The Effects of Derivatives on Firm Risk and Value

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Using a sample of 6,888 non-financial firms from 47 countries, we examine the effect of derivative use on firms' risk measures and value. We control for endogeneity by matching users and non-users on the basis of their propensity to hedge. We also use a new technique to estimate the effect of omitted variable bias on our inferences. We find strong evidence that the use of financial derivatives reduces both total risk and systematic risk. The effect of derivative use on firm value is positive but weak, and is more sensitive to endogeneity and omitted variable concerns. This increased sensitivity could account for the mixed evidence in the literature on the effect of hedging on firm value.

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Abstract

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"...Derivatives are financial weapons of mass destruction ..."

--Warren E. Buffet, 2003 Berkshire Hathaway Annual Report

1 Introduction

Although the use of derivative contracts by firms has increased in the past two decades, the effect of derivatives on the risks and market value of firms is still unknown. Despite more widely available data on derivatives usage, the evidence obtained from empirical research on its effects is mixed. For example, Tufano (1998) finds that gold mining firms that hedge with derivatives have lower exposure to gold prices. Using a sample of firms that initiate derivative use, Guay (1999) finds that the total risk, idiosyncratic risk, and risk exposures to interest rate changes of these firms decline, but he finds no significant change in the market risk of these firms. On the other hand, Faulkender (2005) finds evidence consistent with firms using interest rate derivatives primarily for speculation as opposed to hedging. Similarly, Hentschel and Kothari (2001) find that the difference in risk for firms that use derivatives is economically small compared to firms that do not use them. Allayannis and Weston (2001) present evidence that hedging foreign currency risk is associated with large (approximately 4%) increases in market value; Graham and Rogers (2002) find that hedging can add an economically significant 1.1% to their market value by allowing firms to increase their debt capacity. However, Guay and Kothari (2003) show that the magnitude of the cash flows generated by hedge portfolios is modest and unlikely to account for such large changes in value. Consistent with this, Jin and Jorion (2006) use a sample of oil and gas producers and find insignificant effects of hedging on market value.

One problem that arises in any analysis of hedging effects on risk and value is endogeneity. Thus, hedging behavior may be driven by, rather than a determinant of, differences in risk. As a result, riskier firms may hedge so that their (after-hedging) risk profile is difficult to distinguish from inherently less risky non-hedgers. Alternatively, a significant difference in the risk measures of hedging and non-hedging firms could be due to omitted control variables that determine firm risk and risk management. The papers cited above use different approaches to control for endogeneity. Some authors use econometric procedures such as simultaneous equations to account for this problem (see, e.g., Graham and Rogers, 2002). Others choose samples to mitigate selection bias. Jin and Jorion (2006), for example, control for any significant difference in the hedging propensity of firms across industries by examining firms in a single industry. By examining only firms that initiate derivative use, Guay (1999) uses the same firm prior to derivative use as a control. Of course, although these choices reduce selection bias, they also impose constraints on the data, beyond the usual ones of data availability.

In this paper, we also examine the effect of derivative use on firms' risk and market values. We use a new, larger dataset that includes 6,888 non-financial firms headquartered in 47 different countries. In addition to providing greater statistical power for our tests, our dataset covers a wide range of derivative use and risk measures. Specifically, we investigate the impact of the use of exchange rate (FX), interest rate (IR) and commodity price (CP) derivatives on cashflow volatility, the standard deviation of stock returns, and market betas, as well as market values. The dataset also allows us to measure the effect of derivative use on firms during a sample period that includes a sharp market correction: the global recession of 2000-2001. Consequently, we are able to examine the extent to which firms, either through their use of derivative contracts or other methods (e.g., operational hedges), can mitigate a market-wide decline.

Figure 1 illustrates our primary findings by plotting the time series of cumulative returns for users of derivatives (hedgers) and nonusers (nonhedgers) from 1998 through the end of 2003.[1] The graph shows that hedgers' returns are less volatile than the returns of non-hedgers. Hedgers also have a lower sensitivity to market returns (i.e., a lower market beta) than nonhedgers. This is especially apparent in the 2000-2001 period when sharp sell-offs in the market lead to substantially larger declines for nonhedgers as compared to hedgers. Over the 1998-2003 period the stocks of nonhedgers perform slightly better than those of hedgers, although it is not clear from the graph if this outperformance is enough to compensate for the apparently higher risk of nonhedgers.[2]

Univariate results also strongly suggest that firms use derivatives to reduce risk. Users of derivatives are more exposed to exchange rate risk (due to more foreign sales, foreign income and foreign assets) and interest rate risk (due to higher leverage and lower quick ratios) before considering the potential effects of hedging. They are also more likely to belong to commodity-based industries that are exposed to commodity price risk. Nonetheless, derivatives users exhibit unconditional aver-

[1] We use the terms hedger and derivative user synonymously in the paper since our results indicate that derivatives are used by nonfinancial firms primarily for reducing risk.

[2] Both groups outperform the world market index, because we exclude from our sample financial firms and utilities which significantly underperform other stocks over this period.

age cashflow volatility that is almost 50% lower than non-users and stock return volatility that is on average 18% lower than the return volatility of non-users. In addition, firms that use derivatives have market betas that are on average 6% lower than non-users. Consistent with other papers, we also find that, on average, derivative users tend to be larger and older firms. Consequently, the unadjusted Tobin's *q* of the average derivative user is approximately 17% lower than the average firm that does not use derivatives.

In multivariate tests, we control for the endogenous nature of the hedging decision using a propensity score matching technique; in addition, we are able to provide some evidence for how large any remaining hidden bias would have to be to change inferences drawn from our analysis. Propensity score matching allows us to match firms on the basis of their estimated likelihood of using derivatives, rather than matching on a large number of individual firm characteristics. Specifically, using a binary variable to measure derivative use, we directly estimate firms' propensity to hedge based on their characteristics, and then match hedging and non-hedging firms based on this propensity. Controlling for firms' likelihood to hedge, we find that derivative use is associated with lower cashflow volatility, lower standard deviation of returns, lower systematic risk and weakly *higher* market values. Hedging firms have 10% to 25% lower cashflow volatility, 3% to 10% lower standard deviation of returns, 6% to 22% lower betas, and 1% to 7% higher Tobin's *q*, than matching non-hedging firms, depending on the set of characteristics used to estimate the propensity to hedge.[3]

Any analysis of cross-sectional differences in firm characteristics related to derivative use must be concerned about endogeneity or bias due to an omitted control variable. Using a new technique, we are able to estimate the extent to which our inferences may be driven by a hidden selection bias. Specifically, using the method developed in Rosenbaum (2002), we find that for a hidden selection bias related to an unobserved characteristic to affect our inferences regarding the effect of derivative use on risk, it would have to be large—for example, equivalent to approximately a two standard deviation difference in leverage or more than an additional 100% difference in market capitalization. Thus, while we cannot rule out the possibility that our risk results are driven by an unmeasured selection bias in our sample, the unmeasured characteristics related to that selection bias would generally have to be quite economically significant (as well as unrelated to the large number of observables for which we control). In contrast, the results with respect to value appear to be quite sensitive to the

[3] Results for cashflow volatility, total risk, and market risk are always statistically significant at better than the 0.1% level. Results for Tobin's *q* are always positive but statistically significant in only half of the specifications.

presence of a hidden selection bias. In turn, this sensitivity could explain why value results from previous studies are mixed. Overall, our results suggest that the effect of derivative use in the cross-section is associated with a decline in both total and systematic risk; the effect on value is positive, but weaker. In particular, we cannot rule out the possibility that other omitted control variables, which are associated with derivative use, may be responsible for estimated differences in value.

Finally, we examine the differences in risk and value measures for hedgers and non-hedgers through time. Hedgers have consistently lower total risk and betas throughout the 1998-2003 time period. The results provide some evidence that hedging was more important for firm value during the global economic decline in 2001. This may be because of a change in the (perceived) value of risk management, with the value of firms that hedged increasing during the economic decline. Alternatively, of course, these results may simply reflect the unstable nature of the value results. However, when we examine average alphas (from the market-model regressions that generate market betas), we also find that hedgers significantly outperform non-hedgers in 2001 and 2002.

Our results suggest, at a minimum, that firms do reduce cashflow risk, total risk and systematic risk significantly through financial risk management with derivatives. This result is robust when controlling for differences in a large number of firm characteristics, as well as differences in country and industry. Thus, while it may be difficult to preclude all instances of improper or fraudulent use of derivative instruments, these findings may be reassuring for policymakers, regulators and shareholders (or other stakeholders in the firm, for that matter) regarding their concerns about widespread derivatives speculation by nonfinancial corporations that put the firm and thus shareholder value at undue risks. The value put on this risk reduction in the marketplace, however, is much less certain.

2 Frequency and Effect of Derivative Use by Firms

Beginning with Modigliani and Miller (henceforth MM, 1958), a firm managed by value-maximizing agents, in a world of perfect capital markets, with investors who have equal access to these markets, would not engage in hedging activities since they add no value. Anything the firm could accomplish through hedging could equally well be accomplished by the investor acting on his or her own account. If the perfect capital markets assumption is not met, however, there may be rational reasons for the firm to hedge.

The theoretical literature on hedging relaxes the MM assumptions and develops specific reasons why individual firms may optimally choose to hedge. As one might expect, these reasons tend to involve either market frictions, such as taxes, transactions costs, and informational asymmetries, or agency problems. For example, Smith and Stulz (1985) show that a convex tax function implies that a firm can reduce expected tax liabilities by using hedges to smooth taxable income. In addition, hedging may increase a firm's debt capacity, enabling it to add value by increasing the value of the debt tax shield (Leland, 1998). Froot, Scharfstein and Stein (1993) show that managers facing external financing costs may use hedging to reduce the probability that internal cash flows are insufficient to cover investments; Smith and Stulz (1985) show that hedging can reduce expected costs of distress.

Agency problems may cause managers and investors to view the risk-return trade-offs of the firm differently and lead to the use of derivative contracts. For example, if managerial compensation leaves the manager holding a large portfolio of undiversified firm risk, the manager may have a larger incentive to hedge (Stulz, 1984). Alternatively, if a large fraction of managers' compensation comes in the form of out-of-the-money stock options, the manager may have an incentive to use derivatives to take on, rather than lay off, firm risk. DeMarzo and Duffie (1995) argue that hedging may allow investors to assess managers' abilities more precisely and consequently develop more efficient compensation contracts.

Empirically, the use of derivatives by firms appears to be widespread. A large number of studies have documented the extent and nature of derivatives' use by non-financial firms. Some of these studies are based on survey data, such as the Wharton survey of U.S. non-financial firms (Bodnar, Hayt and Marston, 1998; Bodnar, Hayt and Marston, 1996; Bodnar et al., 1995), as well as other surveys of U.S. firms (e.g. Nance, Smith and Smithson, 1993). Surveys also have been conducted for selected countries outside the United States.[4] Studies have provided information on corporate derivatives use based on disclosure in annual reports (Mian, 1996; Géczy, Minton, and Schrand, 1997; Graham and Smith, 1999; Graham and Rogers, 2002; Bartram, Brown and Fehle, 2007). Finally, detailed data on derivatives' use is available for a few industries, such as in the North-American gold mining industry (e.g. Tufano, 1996; Brown, Crabb, and Haushalter, 2006) or the U.S. oil and gas industry (Haushalter, 2000). Overall, these studies document that the use of derivatives by non-financial firms tends to be the rule rather than the exception.

[4] For example, survey data are available for Belgium (DeCeuster et al., 2000), Canada (Downie, McMillan, and Nosal, 1996), Germany (Bodnar and Gebhardt, 1999), Hong Kong and Singapore (Sheedy, 2002), the Netherlands (Bodnar, Jong, and Macrae, 2002), New Zealand (Berkman, Bradbury, and Magan 1997), Sweden (Alkeback and Hagelin, 1999), Switzerland (Loderer and Pichler, 2000), and the UK (Grant and Marshall, 1997).

Empirical researchers have used data disclosed by firms to examine the question of whether and how hedging affects the risks of the firm. The evidence is mixed. Guay (1999) investigates a sample of 234 U.S. non-financial firms that begin using derivatives in the early 1990s and finds that measures of total and idiosyncratic risk decline in the following year. He finds no significant evidence for changes in systematic risk. Hentschel and Kothari (2001) examine the risk characteristics of a panel of 425 large U.S. non-financial firms from 1991 to 1993. Their results show no significant relationship between derivatives use and stock return volatility even for firms with large derivatives positions.

