Corporate Risk Management under Information Asymmetry: Evidence on R&D and Hedging in the Pharmaceutical Industry

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Abstract

This paper examines the financial and operational hedging activities of 74 pharmaceutical and biotech firms from 2001 to 2003. Risk management is particularly important for the pharmaceutical and biotech industry since firms in this industry are subject to high level of information asymmetry stemming from R&D investments. We find evidence supporting the theory of Froot, Scharfstein and Stein (1993) that financial hedging helps mitigate the under-investment problem. The likelihood of using financial derivatives is increasing with R&D and advertising investments. The usage of financial derivatives is associated with greater firm value, and the value enhancement is larger for firms subject to greater information asymmetry and larger growth opportunities. The results are robust with respect to alternative performance measures and the endogeneity problem. In addition, we find that financial and operational hedging are complementary.

JEL Classification*:* *G32, D82*

Keywords: R&D investment, corporate risk management, financial hedging, operational hedging, information asymmetry.

1. Introduction

With perfect capital markets, risk management would be irrelevant to a firm since shareholders can hedge risk on their own at the same cost. In the real world, market imperfections such as taxes, transaction costs or information asymmetry provide a rationale for corporate risk management of the volatility in earnings, and hence hedging could be a value-enhancing strategy for a firm. Froot, Scharfstein and Stein (1993) theorize that hedging can help relieve the under-investment problem when a firm faces growth opportunities and costly external financing. Uncertainty in the valuation of the firm's asset due to information asymmetry causes under-investment if there is a constraint on external financing which is costlier than internal financing. On the other hand, Smith and Stulz (1985) focus on the manager's personal wealth and utility as a basis of hedging rather than value enhancement for the firm. DeMarzo and Duffie (1995) argue that hedging improves the informativeness of corporate earnings as a signal of management ability. However, managerial and shareholder interests regarding the information transmission may differ, leading to conflicts in optimal hedging policy and uncertain valuation effects.

Empirical studies on corporate hedging mirror these differences in focus and valuation ambiguity. For example, Geczy, Minton and Schrand (1997) document that in a sample of 372 Fortune 500 non-financial firms in 1990, the use of currency derivatives is positively related to growth opportunities and negatively to liquidity. Tufano (1996), in his study of 48 North American gold mining firms for 1991-1993, shows that corporate risk management may be driven by managerial risk aversion more than concern for shareholder value. More recently, researchers directly address the question of whether hedging increases firm value. Based on a sample of 720 U.S. multinational firms during 1990 through 1995, Allayannis and Weston

(2001) find that hedging increases firm value on average by approximately 5%. Carter, Rogers and Simkins (2006) document an even larger hedging premium of about 14% for 28 firms in the U.S. airline industry where under-investment is believed to be severe. In contrast, the hedging premium in the oil and gas industry is more modest or non-existent: Mackay and Moeller (2007) report about 2% for 34 oil refiners, and Jin and Jorion (2006) find that hedging does not affect the value of 119 U.S. oil and gas producers at all during 1998-2001.

In this paper, we examine the implications of information asymmetry for corporate risk management by focusing on financial and operational hedging activities of pharmaceutical and biotech firms. A salient feature of the pharmaceutical and biotech firms is that they are subject to high degree of information asymmetry stemming from R&D investments. High level of information asymmetry due to the essentiality of R&D activities separates the pharmaceutical and biotech firms from firms in gold mining, airline, or oil and gas industries examined in existing work where commodity risk is paramount. While the R&D is essential for product development and growth in the pharmaceutical and biotech industry, the uncertainty of the R&D process is such that the possibility of failure is also real and external financing is especially costly. Aboody and Lev (2000) show that R&D is a major source of information asymmetry between insiders and stockholders. Guo, Lev and Zhou (2004) similarly show that the bid-ask spread – a measure of information asymmetry – is significantly higher for biotech companies than other firms. This characteristic of high information asymmetry, high growth potential and costly external financing makes the pharmaceutical and biotech industry unique and particularly well-suited for an investigation of the information asymmetry hypothesis à la Froot, Scharfstein and Stein (1993).

