A: *RVEPS* and *RVCFO* of portfolios formed by absolute forecast error (*AFE*) and use of derivatives (*H*)

	Low AFE firms (More transparent)	*Medium AFE* firms	*High AFE* firms (Less transparent)	All firms	*RVEPS* mean diff.: *Low – High* (t-statistics)	[*RVCFO*] mean diff.: *Low – High* (t-statistics)
Users of derivatives	3.8594 [4.4350]	4.8063 [4.9970]	6.6867 [5.9448]	5.0241 [5.0822]	-2.8273 *** (-18.19)	[-1.5098 ***] (-8.22)
Non-users of derivatives	4.3782 [5.4024]	5.3077 [5.7007]	6.9687 [6.4791]	5.5556 [5.8590]	-2.5905 *** (-14.20)	[-1.0767 ***] (-5.10)
All firms	4.0717 [4.8289]	5.0040 [5.2735]	6.8149 [6.1864]	5.2454 [5.4043]	-2.7432 *** (-23.15)	[-1.3575 ***] (-9.72)
RVEPS mean diff.: *Users – Non-users* (t-statistics)	-0.5188 *** (-3.18)	-0.5014 *** (-3.26)	-0.2819 (-1.61)	-0.5315 *** (-5.22)		
[*RVCFO*] mean diff.: *Users – Non-users* (t-statistics)	[-0.9674 ***] (-5.13)	[-0.7037 ***] (-4.00)	[-0.5343 ***] (-2.58)	[-0.7768 ***] (-6.98)		

Panel B: *RVEPS* and *RVCFO* of portfolios formed by forecast dispersion (*DISP*) and use of derivatives (*H*)

	Low DISP firms (More transparent)	*Medium DISP* firms	*High DISP* firms (Less transparent)	All firms	*RVEPS* mean diff.: *Low – High* (t-statistics)	[*RVCFO*] mean diff.: *Low – High* (t-statistics)
Users of derivatives	3.7399 [4.2729]	4.5896 [5.0143]	6.7160 [5.9323]	4.9568 [5.0638]	-2.9761 *** (-19.36)	[-1.6593 ***] (-9.06)
Non-users of derivatives	4.6523 [5.6319]	5.0442 [5.6394]	7.0000 [6.4052]	5.5077 [5.0638]	-2.3477 *** (-12.14)	[-0.7733 ***] (-3.47)
All firms	4.1202 [4.8461]	4.7666 [5.2537]	6.8326 [6.1255]	5.1793 [5.3866]	-2.1723 *** (-22.32)	[-1.2794 ***] (-8.90)
RVEPS mean diff.: *Users – Non-users* (t-statistics)	-0.9124 *** (-5.42)	-0.4547 *** (-2.86)	-0.2840 (-1.60)	-0.5509 *** (-5.21)		
[*RVCFO*] mean diff.: *Users – Non-users* (t-statistics)	[-1.3590 ***] (-6.94)	[-0.6251 ***] (-3.41)	[-0.4729 **] (-2.24)	[-0.8023 ***] (-6.97)		

Table XI (cont'd)
Future Earnings and Cash Flow Volatilities for Portfolios Formed After Sorting on Alternative Measures of Transparency and Use of Derivatives

Panel C: *RVEPS* and *RVCFO* of portfolios formed by institution ownership (*INSTP*) and use of derivatives (*H*)

	Low INSTP firms (Less transparent)	*Medium INSTP* firms	*High INSTP* firms (More transparent)	All firms	*RVEPS* mean diff.: *Low – High* (t-statistics)	[*RVCFO*] mean diff.: *Low – High* (t-statistics)
Users of derivatives	5.6206 [5.2422]	5.0212 [5.096]	4.8846 [5.0019]	5.1134 [5.0972]	0.7360 *** (4.02)	[0.2403] (1.22)
Non-users of derivatives	6.2913 [5.6121]	5.4119 [5.6780]	5.5227 [6.4225]	5.1134 [5.8431]	0.7687 *** (3.83)	[-0.8104 ***] (-3.67)
All firms	5.9887 [5.4385]	5.1809 [5.3422]	5.1119 [5.4982]	5.3967 [5.4186]	0.8767 *** (6.57)	[-0.0597] (-0.41)
RVEPS mean diff.: *Users – Non-users* (t-statistics)	-0.6707 *** (-3.33)	-0.3906 ** (-2.41)	-0.6380 *** (-3.49)	-0.6533 *** (-6.31)		
[*RVCFO*] mean diff.: *Users – Non-users* (t-statistics)	[-0.3699 *] (-1.75)	[-0.5817 ***] (-3.26)	[-1.4206 ***] (-6.87)	[-0.7460 ***] (-6.60)		

Panel D: *RVEPS* and *RVCFO* of portfolios formed by size (*SIZE*) and use of derivatives (*H*)