In studies of the North American gold mining industry, Tufano (1996, 1998) presents evidence that is consistent with the use of derivatives for hedging to reduce risk in response to risk-aversion by managers and owners. Allayannis and Ofek (2001) relate derivatives use to the foreign exchange rate exposure of a sample of 378 U.S. non-financial firms and find that the use of derivatives significantly reduces the exposure of the sample firms to exchange rate risk. In work on mutual funds, Koski and Pontiff (1999) show that users of derivatives have similar risk exposure and return performance to nonusers.

The evidence for the effect of derivative use on market value is also mixed. Allayannis and Weston (2001) find that firm value (as measured by Tobin's *q*) is higher for U.S. firms with foreign exchange exposure that use foreign currency derivatives to hedge. Graham and Rogers (2002) calculate that the increase in debt capacity and leverage associated with hedging increases firm value by an average of about 1.1%. MacKay and Moeller (2007) find that oil refiners hedging concave revenues and leaving concave costs unhedged increase firm value 2-3%. Carter, Rogers, and Simkins (2006) find evidence of large value effects (5%-10%) in the U.S. airline industry. However, Guay and Kothari (2003) estimate the cash flow implications from hedging programs for 234 large U.S. non-financial firms and find that the economic significance of the cash flows, and consequently the inferred potential change in market values, is small. Jin and Jorion (2006) examine 119 firms in the oil and gas industry and also find that the effect of hedging on market value is not statistically significant.

Overall, while there is substantial evidence of sustained and growing use of derivatives by firms, the effect of this use on risk and value, and the mechanisms by which value may be affected, are still unclear. Concerns about endogeneity either limit the interpretation of the results or act to limit the sample. In an attempt to mitigate these concerns, we use both a larger sample and different methods to control for endogeneity. Our sample includes a large number of U.S. and international firms and encompasses wide swings in global economic conditions, which may create more dispersion in outcomes for hedging and non-hedging firms. We use a matching method that controls for the differences in the likelihood to hedge; this method also allows us to conduct additional analyses on the extent to which the results may be sensitive to a remaining hidden selection bias. Finally, we examine the difference in the effects of the global recession of 2000 and 2001 on hedgers and non-hedgers.

3 Data

3.1 Sample and Data Sources

The markets for over-the-counter instruments and exchange-traded derivative financial instruments (options, futures, forwards, swaps, etc.) on foreign exchange rates, interest rates and commodity prices have exhibited exponential growth over the past 20 years (e.g., Bartram, 2000). As a result, notional amounts outstanding for OTC derivatives reached over $200 trillion in 2004, with interest rate derivatives accounting for more than three-quarters of the total (BIS, 2005). Along with increased use, regulation for the disclosure of derivatives has developed, requiring firms in many countries to include information about their derivatives' positions in the annual report. In particular, firms in the United States, United Kingdom, Australia, Canada and New Zealand as well as firms complying with International Accounting Standards (IAS) are required to disclose information on their derivatives positions; many other firms do so voluntarily.[5] The resulting availability of data makes the empirical analysis of the use of derivatives by nonfinancial firms in different countries possible.

The sample in this study comprises 6,888 non-financial firms from 47 countries including the United States. It consists of all firms that have accounting data for either the year 2000 or 2001 on the Thomson Analytics database, that have an annual report in English for the same year on the Global Reports database, that are not part of the financial sector (banking, insurance, etc.), and that have at least 36 non-missing daily stock returns on Datastream during the year of the annual report.[6] The 47 countries represent 99% of global market capitalization in 2000 and 2001, and the firms in the sample

[5] For example, the following are recent standards (and effective dates) adopted by so-called G4+1 countries and the International Accounting Standards Board (IASB) as part of the movement toward common reporting standards: United States, FAS 133 (effective June 15, 1999); United Kingdom, FRS 13 (effective March 23, 1999); Australia, AAS 33 (effective January 1, 2000); Canada, AcSB Handbook Section 3860 (Financial Instruments - Disclosure and Presentation, effective January 1, 1996); New Zealand, FRS-31 (effective December 31, 1993); IASB, IAS 32 (March 1995, modified March 1998 to reflect issuance of IAS 39 effective January 1, 2001).

[6] Global reports (www.global-reports.com) is an online information provider of public company documents in full-color, portable document format (PDF).

account for 60.6% of overall global market capitalization or 76.8% of global market capitalization of non-financial firms.[7]

Firms are classified as users or non-users of derivatives based on a search of their annual reports for information about the use of derivatives. The annual reports are evaluated by an automated search. The list of search terms was compiled by manually analyzing a sample of 200 annual reports across all countries.[8] After refining the list of search terms, the automated search routine led to an average reliability of 96.0% for a random sample of annual reports of 100 users and 100 non-users. Subsequently, an index was created based on search hits of terms that were too general to be included in the electronic search, but that are likely to be related to derivative use.[9] A total of 1,709 firms with high scores that were classified as non-users and firms with low scores that were classified as users of derivatives were checked and classified manually, since these firms have higher error rates. As a result, the reliability of the classification improved further, yielding an estimated error rate from a random sample below 2%.[10] In addition to the categorical data on derivatives, information on the underlying (i.e., foreign exchange, interest rates, or commodity price) and type of instruments (i.e., forwards/futures, swaps, and options) are collected.[11] From these binary variables, we create a variable called *Hedging Intensity* equal to the sum of the categories for which we document firms using derivatives. For example, a firm that uses FX forwards, FX options, and interest rate swaps would have a hedging intensity of 3. This approach of characterizing the extent of use of derivatives is crude, but it represents a practical method for such a large sample of firms spanning so many countries and disclosure standards. In addition, the method has some advantage over measures using notional values since firms do not consistently report the directions of their positions (i.e., long or short) or essential

[7] Since the data covers two years, these values are calculated as the sum of each firm's percent of global market capitalization for the year it appears.

[8] A full list of the search terms is available on request.

[9] The terms include futures, swap or swaps, swaption.*, collar.*, derivat.*, call option.* or put option.*, hedg.*, cash flow hedg.*, fair value hedg.*, risk management, effective portion.* or ineffective portion.*, notional amount.*, option.* contract.*, option.* where ".*" signifies any additional characters. The index sums the number of these terms found in the annual report (regardless of the number of times) for a maximum score of 14.

[10] Even careful examination of the annual reports does not always give clear evidence whether a firm uses derivatives or not, because some firms make very general statements about their risk management policy or accounting practices without specifically addressing the particular year in question. Given the systematic way of classifying firms and the fact that users appear to be misclassified about as often as nonusers, the results should at worst suffer from some noise with little effect on the results across the large sample of firms.

[11] Dichotomous variables for the use of foreign debt and stock options are created in the same fashion, since this information is not readily available elsewhere.

details such as strike prices or precise maturities of option contracts. Given these omissions, calculating the degree of derivative use based on notional values is difficult. In any case, the imperfect nature of our measure of hedging intensity should result in a bias against finding significant results.

Summary statistics on the use of derivatives by the sample firms is presented in Table 1. Across all countries, 60.5% of the firms in the sample use at least one type of derivative. The average value of *Hedging Intensity* across all firms (derivatives users and non-users) is 1.2. FX derivatives are the most common (45.5%), followed by interest rate derivatives (33.1%) and commodity price derivatives (9.8%). Though usage rates for particular types of instruments vary considerably across countries, some clear patterns emerge. Forward contracts are the most used FX derivatives, whereas swaps are the instrument of choice for interest rate derivatives. For commodity price derivatives, the distribution of instrument type is more even. Firms in the U.S. are less likely to use FX derivatives than non-U.S. firms, but U.S. firms are more frequent users of interest rate and commodity price derivatives.[12]

All capital market data (i.e., the firms' stock return indices, stock market return indices, and interest rates) are from Datastream. These data are provided at a daily frequency. For each firm, we calculate stock returns in local currency. To begin, all time series are limited to the year of the firm's annual report. Accounting data originate from the Thomson Analytics database.[13] Outliers are eliminated by excluding observations in the top and bottom one percentile as well as those observations where variable values exceed more than five standard deviations from the median. This filter eliminates some apparent data errors where magnitudes suggest data units are not properly reported (e.g., thousands instead of millions). Systematic differences across countries and industries are controlled for with country and 44 industry dummy variables. In order to avoid the cross-sectional results being influenced by the effect of the economic cycle, we use three-year averages of variables where this impact seems most relevant (e.g., coverage, foreign income). In a separate analysis, we examine the performance of derivative users and non-users through time.

[12] Additional details are provided in Bartram, Brown and Fehle (2007).

[13] Data are commonly reported in millions of U.S. dollars. Many of the variables we examine are ratios and are therefore largely comparable across countries and years. However, we also examine a dummy variable for the year (2000 or 2001) and have undertaken robustness checks to make sure that our conclusions are not driven by which year we examine.

3.2 Risk Measures

In order to study the possible determinants of corporate derivatives use, three different categories of risk measures are employed. First, firms may differ with regard to their gross or pre-hedging exposure.[14] For instance, measures of gross exposure with regard to foreign exchange rate risk include foreign sales (relative to total sales), foreign income (relative to total income), and foreign assets (relative to total assets). In addition to these individual proxies of foreign exchange rate exposure, we create a dummy variable *Gross-FX-Exposure* that is one if firms have non-zero values for any of these characteristics (and zero otherwise). Foreign debt may create an exposure as well, but it could also work as a hedge. Similarly, leverage, coverage, or the quick ratio may be indicators for gross interest rate exposure. We define the dummy variable *Gross-IR-Exposure* as equal to one for firms with above median leverage (and zero otherwise). With regard to commodity price exposure, the dummy variable *Gross-CP-Exposure* is assigned the value one for firms in the utilities, oil, mining, steel, and chemicals industries (and zero otherwise). An overall measure of exposure is created as a dummy variable *Gross-Exposure* with value one if any of the variables *Gross-FX-Exposure*, *Gross-IR-Exposure* or *Gross-CP-Exposure* is one and zero otherwise. If firms are using derivatives primarily for hedging purposes, firms should be observed to use derivatives if they have high measures of gross exposure. Firms may also have more incentive to hedge if they are close to default. We use Altman's Z-score measure as a proxy for distress.

Second, firms in different countries face different levels of macroeconomic or country risk. To illustrate, firms operate in a more risky environment if located in a country that is characterized by high volatility of interest rates and exchange rates. Our aggregate measures of country risk are the International Country Risk indices that provide inverse rankings of countries' financial risk (*ICR-Financial*) and economic risk (*ICR-Economic*).[15] It is expected that more firms use derivatives in countries with high risk if hedging is the motivation for the use of these instruments, *ceteris paribus*.

Third, a firm's net (or post-hedging) exposure is the result of the characteristics of its assets and liabilities, and ideally also includes the effects of off-balance sheet transactions such as deriva-

[14] To be precise, gross (or pre-hedging) exposure is a measure of exposure that does not incorporate the effect of financial derivatives.

[15] The *ICR Guide* is published by The PRS Group, 6320 Fly Road, Suite 102, East Syracuse, NY 13057, USA.

tives.[16] Our first measure of net exposure is operating cashflow volatility (σ_{CF}) which we define as the standard deviation of operating margins (operating cashflow divided by total sales) using 5 years of annual data. However, operating cashflow may not be a good measure of net exposure for several reasons. First, it is not measured with much precision given the limited amount of data. Second, managers may be able to systematically manipulate values for accounting variables which could result in "earnings smoothing", or other distortions. Finally, operating cashflow may not account for the use of all derivatives for all firms. Specifically, if FX and CP derivative transactions do not utilize (i.e., qualify for) "hedge accounting" they will not be reflected in operating cashflow.[17] Similarly, the effects of most interest rate derivatives will not be reflected in operating cashflow. However, cashflow volatility will capture other types of risk management activities (such as operational hedging with foreign assets) which has been identified as important hedging tools for FX risk. Thus, cashflow volatility may be affected for derivatives users, even if derivatives do not qualify for hedge accounting, if derivatives are a proxy for broader "corporate hedging."

While the risk of assets and liabilities contain different components and their interactions are difficult to decompose, the assumption of efficient capital markets suggests that net exposures can be estimated empirically using a company's stock price as an aggregate measure of relevant information. Consequently, we construct different firm-specific risk measures from stock prices. In particular, for each firm the standard deviation of its stock returns (σ_E), and the ratio of its stock return standard deviation to the standard deviation of the returns of the local market index (σ_E^*) are calculated. We also examine standardized firm volatility to avoid a potential bias from a spurious correlation between derivatives use and overall market volatility.

The sensitivity of the firm's stock returns to the local market return is estimated using the standard market model on daily returns

$$R_{jt} - r_{ft} = \alpha_j + \beta_j \left(R_{Mt} - r_{ft} \right) + \varepsilon_{jt}, \tag{1}$$

[16] To be precise, net (or post-hedging) exposure is a measure of exposure that incorporates the effect of financial derivatives.

[17] Nonetheless, most derivative users in our sample use FX and CP derivatives.

where R_{jt} is the stock return of firm j on day t, R_{Mt} is the return on the local market index M on day t, and r_{ft} is the (daily) risk free rate of interest.[18] The estimation period consists of the year for which we have the annual report data. The Newey-West procedure is used to correct for autocorrelation and heteroscedasticity. Corporate use of derivatives for hedging purposes would be consistent with lower stock return volatility and lower measures of post-hedging exposures as estimated in the regression framework. Overall (net) market exposure is measured by the estimated values, $\hat{\beta}_j$.

Table 2 reports statistics for the risk variables used in our analysis. Returns for individual stocks, pooled across all observations, and the market index are negative on average over our sample period (-8bps and -4bps per day, respectively). Average volatility of operating cashflow, σ_{CF}, is 8.25% but very positively skewed. Consequently, we primarily examine the natural logarithm of operating cashflow volatility in our statistical analysis. Risk as measured by σ_E averages 0.56 and is somewhat positively skewed. Standardizing σ_E by market volatility (σ_E^*) suggests that the average firm has substantial idiosyncratic risk, with a standard deviation of return that is more than 2.5 times the market's volatility. Estimated market betas average 0.70, indicating that the typical firm in our sample has relatively low systematic risk. This is likely due to a selection bias from requiring an annual report in English and two years of available accounting data—the resulting firms are typically larger, more global, and more established firms with somewhat lower systematic risk. Despite this, we do see substantial cross-sectional dispersion in the beta estimates in the sample—more than 25% of firms in our sample have estimated values for beta that are greater than 1.0. The betas in our sample are also estimated with a good deal of precision. The median p-value for a two-tailed test against a null of zero is 0.001 and more than 80% of betas are different from zero at the 10% confidence level.

We define a proxy for Tobin's q (q) as the sum of equity market capitalization, the book value of total debt and the book value of preferred stock divided by the book values of each of these financing sources. The average q in our sample is 2.33. The primary advantage of this method is its simplicity, which allows us to create values for nearly all firms in our sample. Alternative measures, such as those used by Allayannis and Weston (2002), rely on the use of segment and industry-wide investment data that are not available for many of the firms in our global sample. Table 2 also shows that q

[18] As a proxy for the risk-free rate we use 30-day Eurocurrency rates obtained from DataStream or, when these are unavailable, the shortest-term high quality (e.g., government) rate.

is very positively skewed. This skewness is consistent with the results of many other researchers. As a consequence, similar to Allayannis and Weston (2002), we primarily examine the natural logarithm of q in our statistical analysis.

4 Methodology

4.1 Propensity Score Matching

Previous results in the literature, which we confirm in our sample, suggest that there are substantive differences, on average, in the characteristics of firms that hedge and those that do not. These differences generate a selection bias when estimating the effect of hedging on a firm, and should be controlled for when we estimate the effect that hedging has on risk and market values. Ideally, one would like to estimate the "treatment" or hedging effect by observing the same firm, under identical economic conditions, with hedging and without hedging in place. Since this is not possible, the first method we use attempts to find a "similar" firm to the hedging firm, where to the extent possible the "similar" firm differs only in its choice not to hedge.

Rather than matching on several individual firm characteristics or covariates, the method we choose matches on the propensity score—the estimated likelihood that a firm will hedge. Rosenbaum and Rubin (1983) show that matching on the covariates, and matching on the propensity score, will both result in a distribution of the covariates in the treated and untreated groups which is the same. An advantage of propensity score matching is that it eliminates the 'curse of dimensionality' when one wishes to match on several characteristics. A disadvantage of propensity score matching is that a large sample is required to obtain a meaningful match on the propensity scores, i.e., one that allows for a precise measurement of the treatment effect. (See Zhao (2004) for more discussion on this point.)

To use this method, we model the likelihood that a firm will choose to hedge, $H(W_i)$, based on a set of variables W_i. That is, we model:

$$H_i = \gamma^{'} W_i + u_i \tag{2}$$

where the observed value of H_i is 1 if the firm chooses to hedge, and 0 otherwise. The variables W_i are the characteristics of the firm that are expected to influence the choice of whether a firm hedges. After the propensity scores are estimated, one can choose to match a hedging firm to the single non-hedging firm with the most similar propensity score, or to a weighted grouping of non-hedging firms, whose weighted-average propensity score is similar to that of the hedging firm. One can match with or without replacement and also set up boundaries or 'calipers' of various magnitudes, outside of which no matches are chosen. We use various combinations of these choices to ensure that our results are robust. We also examine various choices of the variables that are presumed to influence hedging, W_i.

4.2 Selection Bias

Clearly, if there are unobserved or hidden variables that affect the hedging choice, bias may remain in the estimated hedging effect. One advantage of the propensity score matching technique is that it allows for a sensitivity analysis on this selection bias. That is, Rosenbaum (2002) shows that it is possible to construct an upper bound on the influence that any omitted variable would have to have on the hedging choice to overturn the inferences drawn. We estimate this bound and provide a comparison to the effect that any hidden bias must have, relative to the influence of the observable characteristics of the firms, to overturn the original inference. Thus, while we are not able to rule out the influence of a hidden characteristic, we can provide a benchmark for how large the effect would have to be, compared to well-known firm characteristics, to change the inferences drawn from the analysis.

4.3 Variable Choice

Many firm characteristics have been hypothesized to be relevant for the relationship between derivatives use and measures of risk and value, and are therefore candidates for use as control variables. In particular, derivative use has been shown to be related to industrial diversification (number of industry segments), firm size (natural logarithm of total assets or alternatively the sum of equity market capitalization, total debt, and preferred stock), and tangible assets (as a fraction of total assets). Firms with more growth options, as measured by research and development expenses (relative to total sales) and capital expenditures (relative to total sales) have been shown to be more likely to use derivatives (see, e.g., Géczy, Minton and Schrand, 1997). As Jin and Jorion (2006) point out, firms in certain industries may be more likely to hedge, if for example they are exposed to more readily identified, larger or more easily hedged types of risk.

Finally, access to derivatives markets could have an important effect on firms' ability to execute hedging strategies. Alternatively, easy access to derivatives may facilitate engaging in derivatives transactions for purposes other than hedging because the costs of entering transactions (or more generally markets) are lower and therefore less likely to require extraordinary actions on the part of managers. As a proxy for access to derivatives markets we use a proxy for the relative size of the derivatives market in a company's home country as measured by the *Derivatives Market Rank* (from Bartram, Brown and Fehle, 2007). The definitions of all variables are presented in Table A-1 in the appendix. Summary statistics are presented in Table 2.

5 Results

5.1 Univariate Results

To begin, we compare the simple averages of risk characteristics in our sample categorized by derivative use. These results are presented in Table 3. We measure the significance of differences between the two types of firms using non-parametric Wilcoxon tests. Table 3 reports the *p*-values of these tests together with the means, medians and differences in means of firm characteristics for derivative users and non-users. While the results in Table 3 only refer to general derivatives use, the tests are also conducted separately for foreign exchange rate derivatives, interest rate derivatives and commodity price derivatives, and differences are mentioned in the text where appropriate.

Panel A of Table 3 shows that firms using derivatives are more exposed to exchange rate risk on a pre-hedging basis: They have significantly more foreign sales, foreign income and foreign assets, and more firms have non-zero values for at least one of these variables (i.e., *Gross-FX-Exposure*). This is consistent with the use of derivatives for hedging. As measured by the existence of foreign debt, the liabilities of derivatives users are also significantly more exposed to exchange rate risk (though FC debt is also used as a risk management tool by many multinational corporations). In addition, derivatives users have significantly higher gross interest rate exposure, as measured by higher leverage, lower quick ratios (not reported), and a higher average *Gross-IR-Exposure*. In contrast, users have higher coverage ratios. Firms are more likely to belong to commodity-based industries if they use derivatives (a higher mean for *Gross-CP-Exposure* than non-users). Finally, derivative users are more likely to have at least one type of financial risk as measured by our *Gross-Exposure* variable. Overall, the results strongly suggest that firms are more likely to use derivatives if they have higher gross (i.e., pre-hedging) exposure. These tests, based on firm characteristics, are robust to analyzing derivatives on exchange rate risk, interest rate risk or commodity price risk.

For most firms, asset and liability risks are unlikely to be independent. Consequently, we examine more comprehensive risk measures based on the firms' cashflow and stock returns. Studying stock prices is informative since they represent an aggregate measure of asset and liability risk and should also incorporate the effects of financial risk management. If derivatives are used for hedging purposes, firms with high pre-hedging exposure should be more likely to use them and, consequently, might exhibit similar, or even lower, post-hedging (net) exposure.

Despite the higher exposures documented in Panel A of Table 3, the univariate results in Panel B of Table 3 shows that derivative users have significantly lower cashflow volatility, total risk and market risk. In particular, average σ_{CF} is more than 30% lower for hedgers, and σ_E and σ_E^* are about 20% lower for derivative users. Likewise, market betas are on average about 6% lower for derivatives users. These results provide some support for the hypothesis that, on average, firms are hedging rather than speculating with derivatives. At a univariate level, the unadjusted Tobin's q of the average derivative user is 17% *lower* than for the average firm that does not use derivatives. However, we also see that the unconditional relative performance of hedgers as measured by the market-model alpha is significantly higher in our sample period.

In addition to the business and financial risk of the firm, risks outside the company, such as country risk, may impact a firm's propensity to use derivatives for hedging or speculative purposes. In this regard, the evidence in Panel C of Table 3 is mixed. The results suggest that firms in countries with higher financial risk are using derivatives more frequently, which is consistent with hedging motives. On the other hand, there is also evidence that more firms use derivatives in countries with low economic risk. Regardless, the differences are economically very small suggesting that country risk factors may be of secondary importance in determining which firms use derivatives. As expected, firms are more likely to use derivatives if the market for derivatives (among dealers) is more developed.

Panel D of Table 3 shows that, conditional on using derivatives, the average firm uses roughly two types of derivatives—the average value of *Hedging Intensity* for derivative users is 1.9. Similar to other researchers, we find that there are further significant differences in the characteristics of derivatives and non-derivative users. For example, derivative users have lower Z-scores, are significantly larger and more diversified as well as more likely to pay dividends and have executive stock options. However, derivatives users also tend to have fewer tangible assets, lower research and development expenses, and lower capital expenditures.

Table 4 repeats the analysis for most of the firm-specific variables after each variable has been adjusted for country and industry fixed-effects. The results are largely unaffected, although in some instances statistical significance is reduced. The most striking difference in this respect is that hedgers no longer have a significantly lower q after taking country and industry effects into account. The results for risk measures are quite similar to those presented in Table 3. Overall, the results in Table 3 and 4 suggest that non-financial firms use derivatives in line with hedging motives. These tables also clearly show large differences in the characteristics of hedging and non-hedging firms, which should be controlled for. In the next section, we undertake a multivariate analysis for this purpose.

5.2 Multivariate Results

5.2.1 Propensity Score Matching: Risk Measures

We begin with a matching analysis. Specifically, we match hedging firms with non-hedging firms on the basis of their propensity score, which is a measure of the firms' propensity to use derivatives based on the firms' unique characteristics. There are several choices that must be made in order to use propensity score matching. As in any matching analysis, in making these choices we are trading off the precision of the matching criteria against the sample size. We explore a number of different specifications, and present several representative specifications. In general, our results are robust across most specifications; we note differences in results where they occur.

In conducting the propensity score matching the first choice is the selection of independent variables on which to match. For the risk measures, the independent variables include variables which have been shown elsewhere to be associated with derivatives use, as well as variables which incorporate the broader nature of our sample. Specifically, we include Altman's Z-score, firm size, leverage, a liquidity variable (quick ratio), market access variables (dividend dummies, as well as the number of share classes), a variable related to managerial incentives to hedge (stock option use) and country and industry dummy variables (where noted). The most important determinants of derivatives use are not surprising. They include size, leverage, the use of employee stock options, and exposure to underlying risks, such as foreign currency risks, interest rate risks or commodity price risks. For q, we also include variables shown by other studies to be associated with firm value such as sales growth, R&D, and Capex.