	Small SIZE firms (Less transparent)	*Medium SIZE* firms	*Large SIZE* firms (More transparent)	All firms	*RVEPS* mean diff.: *Small – Large* (t-statistics)	[*RVCFO*] mean diff.: *Small – Large* (t-statistics)
Users of derivatives	6.3216 [6.0598]	5.3604 [5.9305]	4.6272 [4.2908]	5.2032 [5.2060]	1.6944 *** (10.29)	[1.7690 ***] (9.72)
Non-users of derivatives	6.2906 [6.1333]	5.7701 [6.1732]	4.7706 [4.9574]	5.8263 [5.9451]	1.5200 *** (8.31)	[1.1759 ***] (5.78)
All firms	6.3001 [6.1107]	5.5633 [6.0482]	4.6641 [4.4585]	5.5025 [5.5516]	1.6360 *** (14.87)	[1.6521 ***] (13.53)
RVEPS mean diff.: *Users – Non-users* (t-statistics)	0.0310 (0.18)	-0.4097 *** (-2.91)	-0.1434 (-0.83)	-0.6231 *** (-7.03)		
[*RVCFO*] mean diff.: *Users – Non-users* (t-statistics)	[-0.0735] (-0.37)	[-0.2427] (-1.62)	[-0.6666 ***] (-3.60)	[-0.7391 ***] (-7.60)		

Table XII
Robustness Tests: 2SLS and Treatment effects Models of Mispricing on Use of Derivatives, Controlling for Future Earnings Volatility in the First Stage Model

This table reports probit, 2SLS, and the treatment effects regression results, as in Table V and VII, adding the decile rank of EPS variation (*RVEPS*) in the first stage of the estimation. The first step involves a probit model wherein *H* is estimated. The variables examined are defined as follows. Dependent variable is the mispricing index, *MI*, created as the average, scaled cross-sectional ranking over the following five mispricing measures: |*ARET*|, |*EXVRI*|, |*EXVIA*|, |*EXVRK*|, and |*MBIA*|. The mispricing measures are computed as absolute values of deviations from five alternative fair value benchmarks. The five aforementioned mispricing measures are defined in Table I. *EXVI* is computed in the same way as *MI*, but uses the raw, rather than the absolute, values of *ARET*, *EXVRI*, *EXVIA*, *EXVRK*, and *MBIA*. Firms belonging to the lowest and highest 30th percentile are classified in the *Low* and *High EXVI* group, respectively. *H* is an indicator variable, which takes the value one if the firm used derivatives and zero otherwise. *RVEPS* is decile rank of EPS variation, computed as the ratio of standard deviation to mean of the EPS over twenty-quarters (five-years) ahead. *AFE* is the absolute value of the median forecast error, computed as the difference between the median one-year ahead EPS forecast and the actual EPS. *DISP*, the dispersion, is the standard deviation of the one-year ahead forecasts. *AFE* and *DISP* are measured in June of each year. *INSTP* is the percentage of common shares outstanding owned by institutions. *SIZE* is measured by the firm's total assets. *RBM* is the book-to-market decile ranking, computed as using NYSE benchmarks for BM measured as in Fama and French (1993). *DAT* is the debt ratio, measured as total debt over total assets. *NAFR* is the residual from regression of *NAF* on *SIZE*, where *NAF* is the number of non-stale one-year ahead analyst EPS forecasts. *, *, and *** indicate significance at the 10%-, 5%-, and 1%-levels, respectively.

Table XII (cont'd)

Robustness Tests: 2SLS and Treatment effects Models of Mispricing on Use of Derivatives, Controlling for Future Earnings Volatility in the First Stage Model

Variables	Probit	2SLS		Treatment
	Dep. var: *H*	Dep. var: *MI*		Dep. var: *MI*
Intercept	-0.4751 *** (-2.94)	0.6345 *** (28.52)	0.7251 *** (24.66)	0.6336 *** (29.09)
H		-0.1247 *** (-4.83)		-0.1289 *** (-5.11)
*H*HEXVI*			0.0492 (1.25)	
*H**(1 – *HEXVI*)			-0.2444 *** (-4.81)	
AFE		0.0325 ** (2.40)	0.0089 (0.60)	0.0312 ** (2.41)
DISP		0.1173 *** (4.10)	0.1219 *** (3.23)	0.1176 *** (4.33)
INSTP		-3.52×10^{-5} (-0.16)	-0.0004 (-1.39)	2.18×10^{-6} (0.01)
SIZE	0.0001 *** (6.57)	2.61×10^{-7} (0.90)	2.97×10^{-7} (0.96)	2.77×10^{-7} (0.96)
RBM	0.0159 (1.00)	-0.0155 *** (-8.26)	-0.0195 *** (-8.35)	-0.0154 *** (-8.23)
DAT		-0.0008 *** (-2.71)	-0.0003 (-0.86)	-0.0007 *** (-2.61)
NAFR	0.0051 (0.75)	0.0008 (1.17)	-0.0001 (-0.13)	0.0008 (1.12)
RVEPS	-0.0259 * (-1.84)			
TFSALEP	0.0158 *** (8.50)			
PROF	1.9012 *** (3.31)			
DVPOR	0.0011 * (1.15)			
TXPD	-0.0607 (-0.87)			
FREECFL	0.3091 (0.59)			
Lambda				0.0668 *** (4.13)
Test: *H*HEXVI* =*H**(1–*HEXVI*) [p-value]			12.29 *** [0.0005]	
Hausman Test [p-value]		36.92 *** [0.0000]	54.78 *** [0.0000]	
Year Dummies	Yes	Included in the first stage	Included in the first stage	Included in the first stage
Number of obs.	1,406	1,406	753	1,406
R^2 (or Pseudo R^2)	0.1280	0.0922	0.1285	
F (or χ^2) [Prob. > F (or χ^2)]	241.20 *** [0.0000]	17.73 *** [0.0000]	12.17 *** [0.0000]	181.28 *** [0.0000]