The second choice in the matching analysis is the identification of the matching "non-hedging firm." The analysis can simply choose a single, "nearest neighbor" match, or use a weighted average of many (or all) non-hedging firms to construct a match. One can sample from the non-hedging firms with or without replacement. One can set conditions outside of which no matches will be found (i.e., caliper matching). We report results from two different matching criteria, and three different choices of matching parameters, for six specifications in all.

In Table 5, we report the extent to which the propensity score matching succeeds in removing the selection bias in the observed characteristics of firms in the two sub-samples. That is, we report the following measure

$$Bias = \left| \frac{100(\mu_T - \mu_C)}{\sqrt{\frac{(s_T^2 - s_C^2)}{2}}} \right|$$

where μ_T and s_T are the sample mean and standard deviation of the characteristic for the hedging firm, and μ_C and s_C are the sample mean and standard deviation for the characteristic in the matching control firms. We report this bias measure for both the raw and matched samples for the two matching specifications that we use.

The bias in the characteristics in the raw data is quite large; for example, the bias in market capitalization is greater than 90%, while the biases in leverage, foreign exposure and foreign debt are all greater than 40%. Both of the matching specifications we consider reduce the bias considerably; however, the specification that does not allow for replacement still contains substantial biases with respect to market capitalization, foreign debt and foreign exposure. The specification that allows for replacement of the non-treated firms in the sample reduces the bias more—none of the characteristics is associated with a bias of more than 16%, and most are below 10%. Overall, the matching procedure does a good job of producing "balanced covariates" across the two sub-samples.

Table 6 presents the results of representative propensity score estimation for each of the four primary variables we examine (σ_{CF}, σ_E, β, and q). For each of these four variables, we report the number of firms, mean, and median values of the characteristic for the firms that use derivatives and those that do not, and provide a measure of the difference in means as well as a statistical test of the significance of the difference between the two sub-samples of firms.

Regardless of the parameters chosen for the identification of the matching non-derivative users, we find significantly lower values for cashflow volatility (σ_{CF}), standard deviation of returns (σ_E), and beta risk (β) for firms that use derivatives (Panels A, B, and C, respectively). Across the various specifications, the differentials in σ_{CF} range from about 10% to 25%; for σ_E the reduction varies from between 3% to10%; the differential in β varies from between 6% and 22%. Calculating the differentials using medians gives a similar result, as do all the other specifications we consider.

In Panel D of Table 6, we present the difference in Tobin's q across derivatives users and non-users for each of the matching specifications. Regardless of the specification, we find that the average values of q for firms that use derivatives are higher than those which do not; however, the result is statistically significant in only half of the specifications. The magnitude of the effect also varies greatly across different specifications, ranging from about 1% to 10%.

The results in Table 6 suggest that, after controlling for other firm characteristics, derivative contract use is associated with statistically and economically significantly lower cash flow and stock return volatility, as well as lower systematic risk. The statistical evidence for an increase in value is weaker; however, the economic magnitude of the estimated change in value is non-trivial.[19]

5.2.2 What About the Selection Bias?

Although the propensity score matching represents one way to correct for selection bias, it assumes that all of the differences between firms that drive the difference in hedging use are observable; Rosenbaum and Rubin (1983) call this assumption 'unconfoundedness'. More specifically, they assume that observations with the same propensity score have the same distribution of unobservable characteristics, independent of their treatment status. If this assumption does not hold then there will be a hidden bias in the results. That is, if there are unobserved variables that affect whether a firm decides to use derivatives, as well as the risk and value outcomes, then our inferences may be incorrect.

Since the problem variables are, by definition, unobserved, we cannot estimate their effect directly. However, using the propensity score matching technique, Rosenbaum (2002) calculates a bound on how large an effect the unobserved variables would have to have on the selection process in

[19] As a robustness check on the matching results, we use the same binary variable to measure derivative use, and estimate a treatment effects model as in Heckman (1979). We find similar results: derivative use is associated with significantly lower measures of risk. Likewise, the relation of derivative use to Tobin's q is significantly positive. Finally, we use a crude measure of hedging intensity, rather than merely derivative use, and an instrumental variables technique to measure the effect of hedging on the firm. The results are similar in sign, but weaker in statistical significance. The use of a broader array of derivative contracts is associated with lower cashflow volatility; the results for idiosyncratic volatility and systematic risk are negative, but not statistically significant, while the relation between additional contract use and relative market value is positive but not statistically significant. This indicates that the documented differences in risk and value are more strongly associated with *any* use of derivatives rather than the *extent* of use of derivatives. In turn, this may suggest that derivative use serves as a proxy for broader financial risk management policies.

order to change the inferences provided by the propensity score matching analysis. Intuitively, this bound is based on the calculation of an odds ratio. If two firms have identical observable characteristics, the expected value of the odds ratio that they will choose to use derivatives is one in the absence of a hidden bias. However, if there is a hidden bias in the estimation, and the firms differ in the unobserved characteristic, then the chance that the firms will differ in their choice of hedging varies more widely, and the precision of the inferences declines. The calculation of the bounds is thus essentially a sensitivity analysis; first, one sets the size of the hidden bias, or the size of its effect on the odds ratio, to a particular level. Next, following Rosenbaum (2002), one re-calculates a new (larger) confidence interval for the *p*-value on the difference of each of the relevant characteristics based on this level of hidden bias. The level of hidden bias is then incremented, and the re-calculation is repeated. As DiPrete and Gangl (2004) point out, the Rosenbaum bound is a "worst-case" scenario: it tells the observer not that the treatment effect is not present, but at what point the confidence interval would include zero "if this [unobserved] variable's effect … was so strong as to almost perfectly determine [the effect of hedging] for each pair of matched cases in the data." In that respect, the results of the Rosenbaum bound analysis are conservative.

In Table 7, we calculate the Rosenbaum bounds for the six propensity score matching specifications presented in Table 6, where the variables of interest across the hedging and non-hedging samples are σ_{CF}, σ_E, β, and q. As we move down the rows in each Panel, the gamma variable indicates the generated, or pre-set, size of the hidden bias for each specification which is required for the critical *p*-value associated with that inference to be larger than 0.05. For example, a gamma of 1.5 indicates that the unobserved variable is associated with a 50% change in the odds ratio of whether a firm uses derivatives. In the first row of Panel A, we see that the bias level (gamma value) of 1.47 is associated with the critical probability of 5%; thus, to overturn the inverence on cash flow volatility in the data, or, equivalently, to become less than 95% confident that hedging is associated with a decline in cash flow volatility, hedgers would have to be 47% more likely to possess some hidden trait than non-hedgers. Clearly, higher values of gamma suggest a less important potential hidden bias problem.

Once the bound is calculated, the interpretation of how severe the hidden bias problem is, or the interpretation of the level of gamma required to overturn inferences, is subjective. However, following DiPrete and Gangl (2004), we can compare the change in inferences which is potentially caused by *unobserved* variables, given by the Rosenbaum bounds, to the equivalent effect of *observed* variables, since we have estimates of the effect of the observables on the hedging decision. These values are given in the remaining (numeric) columns of Table 7.

For example, in the specification in the first row of Panel B, we see that for an unobserved variable to cause a hidden bias that affects our inferences on standard deviation of total return, that variable would have to have an effect equivalent to at least a difference of 0.370 in leverage. This difference is approximately twice the *average* leverage level of non-users in the sample, or approximately 1.5 times the standard deviation of leverage for non-users. Similarly, a missing variable would have to be equivalent to the effect of a difference in log size of 0.73. This represents a dollar difference of about 700 million, or several times the *average* market value of non-users in our sample.

The general interpretation of Panels A and B in Table 7 for the inferences on the effect of derivative use on cashflow volatility and total risk is similar: to overturn the inference that derivative use reduces risk, an unobserved confounding variable must have an impact that is comparable in magnitude to economically large changes in firm characteristics, such as leverage, market capitalization, or risk exposure. Moreover, such an unobserved variable would have to be unrelated to the other control variables we use.

The inferences for the effect of derivative use on systematic risk appear to be slightly more sensitive to selection bias. For example, Panel C of Table 7 shows that, in two of the six specifications, if hedgers are only about 5% more likely to possess some hidden characteristic that is associated with derivative use, the inferences could be overturned. In the remaining specifications, the magnitude of the hidden bias are comparable to those estimated for total risk, and suggest that any omitted variable would have to be very economically significant to change the inference that betas decline with derivative use. The average gammas and sensitivities are comparable to those for cashflow volatility and total risk.

Finally, the results with respect to the value premium appear to be even more sensitive to hidden bias, using most of the propensity score matching techniques. For example, the second row of Panel D of Table 7 shows that inferences are potentially overturned at any level of bias.[20] Consequently, the effect of derivative use on market value is highly affected by even a small degree of selection bias in the sample. The sensitivity of the value differential associated with hedging to selection

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[20] Note that the *p*-value is above the critical value at a gamma level of 1.0 Recall that in this specification of the propensity score matching, the difference in Tobin's *q* across hedgers and non-hedgers is not significant; see Table 5.

bias may explain the mixed results in the literature. This result suggests that the estimated value premium (or discount) may be heavily dependent on the sample, the control variables used, and the specification method employed in the tests. At a minimum, these results suggest that the inference that hedging increases firm value should be treated very cautiously.

5.3 Time-Series of Hedging Effects

As noted already, our sample period encompasses a sharp market correction. During 2000 and 2001, the majority of large stock markets, as well as economies, experienced significant downturns. The economic and financial dislocation led to an up-tick in corporate bankruptcies as well as a drastic decline in new and seasoned equity issuances.[21] Consequently, if one goal of financial risk management with derivatives is to lower the probability of financial distress, then firms that manage risk may have experienced significant benefits during this period. We examine this hypothesis by calculating the annual differences in adjusted risk measures from 1998 to 2003 for the firms in our sample for which sufficient data are available. Since several additional years of data are necessary to calculate cash flow volatility, we omit this variable from our analysis. We assume that derivative use is constant over this time period and so classify firms as users or non-users over the entire period.[22]

Table 8 reports the results of this analysis using the matched sample method presented in Table 6; for brevity, we report results for only one matching specification (specification 4). Results for standard deviation in Panel A show that hedgers have lower total risk in each year (at better than the 0.001 significance level). The differences in 2000 and 2001 are larger than average but do not stand out. Results for market beta in Panel B also show consistently lower levels of risk for derivative users. The results are fairly stable across years, with the differences for 2000 and 2001 only slightly higher than the average of all years.

Although we observe consistently lower levels of risk for hedgers throughout our sample period, lower risk may add more value in times of financial or economic declines. To examine this possibility, Panel C of Table 8 shows annual differences in Tobin's *q* over this period. The only year with a statistically significant hedging premium is 2001 (a year that witnessed both the slowest global

[21] For example, data provided by Jay Ritter (http://bear.cba.ufl.edu/ritter/publ_papers/IPOALL.xls) shows that the number of initial public offerings in the United States declined from 505 in 1999 to only 84 in 2001.

[22] To evaluate the validity of this assumption we examined the use of a random sample of 50 users and 50 non-users in 1998 and 2003. Of the firms with available data, 84% of the non-users and 82% of the users followed the same strategy in 1998 and 2003 as in 2000-2001.

GDP growth in over a decade and a recession in the United States). Given the Table 7 evidence that the hedging premium is particularly sensitive to omitted variable bias, we also investigate relative value and performance over time by examining the variation in the alphas (α_j) from our estimates of equation (1). Panel D presents differences in matched alphas for each year. Hedgers experience significantly higher values than non-hedgers in 1999, 2001, and 2002 (and never significantly lower values). The differences in 2001 and 2002, at 0.030, are the largest in the sample period.

These results suggest some potentially important time variation in firm's risk and value measures related to financial or economic conditions. In particular, it appears that hedging is more valuable during market downturns. To examine this possibility, we condition our analysis on broad market returns in a firm's home country. Specifically, we create two equally weighted portfolios that are long hedgers and short matching nonhedgers: the first portfolio includes companies in countries only when the domestic stock market index is up for the quarter; likewise, the second portfolio includes companies in countries only when the domestic stock market index is down for the quarter. We then examine the risk and return by estimating equation (1) for the years 2000-2002 and calculate the differences in market beta and alpha of each portfolio. We hypothesize that if hedging provides for lower risk in declining markets that the estimated beta will be significantly lower for the down-market portfolio as compared to the up-market portfolio. Similarly, a difference in value would be reflected in significantly higher alphas for the down-market portfolio.