Figure I
A Comparison of Mispricing and Future Earnings Volatility of High Excess Value Users, Low Excess value Users and All Other Firms

Figure I.A compares the mean values of mispricing and future earnings volatilitiy between users with low *EXVI* and all other firms. Figure I.B compares the mean values of mispricing and future earnings volatilitiy between users with high *EXVI* are also compared with all other firms. The mispricing index, *MI*, is created as the average, scaled cross-sectional ranking over the following five mispricing measures: |*ARET*|, |*EXVRI*|, |*EXVIA*|, |*EXVRK*|, and |*MBIA*|. The mispricing measures are computed as absolute values of deviations from five alternative fair value benchmarks. The five aforementioned mispricing measures are defined in Table I. *EXVI* is computed in the same way as *MI*, but uses the raw, rather than the absolute, values of *ARET*, *EXVRI*, *EXVIA*, *EXVRK*, and *MBIA*. Firms belonging to the lowest and highest 30th percentile are classified in the *Low* and *High EXVI* group, respectively. *H* is an indicator variable, which takes the value one if the firm used derivatives and zero otherwise. *RVEPS* is decile rank of EPS variation, computed the ratio of the standard deviation to the mean of the EPS over twenty-quarters (five-years) ahead.

Figure I. A: Comparison of the mean values of mispricing index (*MI*) and of future earnings volatility (*RVEPS*) between low excess value users of derivatives and all other firms.

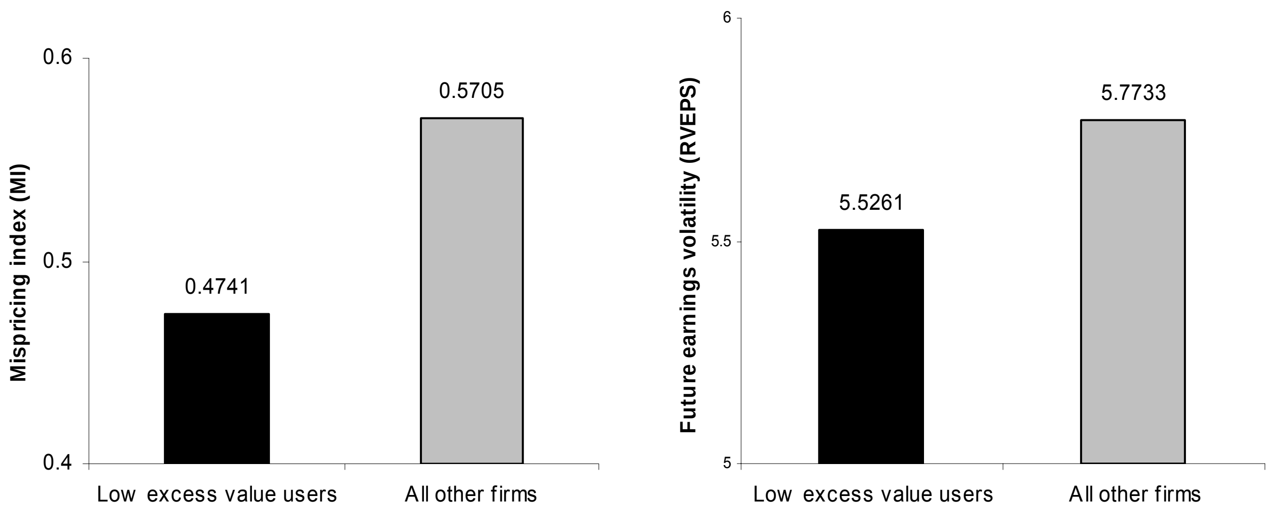

Figure I. B: Comparison of the mean values of mispricing index (*MI*) and of future earnings volatility (*RVEPS*) between high excess value users of derivatives and all other firms.