Table 9 reports the results of this analysis. The table shows that the beta of the long-short portfolio is significantly negative in down-markets. This simply restates the previous finding that hedgers have lower betas than nonhedgers. In addition, the *difference* in betas between the down-market and up-market portfolios is negative which is consistent with the prediction that hedging provides down-side risk protection: non-hedgers are significantly more sensitive to the market portfolio, relative to hedgers, during periods of poor market returns. In fact, the statistically insignificant estimate for the beta of the up-market portfolio suggests that hedging only provides for lower risk in down-markets, precisely when one would wish for lower market exposure. The estimates of alpha are not statistically significant for either portfolio though the larger value for down-markets is consistent with the hypothesis that hedging adds more value in down markets. Note that the weak results for portfolio alphas are consistent with the weak results for Tobin's q discussed in the previous section.

Taken together these results have important implications. First, since the adjusted risk measures for hedgers are lower throughout the sample period, it is unlikely that the results for 2000-2001 are unique to those years. Second, and more interestingly, the evidence suggests the possibility that derivative use primarily lowers downside risk. Third, if part of the risk reduction from hedging comes from limiting exposure to financial or economic downturns, this provides a direct mechanism for understanding why hedging affects market value. Specifically, if hedging lowers a firm's business-cycle risk, this may lead to a lower market beta, a lower discount rate, and therefore a higher firm value.

6 Conclusion

In this paper, we use a large sample of firms operating in 47 countries to analyze the effect of derivative use on measures of risk and value. In univariate tests, we find that derivative use is more prevalent in firms with higher exposures to interest rate risk, exchange rate risk and commodity prices. Despite this, firms that use derivatives have lower estimated values of both total and systematic risk, suggesting that derivatives are used to hedge risk, rather than to speculate. There are significant differences between derivative users and non-users along other dimensions, emphasizing the importance of multivariate tests.

We concentrate our multivariate analysis on propensity score matching, in which derivative users and non-users are matched on the basis of their estimated propensity to use derivatives. Compared to firms that do not use derivatives, we find that hedging firms have lower cash flow volatility, idiosyncratic volatility and systematic risk; these results are robust to a number of different matching specifications, and the differences are both statistically and economically significant. This suggests that nonfinancial firms overall employ derivatives with the motive and effect of risk reduction. Consistent with the evidence in Allayannis and Weston (2001), derivative use is associated with a value premium, although the statistical significance of this premium is weak.

We also estimate the potential importance of selection bias on the inferences drawn from our tests, by estimating bounds beyond which the inferences would change. These results suggest that the estimated effects of derivative use on risk measures are robust: while we cannot rule out the possibility that selection bias is driving our results, any omitted control variable would have to be quite significant in its effect on risk to overturn the inference that the risk of firms that use derivatives is lower. In contrast, the value effects of derivative use are quite sensitive to selection bias. This result may explain the differences in inferences in the literature–even small differences in sample construction, control variables and testing method could change the estimated effect.

Finally, we document that the reductions in risk we find are unlikely to be specific to our primary sample period; however, we do find that market betas vary in a way that is consistent with firms hedging down-side risk. Lower betas may indicate that hedging has an effect on a firm's cost of capital and thus the investment policy and economic profitability of a firm. This in turn may explain why some of our evidence indicates that hedgers have higher values and risk-adjusted market returns.

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Figure 1: Cumulative Returns of Hedgers and Nonhedgers

This plot shows cumulative returns for market-value (in U.S. dollars) weighted indices of hedgers (dashed line) and nonhedgers (solid line) from January 1998 through December 2003. The world market index is also plotted for reference. A Hedger is defined as a firm using any type of derivative in 2000 or 2001. The indices are constructed using daily returns obtained from averaging returns each day for all firms with available return data. Returns are measured in local currency. Both hedgers and nonhedgers outperform the world market index because we exclude financial firms and utilities which significantly underperform other stocks over this period.

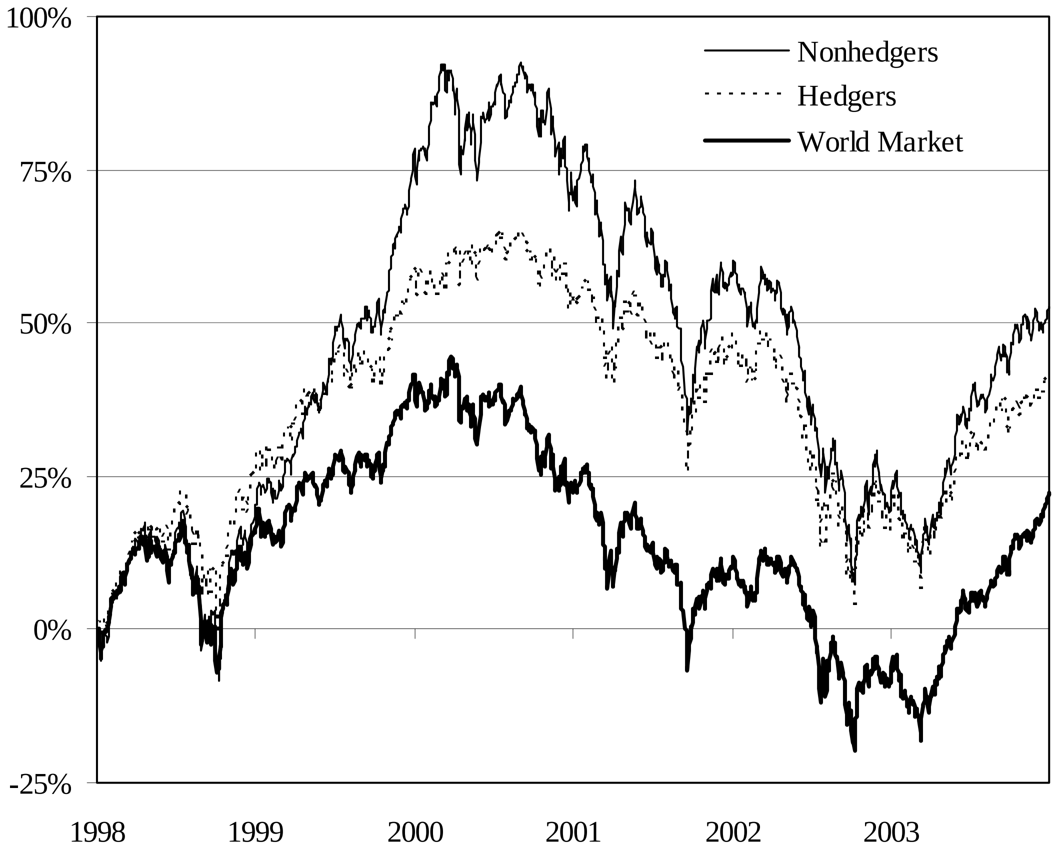

Table 1: Summary Statistics of Derivatives Use of Sample Firms

The table shows summary statistics of derivatives use by country. In particular, it presents the number of firms and the percentage of firms using derivatives, for general derivatives use, foreign exchange rate derivatives, interest rate derivatives and commodity price derivatives. Hedging Intensity reports the average number of different instruments firms use. Firms are required to be outside the financial sector, to have an annual report on the Global Reports database, accounting data on Thomson Analytics and at least 36 non-missing daily stock returns for the year of the annual report on Datastream. We create a category called "Other countries" for countries with less than 10 observations (i.e., Bahamas, Bermuda, Cayman Islands, Egypt, Indonesia, Peru, Portugal, Turkey, and Venezuela).

			Hedge	Foreign Exchange Derivatives				Interest Rates Derivatives				Commodity Price Derivatives			
	Firms	General	Intensity	General	Forward	Swap	Option	General	Forward	Swap	Option	General	Future	Swap	Option
Argentina	10	70.0	1.9	70.0	40.0	20.0	0.0	60.0	0.0	40.0	30.0	40.0	0.0	20.0	30.0
Australia	301	66.4	1.6	52.2	48.5	8.6	17.9	42.2	3.7	38.9	15.0	14.3	2.0	3.7	5.0
Austria	41	56.1	1.2	56.1	43.9	17.1	22.0	22.0	0.0	17.1	7.3	7.3	2.4	4.9	2.4
Belgium	60	50.0	0.8	36.7	26.7	8.3	6.7	23.3	0.0	21.7	3.3	3.3	0.0	1.7	0.0
Brazil	16	81.3	1.2	56.3	18.8	25.0	12.5	18.8	0.0	12.5	6.3	18.8	0.0	6.3	0.0
Canada	537	60.3	1.1	46.2	34.3	8.0	8.2	27.2	0.4	24.2	3.2	17.7	2.8	5.2	5.4
Chile	13	100.0	1.8	84.6	61.5	23.1	7.7	53.8	0.0	38.5	7.7	15.4	0.0	7.7	7.7
China	32	12.5	0.2	6.3	6.3	3.1	0.0	3.1	0.0	3.1	0.0	3.1	3.1	0.0	0.0
Czech Republic	23	26.1	0.4	13.0	13.0	4.3	4.3	17.4	0.0	13.0	0.0	0.0	0.0	0.0	0.0
Denmark	80	87.5	1.5	80.0	72.5	12.5	18.8	26.3	1.3	21.3	6.3	5.0	1.3	2.5	1.3
Finland	100	64.0	1.6	58.0	45.0	18.0	27.0	37.0	9.0	29.0	17.0	8.0	3.0	1.0	3.0
France	159	66.0	1.5	52.8	37.1	22.6	25.8	44.7	1.9	38.4	15.1	3.8	1.3	1.3	0.6
Germany	395	47.1	0.9	39.0	27.3	10.6	12.4	24.1	1.8	17.7	9.4	4.8	1.8	0.5	0.5
Greece	19	21.1	0.4	21.1	10.5	5.3	5.3	10.5	0.0	10.5	0.0	5.3	5.3	0.0	0.0
Hong Kong	319	23.2	0.3	18.5	13.8	4.4	1.3	7.2	0.3	5.6	1.3	0.3	0.0	0.0	0.0
Hungary	15	40.0	0.8	33.3	33.3	6.7	13.3	13.3	0.0	13.3	0.0	13.3	0.0	6.7	0.0
India	40	70.0	0.9	62.5	60.0	7.5	0.0	12.5	0.0	12.5	0.0	5.0	2.5	0.0	0.0
Ireland	46	84.8	1.9	69.6	63.0	28.3	8.7	52.2	4.3	47.8	8.7	13.0	2.2	6.5	4.3
Israel	48	72.9	1.1	68.8	43.8	2.1	22.9	12.5	0.0	10.4	4.2	2.1	2.1	0.0	0.0
Italy	93	61.3	1.0	38.7	29.0	16.1	3.2	33.3	3.2	23.7	3.2	2.2	1.1	2.2	0.0
Japan	366	81.1	2.1	75.4	71.0	33.1	17.8	60.4	0.5	59.3	14.2	9.6	3.8	1.6	1.6
Korea, Republic of	24	70.8	1.3	54.2	41.7	20.8	12.5	25.0	0.0	25.0	0.0	8.3	0.0	0.0	4.2
Luxembourg	11	63.6	1.2	45.5	45.5	9.1	18.2	27.3	0.0	18.2	9.1	9.1	9.1	0.0	0.0
Malaysia	289	20.1	0.2	16.3	12.5	1.4	0.7	4.2	0.0	3.8	1.0	1.0	0.7	0.0	0.0
Mexico	35	60.0	1.1	34.3	25.7	5.7	11.4	37.1	2.9	37.1	0.0	14.3	8.6	2.9	2.9
Netherlands	131	56.5	1.1	48.1	38.9	18.3	12.2	33.6	1.5	27.5	9.2	4.6	0.8	0.8	0.8
New Zealand	39	94.9	2.6	79.5	74.4	17.9	35.9	76.9	5.1	71.8	33.3	17.9	0.0	10.3	10.3

(continued)

Table 1: Summary Statistics of Derivatives Use of Sample Firms (continued)

			Hedge	Foreign Exchange Derivatives				Interest Rates Derivatives				Commodity Price Derivatives			
	Firms	General	Intensity	General	Forward	Swap	Option	General	Forward	Swap	Option	General	Future	Swap	Option
Norway	85	67.1	1.4	56.5	48.2	17.6	17.6	29.4	2.4	24.7	5.9	8.2	2.4	0.0	3.5
Other countries	21	52.4	0.9	42.9	33.3	19.0	4.8	9.5	0.0	9.5	0.0	9.5	0.0	4.8	9.5
Philippines	12	50.0	0.8	41.7	41.7	16.7	0.0	16.7	0.0	16.7	0.0	8.3	0.0	8.3	0.0
Poland	11	45.5	1.1	36.4	18.2	18.2	27.3	18.2	9.1	9.1	9.1	9.1	0.0	0.0	0.0
Singapore	218	55.5	0.8	50.9	42.7	6.0	3.7	11.5	0.5	9.6	1.8	2.3	0.0	1.8	0.0
South Africa	55	89.1	1.7	89.1	87.3	9.1	14.5	38.2	0.0	32.7	5.5	14.5	5.5	0.0	1.8
Spain	29	62.1	1.3	37.9	27.6	10.3	10.3	37.9	3.4	34.5	13.8	20.7	6.9	6.9	6.9
Sweden	135	63.7	0.9	45.2	35.6	7.4	8.1	13.3	2.2	9.6	2.2	4.4	0.7	0.7	1.5
Switzerland	119	77.3	1.6	68.1	61.3	14.3	23.5	42.9	3.4	35.3	7.6	5.9	0.8	0.8	0.8
Thailand	25	72.0	1.2	68.0	56.0	36.0	0.0	24.0	4.0	20.0	0.0	0.0	0.0	0.0	0.0
United Kingdom	860	64.4	1.3	55.0	49.4	17.1	7.8	36.5	0.6	32.1	10.8	3.7	1.5	1.4	0.7
United States	2,076	65.1	1.2	37.8	30.9	6.4	7.5	40.4	0.7	36.0	6.8	16.1	6.0	5.2	3.3
All excluding U.S.	4,812	58.5	1.1	48.9	40.9	13.2	10.8	29.9	1.3	26.2	7.7	7.0	1.7	1.9	1.8
All firms	6,888	60.5	1.2	45.5	37.9	11.2	9.8	33.1	1.1	29.1	7.4	9.8	3.0	2.9	2.3

Table 2: Summary Statistics on Capital Market Data and Risk Measures

The table shows the mean, standard deviation (Std.Dev.), minimum, 5th, 25th, 50th (median), 75th and 95th percentile as well as the maximum of selected variables. In particular, it shows capital markets data such as the daily returns of the sample firms and the corresponding returns of the domestic market indices. It also presents descriptive statistics of cashflow volatility (σ_{CF}) the annualized standard deviation of local currency stock returns (σ_E), and the standard deviation of local currency stock returns standardized by the standard deviation of the local market index (σ_E^*). β is the coefficient of a regression of stock returns on market index returns, and *p*-value is the corresponding significance level. Finally, the table shows summary statistics of other firm characteristics. All variables are defined in Table A-1 in the appendix.

			Percentiles						
	Mean	Std.Dev.	Min	5th	25th	Median	75th	95th	Max
Capital Markets Data									
Stock Return	-0.08	3.71	-12.52	-6.19	-1.50	0.00	1.24	6.12	13.04
Market Return	-0.04	1.44	-18.24	-2.31	-0.79	0.00	0.73	2.23	17.03
Risk & Value Measures									
σ_{CF} (%)	8.25	12.65	0.59	0.59	1.59	3.36	7.91	50.83	52.91
σ_{CF} (log)	1.34	1.19	-0.52	-0.52	0.46	1.21	2.07	3.93	3.97
σ_E	0.56	0.23	0.18	0.25	0.37	0.51	0.71	1.01	1.16
σ_E*	2.56	1.14	0.72	1.10	1.70	2.32	3.24	4.74	6.05
β	0.70	0.58	-0.18	0.01	0.27	0.57	1.01	1.89	2.55
β (p-values)	0.10	0.21	0.00	0.00	0.00	0.00	0.07	0.65	1.00
q	2.33	2.67	0.42	0.62	1.00	1.43	2.48	7.18	21.22
q (log)	0.51	0.74	-0.86	-0.48	0.00	0.36	0.91	1.97	3.06
Other Firm Characteristics									
Hedging Intensity	1.15	1.34	0.00	0.00	0.00	1.00	2.00	4.00	9.00
Alpha	-0.13	0.63	-2.28	-1.37	-0.40	-0.03	0.24	0.75	1.24
Size (log)	5.87	2.00	0.90	2.70	4.45	5.80	7.25	9.36	10.57
Sales (log)	5.59	2.22	-0.71	1.82	4.14	5.63	7.16	9.18	10.36
Leverage	0.26	0.25	0.00	0.00	0.03	0.19	0.43	0.74	0.89
Quick Ratio	1.80	2.16	0.10	0.27	0.66	1.03	1.85	7.40	10.00
Multiple Share Classes	0.13	0.33	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Stock Options	0.81	0.39	0.00	0.00	1.00	1.00	1.00	1.00	1.00
FX Exposure	0.53	0.50	0.00	0.00	0.00	1.00	1.00	1.00	1.00
FC Debt	0.82	0.38	0.00	0.00	1.00	1.00	1.00	1.00	1.00
Z-Score	6.72	7.94	-8.10	-1.72	1.82	3.96	8.68	24.77	27.18
Industry Segments	3.66	1.99	1.00	1.00	2.00	3.00	5.00	8.00	8.00
Dividend (Dummy)	0.52	0.50	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Gross Profit Margin	0.25	0.27	-1.00	-0.12	0.14	0.25	0.39	0.66	0.86
ROA	0.00	0.21	-1.00	-0.50	-0.01	0.05	0.09	0.19	0.46
Foreign Sales	0.23	0.30	0.00	0.00	0.00	0.04	0.42	0.89	1.00
Sales Growth (%)	11.66	20.05	-17.20	-16.91	-0.83	7.05	19.46	64.33	64.83
R&D / Size	0.02	0.04	0.00	0.00	0.00	0.00	0.01	0.08	0.28
Capex / Size	0.15	0.34	0.00	0.00	0.02	0.05	0.11	0.59	2.64

Table 3: Univariate Tests of Corporate Risk Measures and Derivatives Use

The table shows the number of observations (N), mean, median and difference in mean of different risk characteristics for derivatives users and derivatives non-users. The last column presents p-values of Wilcoxon rank sum tests between derivatives users and non-users. All variables are defined in Table A-1 in the appendix.

	User			Non-User			Difference	Wilcoxon
Variable	N	Mean	Median	N	Mean	Median	in Means	*p*-value
Panel A: Gross Exposure								
Foreign Sales	4,167	0.272	0.152	2,721	0.164	0.000	0.108	<0.001
Foreign Income	2,421	0.235	0.056	1,477	0.143	0.000	0.092	<0.001
Foreign Assets	2,349	0.182	0.099	1,205	0.114	0.000	0.068	<0.001
Gross-FX-Exposure	4,167	0.621	1.000	2,721	0.395	0.000	0.226	<0.001
Foreign Debt	4,167	0.882	1.000	2,721	0.725	1.000	0.157	<0.001
Leverage	4,091	0.297	0.254	2,643	0.189	0.081	0.108	<0.001
Coverage	4,114	3.852	3.657	2,655	2.542	3.333	1.310	<0.001
Gross-IR-Exposure	4,091	0.601	1.000	2,643	0.344	0.000	0.257	<0.001
Gross-CP-Exposure	4,167	0.156	0.000	2,721	0.082	0.000	0.074	<0.001
Gross-Exposure	4,167	0.865	1.000	2,721	0.612	1.000	0.253	<0.001
Panel B: Net Risk & Value								
σ_{CF} (%)	3,365	6.200	2.848	1,768	12.162	4.994	-5.962	<0.001
σ_{CF} (log)	3,365	1.144	1.046	1,768	1.717	1.608	-0.573	<0.001
σ_E	4,167	0.510	0.461	2,721	0.624	0.604	-0.114	<0.001
σ_E*	4,167	2.380	2.140	2,721	2.842	2.705	-0.462	<0.001
β	4,165	0.686	0.540	2,721	0.732	0.618	-0.046	<0.001
q	3,980	2.154	1.392	2,559	2.605	1.564	-0.451	0.005
q (log)	3,980	0.480	0.331	2,559	0.556	0.447	-0.076	0.005
Panel C: Country Factors								
ICR-Financial	4,167	38.455	37.000	2,721	38.915	37.000	-0.460	<0.001
ICR-Economic	4,167	42.188	42.000	2,721	42.150	42.000	0.038	<0.001
Derivative Market Rank	4,167	38.299	43.000	2,721	36.083	41.000	2.216	<0.001
Panel D: Other Firm Characteristics								
Hedging Intensity	4,167	1.902	1.000	2,721	0.000	0.000	1.902	
Alpha	4,165	-0.061	0.008	2,721	-0.236	-0.114	0.175	<0.001
Z-Score	3,566	5.515	3.471	1,971	8.888	5.688	-3.373	<0.001
Size (log)	4,126	6.580	6.555	2,680	4.783	4.731	1.797	<0.001
Sales (log)	4,091	6.713	6.691	2,643	5.063	4.941	1.650	<0.001
Industry Segments	4,150	3.823	3.000	2,710	3.420	3.000	0.403	<0.001
Dividend (Dummy)	4,167	0.598	1.000	2,721	0.400	0.000	0.198	<0.001
R&D / Size	4,167	0.044	0.000	2,721	0.121	0.000	-0.077	<0.001
Capex / Size	4,172	0.126	0.050	2,724	0.174	0.047	-0.048	0.011
Tangible Assets	3,882	0.874	0.943	2,554	0.888	0.973	-0.014	<0.001
Stock Options	4,172	0.828	1.000	2,724	0.792	1.000	0.036	<0.001
Sales Growth	3,452	10.513	6.450	1,821	13.774	8.861	-3.261	<0.001

Table 4: Tests of Country- and Industry-adjusted Corporate Risk Measures and Derivatives Use

The table shows the number of observations (N), mean, and median of different risk characteristics for derivatives users and derivatives non-users. The last column presents p-values of Wilcoxon rank sum tests between derivatives users and non-users. The firm-specific variables are adjusted for country (47), industry (44) and year effects (where appropriate). All variables are defined in Table A-1 in the appendix.

	User			Non-User			Difference	Wilcoxon
Variable	N	Mean	Median	N	Mean	Median	in Means	*p*-value
Panel A: Gross Exposure								
Foreign Sales	4,167	0.039	-0.029	2,721	-0.060	-0.122	0.099	<0.001
Foreign Income	2,421	0.032	-0.047	1,477	-0.053	-0.130	0.085	<0.001
Foreign Assets	2,349	0.017	-0.034	1,205	-0.032	-0.063	0.049	<0.001
Gross-FX-Exposure	4,167	0.621	1.000	2,721	0.395	0.000	0.226	<0.001
Foreign Debt	4,167	0.882	1.000	2,721	0.725	1.000	0.157	<0.001
Leverage	4,091	0.029	-0.005	2,643	-0.045	-0.089	0.074	<0.001
Coverage	4,114	0.256	0.041	2,655	-0.396	0.124	0.652	0.057
Gross-IR-Exposure	4,091	0.601	1.000	2,643	0.344	0.000	0.257	<0.001
Gross-CP-Exposure	4,167	0.156	0.000	2,721	0.082	0.000	0.074	<0.001
Gross-Exposure	4,167	0.865	1.000	2,721	0.612	1.000	0.253	<0.001
Panel B: Net Risk & Value								
σ_{CF} (%)	3,365	-1.270	-2.549	1,768	2.417	-1.865	-3.687	<0.001
σ_{CF} (log)	3,365	-0.110	-0.172	1,768	0.209	0.110	-0.319	<0.001
σ_E	4,167	-0.023	-0.038	2,721	0.035	0.021	-0.058	<0.001
σ_E*	4,167	-0.109	-0.173	2,721	0.167	0.101	-0.276	<0.001
β	4,165	0.009	-0.043	2,721	-0.014	-0.081	0.023	0.002
q	3,980	-0.099	-0.475	2,559	0.154	-0.445	-0.253	0.188
q (log)	3,980	-0.020	-0.093	2,559	0.032	-0.059	-0.052	0.015
Panel C: Country Risk								
ICR-Financial	4,167	38.455	37.000	2,721	38.915	37.000	-0.460	<0.001
ICR-Economic	4,167	42.188	42.000	2,721	42.150	42.000	0.038	<0.001
Derivative Market Rank	4,167	38.299	43.000	2,721	36.083	41.000	2.216	<0.001
Panel D: Other Firm Characteristics								
Hedging Intensity	4,167	1.902	1.000	2,721	0.000	0.000	1.902	
Alpha	4,165	0.034	0.062	2,721	-0.052	0.009	0.086	<0.001
Z-Score	3,566	-0.812	-2.033	1,971	1.469	-0.583	-2.281	<0.001
Size (log)	4,126	0.481	0.365	2,680	-0.740	-0.711	1.221	<0.001
Sales (log)	4,091	0.435	0.324	2,643	-0.674	-0.673	1.109	<0.001
Industry Segments	4,150	0.191	-0.052	2,710	-0.293	-0.524	0.484	<0.001
Dividend (Dummy)	4,167	0.598	1.000	2,721	0.400	0.000	0.198	<0.001
R&D / Sales	4,167	-0.021	-0.028	2,721	0.032	-0.024	-0.053	0.220
Capex / Sales	4,167	-0.014	-0.039	2,721	0.021	-0.054	-0.035	<0.001
Tangible Assets	3,879	-0.004	0.024	2,551	0.007	0.030	-0.011	<0.001
Stock Options	4,167	0.828	1.000	2,721	0.792	1.000	0.036	<0.001
Sales Growth	3,449	-0.799	-3.198	1,818	1.515	-1.892	-2.314	0.001

Table 5: Propensity Score Matching and Covariate Balance

The table shows average values of various firm characteristics used to match hedgers (treated) and non-hedgers (control) for the analysis of different outcome variables. The table shows results before and after matching, as well statistics of the bias and the bias reduction. The last column presents p-values of Wilcoxon rank sum tests between matched samples of derivatives users and non-users. Panel A shows results for matching without replacement, while Panel B shows results for matching with replacement using the matching options "caliper (0.01) trim(1) common". Results are based on the following variables as explanatory variables of derivatives usage: For cashflow volatility, stock return volatility, and market betas: size (log), Z-score, leverage, quick ratio, multiple share classes, stock options, FX exposure, FC debt, industry and country dummies. For Tobin's q: sales (log), Z-score, sales growth, r&d/size, capex/size, age (log), quick ratio, dividend, multiple share classes, stock options, FX exposure, FC debt, industry and country dummies. All variables are defined in Table A-1 in the appendix.

		Before Matching			After Matching				Wilcoxon
Outcome Variables	Independent Variable	Treated	Control	Bias	Treated	Control	Bias	Reduction	p-value
Panel A: Matching without replacement									
σ_{CF}, σ_E, β	Size (log)	6.713	5.063	91.3	5.992	5.459	33.2	-63.6	<0.001
	Z-Score	5.515	8.888	41.4	7.476	8.536	12.9	-68.9	0.003
	leverage	0.297	0.189	45.2	0.265	0.251	5.9	-86.9	0.025
	Quick Ratio	1.380	2.455	48.4	1.411	1.691	16.4	-66.2	0.001
	Multiple Share Class	0.153	0.083	21.9	0.148	0.112	10.6	-51.7	0.008
	Stock Options	0.828	0.792	9.4	0.798	0.748	11.8	25.9	0.003
	FX-Exposure	0.621	0.395	46.4	0.541	0.451	18.2	-60.9	<0.001
	FC Debt	0.882	0.725	40.3	0.777	0.710	15.3	-62.1	<0.001
q	Sales (log)	6.366	4.353	100.7	5.814	5.052	46.9	-53.4	<0.001
	Z-Score	5.515	8.888	41.4	7.350	8.648	15.7	-62.0	<0.001
	Sales Growth	10.527	13.805	15.8	12.999	12.533	2.3	-85.7	0.266
	R&D / Size	0.044	0.121	21.5	0.038	0.068	11.0	-48.9	0.001
	Capex / Size	0.126	0.175	13.5	0.092	0.096	2.8	-79.0	0.698
	Age (log)	2.372	1.835	57.8	2.362	2.241	16.2	-72.0	<0.001
	Quick Ratio	1.380	2.455	48.4	1.366	1.655	17.4	-64.2	0.003
	Dividend	0.598	0.400	40.3	0.601	0.547	10.9	-73.0	0.013
	Multiple Share Class	0.153	0.083	21.9	0.158	0.113	13.1	-40.3	0.002
	Stock Options	0.828	0.792	9.4	0.767	0.733	7.8	-17.1	0.061
	FX-Exposure	0.621	0.395	46.4	0.559	0.454	21.1	-54.6	<0.001
	FC Debt	0.882	0.725	40.3	0.793	0.721	16.8	-58.2	<0.001

Table 5: Propensity Score Matching and Covariate Balance (continued)

		Before Matching			After Matching				Wilcoxon
Outcome Variables	Independent Variable	Treated	Control	Bias	Treated	Control	Bias	Reduction	*p*-value
Panel B: Matching with replacement									
σ_{CF}, σ_E, β	Size (log)	6.713	5.063	91.3	6.943	6.981	2.1	-97.7	0.239
	Z-Score	5.515	8.888	41.4	5.598	4.842	11.7	-71.7	<0.001
	leverage	0.297	0.189	45.2	0.311	0.343	13.5	-70.1	<0.001
	Quick Ratio	1.380	2.455	48.4	1.148	1.090	5.3	-89.0	0.006
	Multiple Share Class	0.153	0.083	21.9	0.168	0.168	0.1	-99.6	0.971
	Stock Options	0.828	0.792	9.4	0.824	0.793	7.8	-17.1	0.003
	FX-Exposure	0.621	0.395	46.4	0.682	0.675	1.4	-96.9	0.565
	FC Debt	0.882	0.725	40.3	0.882	0.890	2.5	-93.9	0.316
q	Sales (log)	6.366	4.353	100.7	6.813	6.957	8.0	-92.1	<0.001
	Z-Score	5.515	8.888	41.4	5.637	4.972	10.6	-74.3	<0.001
	Sales Growth	10.527	13.805	15.8	10.115	8.614	8.9	-43.8	<0.001
	R&D / Size	0.044	0.121	21.5	0.028	0.023	4.8	-77.7	<0.001
	Capex / Size	0.126	0.175	13.5	0.093	0.091	1.3	-90.7	0.617
	Age (log)	2.372	1.835	57.8	2.628	2.630	0.2	-99.7	0.405
	Quick Ratio	1.380	2.455	48.4	1.131	1.031	9.7	-80.0	<0.001
	Dividend	0.598	0.400	40.3	0.698	0.721	5.2	-87.1	0.067
	Multiple Share Class	0.153	0.083	21.9	0.172	0.211	10.0	-54.4	0.001
	Stock Options	0.828	0.792	9.4	0.807	0.836	7.6	-19.2	0.009
	FX-Exposure	0.621	0.395	46.4	0.690	0.689	0.2	-99.6	0.947
	FC Debt	0.882	0.725	40.3	0.887	0.905	5.7	-85.7	0.038

Table 6: Matched-Sample Tests of Corporate Risk Measures and Derivatives Use

The table shows the number of observations (N), mean, and median of different outcome variables for derivatives users and derivatives non-users as well as the corresponding propensity scores (p-score). The last column presents p-values of Wilcoxon rank sum tests between derivatives users and non-users. Panel A shows results for cashflow volatility (σ_{CF}), Panel B shows results for total risk as measured by the annualized standard deviation of stock returns (σ_E). Panel C shows results for market betas (β) estimated using equation (1). Panel D shows results for Tobin's q. Specification 1 and 2 report results with and without replacement, respectively, for cashflow volatility, stock return volatility and market betas using the independent variables: Z-Score, leverage, quick ratio, size (log), multiple share classes, stock options, gross FX exposure, foreign currency debt, industry and country dummies, and for Tobin's q the independent variables Z-Score, sales growth, r&d/size, capex/size, age (log), quick ratio, sales (log), dividend (dummy), multiple share classes, stock options, gross FX exposure, foreign currency debt, industry and country dummies. Specifications 3 and 4 report results with and without replacement for the same variables as specifications 1 and 2 but using the matching options "caliper (0.01) trim(1) common". Specifications 5 and 6 report results with and without replacement, respectively, for cashflow volatility, stock return volatility and market betas using the independent variables: Z-Score, size (log), foreign currency debt, leverage, multiple share classes, quick ratio, and for Tobin's q the independent variables Z-Score, sales growth, r&d/size, capex/size, age (log), sales (log), foreign currency debt, dividend, multiple share classes, quick ratio. All variables are defined in Table A-1 in the appendix.

Panel A: Cashflow Volatility

				Users			Non-Users				
Specification		Replacement	Country/ Industry Dummies	N	Mean	Median	N	Mean	Median	Difference in Means	Wilcoxon p-value
1	Values	No	Yes	1,294	1.237	1.124	1,294	1.590	1.459	-0.353	<0.001
	p-score				0.628	0.680		0.459	0.451		
2	Values	Yes	Yes	2,807	1.061	0.969	2,807	1.174	1.037	-0.113	<0.001
	p-score				0.790	0.857		0.790	0.856		
3	Values	No	Yes	1,294	1.231	1.125	1,294	1.590	1.459	-0.359	<0.001
	p-score				0.626	0.677		0.463	0.464		
4	Values	Yes	Yes	2,807	1.062	0.971	2,807	1.200	1.089	-0.138	<0.001
	p-score				0.788	0.852		0.788	0.853		
5	Values	No	No	1,294	1.261	1.121	1,294	1.590	1.459	-0.329	<0.001
	p-score				0.596	0.628		0.549	0.558		
6	Values	Yes	No	2,842	1.063	0.973	2,842	1.312	1.174	-0.249	<0.001
	p-score				0.751	0.790		0.751	0.790		

Table 6: Matched-Sample Tests of Corporate Risk Measures and Derivatives Use (continued)

Panel B: Stock Return Volatility

				Users			Non-Users				
Specification		Replace-ment	Country/ Industry Dummies	N	Mean	Median	N	Mean	Median	Difference in Means	Wilcoxon p-value
1	Values	No	Yes	1,294	0.522	0.485	1,294	0.565	0.531	-0.043	<0.001
	p-score				0.628	0.680		0.459	0.451		
2	Values	Yes	Yes	2,807	0.476	0.438	2,807	0.494	0.427	-0.018	0.002
	p-score				0.790	0.857		0.790	0.856		
3	Values	No	Yes	1,294	0.525	0.485	1,294	0.565	0.531	-0.040	<0.001
	p-score				0.626	0.677		0.463	0.464		
4	Values	Yes	Yes	2,807	0.476	0.439	2,807	0.504	0.469	-0.028	<0.001
	p-score				0.788	0.852		0.788	0.853		
5	Values	No	No	1,294	0.513	0.472	1,294	0.565	0.531	-0.052	<0.001
	p-score				0.596	0.628		0.549	0.558		
6	Values	Yes	No	2,842	0.475	0.437	2,842	0.531	0.502	-0.056	<0.001
	p-score				0.751	0.790		0.751	0.790		

Table 6: Matched-Sample Tests of Corporate Risk Measures and Derivatives Use (continued)

Panel C: Market Betas

Specification		Replace-ment	Country/ Industry Dummies	Users N	Users Mean	Users Median	Non-Users N	Non-Users Mean	Non-Users Median	Difference in Means	Wilcoxon p-value
1	Values	No	Yes	1,294	0.660	0.499	1,294	0.702	0.580	-0.042	0.034
	p-score				0.628	0.680		0.459	0.451		
2	Values	Yes	Yes	2,807	0.654	0.526	2,807	0.770	0.692	-0.116	<0.001
	p-score				0.790	0.857		0.790	0.856		
3	Values	No	Yes	1,294	0.658	0.498	1,294	0.702	0.580	-0.044	0.025
	p-score				0.626	0.677		0.463	0.464		
4	Values	Yes	Yes	2,807	0.654	0.526	2,807	0.733	0.643	-0.079	<0.001
	p-score				0.788	0.852		0.788	0.853		
5	Values	No	No	1,294	0.576	0.422	1,294	0.702	0.580	-0.126	<0.001
	p-score				0.596	0.628		0.549	0.558		
6	Values	Yes	No	2,842	0.653	0.524	2,842	0.834	0.696	-0.181	<0.001
	p-score				0.751	0.790		0.751	0.790		

Table 6: Matched-Sample Tests of Corporate Risk Measures and Derivatives Use (continued)

Panel D: Tobin's *q*

Specification		Replace-ment	Country/ Industry Dummies	Users N	Users Mean	Users Median	Non-Users N	Non-Users Mean	Non-Users Median	Difference in Means	Wilcoxon p-value
1	Values	No	Yes	1,098	0.462	0.311	1,098	0.396	0.259	0.066	0.015
	p-score				0.635	0.685		0.435	0.433		
2	Values	Yes	Yes	2,341	0.462	0.312	2,341	0.448	0.306	0.014	0.877
	p-score				0.798	0.870		0.798	0.870		
3	Values	No	Yes	1,098	0.459	0.312	1,098	0.396	0.259	0.063	0.009
	p-score				0.634	0.684		0.439	0.446		
4	Values	Yes	Yes	2,303	0.464	0.312	2,303	0.457	0.326	0.007	0.960
	p-score				0.793	0.866		0.793	0.866		
5	Values	No	No	1,098	0.422	0.291	1,098	0.396	0.259	0.026	0.155
	p-score				0.601	0.633		0.519	0.528		
6	Values	Yes	No	2,373	0.457	0.310	2,373	0.388	0.262	0.069	0.001
	p-score				0.760	0.807		0.760	0.806		

Table 7: Rosenbaum Bounds for Matching

The table shows the Rosenbaum bounds and hidden bias equivalents for different outcome variables. Each panel shows columns for gamma (the change in the odds ratio), for a critical *p*-value of 0.05 as well as hidden bias equivalents for various firm characteristics. Hedgers and non-hedgers as matched by propensity scores sampling without replacement. Panel A shows results for cashflow volatility (σ_{CF}), Panel B for stock return volatility (σ_E), Panel C for market betas (β), and Panel D for Tobin's q (log). Propensity scores are based on the set of variables in the column headings as well as industry and country dummies. All variables are defined in Table A-1 in the appendix.

Panel A: Cashflow Volatility

Specification	Gamma	Replacement	Country & Industry Dummies	Z-Score	Leverage	Quick Ratio	Size (log)	Multiple Share Classes	Stock Options	FX Exposure	FC Debt
1	1.47	No	Yes	-36.99	0.68	-5.52	1.36	1.50	1.05	2.29	0.57
2	1.19	Yes	Yes	-16.70	0.31	-2.49	0.62	0.68	0.47	1.04	0.26
3	1.43	No	Yes	-33.90	1.19	0.47	0.65	1.47	-5.01		
4	1.08	Yes	Yes	-7.30	0.26	0.10	0.14	0.32	-1.08		
5	1.40	No	No	-26.38	1.20	0.48	1.69	2.41	-3.63		
6	1.27	Yes	No	-18.74	0.85	0.34	1.20	1.71	-2.58		
Mean	1.31			-23.33	0.75	-1.10	0.94	1.35	-1.80	1.66	0.42

Panel B: Stock Return Volatility

Specification	Gamma	Replacement	Country & Industry Dummies	Z-Score	Leverage	Quick Ratio	Size (log)	Multiple Share Classes	Stock Options	FX Exposure	FC Debt
1	1.23	No	Yes	-19.88	0.37	-2.96	0.73	0.81	0.56	1.23	0.31
2	1.32	Yes	Yes	-26.66	0.49	-3.98	0.98	1.08	0.75	1.65	0.41
3	1.18	No	Yes	-15.69	0.55	0.22	0.30	0.68	-2.32		
4	1.14	Yes	Yes	-12.42	0.44	0.17	0.24	0.54	-1.83		
5	1.30	No	No	-20.57	0.93	0.38	1.32	1.88	-2.83		
6	1.50	Yes	No	-31.79	1.44	0.58	2.04	2.91	-4.38		
Mean	1.28	Mean		-21.17	0.70	-0.93	0.93	1.32	-1.67	1.44	0.36

Table 7: Rosenbaum Bounds for Matching (continued)

Panel C: Market Betas

Specification	Gamma	Replacement	Country & Industry Dummies	Z-Score	Leverage	Quick Ratio	Size (log)	Multiple Share Classes	Stock Options	FX Exposure	FC Debt
1	1.03	No	Yes	-2.84	0.05	-0.42	0.11	0.12	0.08	0.18	0.04
2	1.39	Yes	Yes	-31.62	0.58	-4.72	1.17	1.28	0.89	1.96	0.49
3	1.01	No	Yes	-0.94	0.03	0.01	0.02	0.04	-0.14		
4	1.24	Yes	Yes	-20.39	0.72	0.28	0.39	0.88	-3.01		
5	1.38	No	No	-25.25	1.15	0.46	1.62	2.31	-3.48		
6	1.50	Yes	No	-31.79	1.44	0.58	2.04	2.91	-4.38		
Mean	1.26	Mean		-18.80	0.66	-0.63	0.89	1.26	-1.67	1.07	0.27

Panel D: Tobin's *q*

Specification	Gamma	Replacement	Country & Industry Dummies	Z-Score	Sales Growth	R&D/ Sales	Capex	Age (log)	Quick Ratio	Dividend	Multiple Share Classes	Sales (log)
1	1.07	No	Yes	-3.48	-18.79	-0.45	0.08	-3.62	31.68	-0.67	0.29	0.20
2	1.00	Yes	Yes	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
												FC Debt
3	1.11	No	Yes	-5.36	-31.08	-0.75	0.12	-3.16	0.29	-0.97	0.47	0.12
4	1.07	Yes	Yes	-3.47	-20.15	-0.48	0.08	-2.05	0.19	-0.63	0.31	0.08
5	1.06	No	No	-3.58	-271.52	6.06	0.07	0.47	0.18	-1.63	0.49	0.08
6	1.18	Yes	No	-10.16	-771.27	17.22	0.21	1.33	0.52	-4.63	1.40	0.23
Mean	1.08			-4.34	-185.47	3.60	0.09	-1.17	5.48	-1.42	0.49	0.12

Table 8: Matched Sample Tests of Corporate Risk Measures and Derivatives Use Across Time

The table shows the mean value of risk and value measures by year for derivative users and non-users based on propensity score matched samples. The *p*-values are from Wilcoxon rank sum tests between derivatives users and non-users. Results are shown for matching by year with replacement using the matching options "caliper (0.01) trim(1) common". The following variables are used as explanatory variables of derivatives usage. For stock return volatility and market betas: Z-Score, leverage, quick ratio, size (log), multiple share classes, stock options, gross FX exposure, FC debt, industry and country dummies; for Tobin's *q* and Alpha: Z-Score, sales growth, r&d/size, capex/size, age (log), quick ratio, sales (log), dividend (dummy), multiple share classes, stock options, gross FX exposure, FC debt, industry and country dummies. All variables are defined in Table A-1 in the appendix.

	1998	1999	2000	2001	2002	2003
Panel A: Standard Deviation						
User	0.434	0.428	0.487	0.462	0.443	0.372
Non-user	0.452	0.455	0.524	0.489	0.462	0.414
Difference	*-0.018*	*-0.027*	*-0.037*	*-0.027*	*-0.019*	*-0.042*
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Panel B: Market Beta						
User	0.678	0.504	0.576	0.684	0.700	0.741
Non-user	0.752	0.566	0.656	0.771	0.782	0.839
Difference	*-0.074*	*-0.062*	*-0.080*	*-0.087*	*-0.082*	*-0.098*
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Panel C: Tobin's *q*						
User	0.565	0.563	0.511	0.430	0.287	0.435
Non-user	0.556	0.583	0.624	0.361	0.262	0.464
Difference	*0.009*	*-0.020*	*-0.113*	*0.069*	*0.025*	*-0.029*
p-value	0.814	0.021	<0.001	<0.001	0.146	0.018
Panel D: Alpha (annualized)						
User	-0.150	0.001	-0.048	-0.011	-0.061	0.138
Non-user	-0.133	-0.020	-0.056	-0.041	-0.091	0.133
Difference	*-0.017*	*0.021*	*0.008*	*0.030*	*0.030*	*0.005*
p-value	0.137	0.026	0.575	0.004	0.003	0.952

Table 9: Characteristics of a Portfolios Long Hedgers and Short Nonhedgers

This table reports characteristics of stock portfolios with equal weighted positive investments in firms that use derivatives (hedgers) and short positions in matched firms that do not use derivatives (nonhedgers). Two portfolios are generated. The first portfolio includes only firms in countries where the local stock market index experiences a positive quarterly return (Domestic Stock Market Up) and the second portfolio includes only firms in countries where the local stock market index experiences a negative quarterly return (Domestic Stock Market Down). Values are reported for market beta, and alpha. Values are estimated for the 2000-2002 period which includes 687 down-market observations and 623 up-market observations (no domestic markets in our sample experienced positive returns in the second and third quarters of 2002). Matched samples are created with replacement using the matching options "caliper (0.01) trim(1) common." The following set of variables is used as explanatory variables of derivatives usage: Z-Score, leverage, quick ratio, size, multiple share classes, stock options, gross FX exposure, foreign debt, industry and country dummy variables. All variables are defined in Table A-1 in the appendix.

	Domestic Stock Market		
	Down	Up	Difference
Market Beta	-0.079	-0.005	-0.074
p-value	<0.001	0.815	<0.001
Alpha (annualized)	0.064	0.032	0.032
p-value	0.110	0.508	0.640

Table A-1: Variable Definitions

The table reports the variables of the study and their definition. Panel A refers to firm characteristics and Panel B to country-specific variables. A suffix of “(Ny)” to a variable indicates a N-year average.

Variable	Definition
Panel A: Firm characteristics	
Hedging Intensity	Count of the number of different types of derivatives a firm is using (between 0 and 12)
Derivatives	Dummy variables with value 1 if firm uses derivatives; 0 otherwise
Foreign Assets	International Assets / Total Assets
Foreign Income	International Operating Income / Operating Income (3y)
Foreign Sales	International Sales / Net Sales or Revenues (missing set to zero)
Gross-FX-Exposure	Dummy variable with value 1 if any foreign assets, foreign income or foreign sales are reported; 0 otherwise
Foreign Debt	Dummy variable with value 1 if any foreign debt is reported; 0 otherwise
Leverage	Total Debt / Size
Coverage	EBIT / Interest Expense on Debt (3y)
Quick Ratio	(Cash & Equivalents + Receivables (Net)) / Current Liabilities-Total
Z-Score	Altman Z-score (6.56*(WorkingCapital/TotalAssets) + 3.26*(RetainedEarnings/TotalAssets) + 6.72* (EBIT/TotalAssets) + 1.05*((BVEquity+PreferredStock)/TotalDebt))
Gross-IR-Exposure	Dummy variable with value 1 if the firm has leverage higher then the median leverage in its country; 0 otherwise
Gross-CP-Exposure	Dummy variable with value 1 if the firm is in one of the industries chemicals, mines, oil, steel, or utilities; 0 otherwise
Gross-Exposure	Dummy variable with value 1 if any of the dummy variables for foreign exchange rate exposure, interest rate exposure or commodity price exposure are 1; 0 otherwise
Industry Segments	Number of business segments (SIC codes) that make up the company's revenue (between 1 and 8)
Size (log)	Natural logarithm of the sum of market capitalization, total debt and preferred stock
Sales (log)	Natural logarithm of Total Sales
Dividend (Dummy)	Dummy variable with value 1 if dividend yield, dividend payout or dividend per share is positive; 0 otherwise
Gross Profit Margin	Gross Income / Net Sales or Revenues (3y)
Book-to-Market	Book Value Per Share / Market Price-Year End
ROA	Return on Assets (3y)
R&D / Sales	Research and Development Expense / Sales (missing set to zero)
Capex / Sales	Capital Expenditures / Net Sales or Revenues (missing set to zero)
Tangible Assets	(Total Assets - Intangibles) / Total Assets
Tobin’s q (log)	Size / (MarketCap/Market_to_Book + Total_Debt + Pref_Stock) (Natural logarithm)
Multiple Share Class	Dummy variable with value 1 if currently multiple share classes exist; 0 otherwise
Stock Options	Dummy variable with value 1 if stock options are reported in the annual report; 0 otherwise

(continued)

Table A-1: Variable Definitions (continued)

Variable	Definition
Stock Return	Daily stock return in local currency
Market Return	Daily local stock market return in local currency
Cashflow Volatility (σ_{CF})	5-year standard deviation of operating cashflow/sales
p-score	Propensity score used for matching, as predicted value from probit regression
σ_E	Standard deviation of local currency stock returns (annualized)
σ_E^*	Ratio of the daily local currency stock return standard deviation and the local currency market index standard deviation
β	Coefficient of the market index from a regression of local currency stock returns on returns of the local market index
β (p-value)	P-value of the coefficient of the market index from a regression of local currency stock returns on returns of the local market index
Alpha	Intercept from a regression of local currency stock returns on returns of the local market index
Alpha (*p*-value)	P-value of the intercept from a regression of local currency stock returns on returns of the local market index
Sales Growth	4-year growth rate of sales (4y)
Age (log)	Natural logarithm of the age of the firm in years
Panel B: Country characteristics	
ICR-Financial	International Country Risk index of financial risk (from PRS Group)
ICR-Economic	International Country Risk index of economic risk (from PRS Group)
DerMktRank	Inverse ranking of the size of the derivatives market relative to the market of the other countries in the sample. Size is calculated by summing daily turnover in the FX and IR markets in 2001 for non-financial firms and standardizing by nominal GDP. We use the rank because the unranked values are extremely positively skewed by countries with FX trading centers (e.g., the U.K.).