We find that the use of financial derivatives increases with R&D and advertising intensity (measures of growth opportunities) and the extent of operational hedging. Firms using financial derivatives are valued significantly higher than those not engaged in financial hedging. We estimate that the hedging premium of our pharmaceutical firms is about 5 to 15%. This is in contrast to Jin and Jorion (2006) who found no hedging premium for oil and gas firms, but is comparable to the result for airline firms documented by Carter, Rogers and Simkins (2006). Unlike existing work, we addressed the problem of endogeneity directly by using an instrumental variables approach and a simultaneous system of equation method. The results are robust, and the enhanced value is not driven by reverse causality. We also use detailed measures of operational hedging and growth opportunities specific to the pharmaceutical industry. The results are consistent with Allayannis, Ihrig and Weston (2001) and show that operational hedging, used alone, has little significant effect on firm value but can add value when used in conjunction with financial hedging. More importantly, we provide evidence in favor of the information asymmetry hypothesis that firms with greater information asymmetry and larger growth opportunities experience greater value enhancement through financial hedging. Interpreting this in light of Froot, Scharfstein and Stein (1993) suggests that the value enhancement derives from the fact that hedging helps relieve the under-investment problem and allows the firm to take advantage of positive NPV projects at times when external financing is costly.

The rest of the paper is organized as follows. Section 2 reviews existing work and develops hypothesis. Section 3 describes data and variables used in our empirical tests. In section 4, we present basic empirical results, and section 5 reports additional results as robustness check. Section 6 concludes the paper.

2. Existing Work and Hypothesis Development

2.1 Financial Hedging

Prior research has explored several theories of hedging, in which optimal hedging policies are derived from introducing some friction in the classic Modigliani and Miller (1958) world. Smith and Stulz (1985) argue that financial hedging can reduce expected tax liability if taxes are a convex function of earnings. They further suggest, as well as Mayers and Smith (1982), that hedging can reduce the likelihood of financial distress and hence enhance the expected firm value. The increase in firm value arises from a reduction in deadweight cost of bankruptcy. Froot, Scharfstein and Stein (1993) present a model in which managers have private information, and the information asymmetry between the managers and outsider investors causes external financing more costly than internal funding. They argue that the stability of internal funds that can be achieved by corporate hedging might be helpful in mitigating the underinvestment problem, suggesting that hedging will be more valuable to firms with greater growth opportunities and with more costly external financing. Hedging would be value-enhancing to the extent that the firm has sufficient internal capital to take advantage of investment opportunities.

Another line of theory argues that hedging is a result of managers' incentive to maximize their personal utility function (Stulz, 1984; Smith and Stulz, 1985). Poorly diversified managers in their personal wealth would prefer to hedge. Thus the incentive for a firm to hedge should increase with managers' stock ownership. DeMarzo and Duffie (1995) suggest that hedging improves the informativeness of corporate earnings as a signal of management ability and project quality by eliminating extraneous noise. Nevertheless, this line of theories does not suggest any value enhancement by corporate hedging because of a conflict between managerial and shareholder objectives and their views concerning the information transmission.

Most empirical studies on corporate hedging have focused on the relationship between hedging policy and firm characteristics. For example, Dolde (1995) and Haushalter (2000) document a significantly positive relation between hedging and leverage, lending support to a view that hedging mitigates the likelihood of financial distress and thereby increases debt capacity. Graham and Rogers (2002) also find that debt capacity is important but tax is not a primary driver of the firm's hedging policy. Various empirical studies such as Nance, Smith and Smithson (1993), Geczy, Minton, and Schrand (1997), and Allayannis and Ofek (2001) documented a positive relation between the hedging policy and the firm's growth opportunities. Regarding the valuation impact, Allayannis and Weston (2001) find that the Tobin's Q of the U.S. multinational firms using foreign currency derivatives is 5.7% higher than that of the non-users during 1990-1995. Kim, Mathur and Nam (2006) also show a hedging premium of the similar magnitude for U.S. firms in 1998. Focusing on nonlinearity, MacKay and Moeller (2007) report that hedging concave revenues and leaving concave costs exposed each represent about 2% of firm value for 34 oil refiners for the period from 1985 to 2004. In contrast, Jin and Jorion (2006) study 119 U.S. oil and gas producers during 1998-2001 and find no evidence that financial hedging affects firm value.

2.2 Operational Hedging

An alternative way of managing risk for corporations is to hedge through business operations. Multinationals, which have operations in different countries, may benefit from offsetting changes in currency exchange rates as well as risk reduction due to diversified operations. In addition, multinationals can exploit their network to utilize various channels of international fund transfers, inter-company loans, and lead and lag of trade credits. Also, multinationals can access segmented capital markets to lower their overall costs of capital, shift profits to lower its taxes, and take advantage of international diversification of markets and production sites to reduce the riskiness of their earnings (Shapiro, 1999).

Nevertheless, the cost of setting up operational hedging program will be substantial and will have long-term implications. Chowdhry and Howe (1999) develop a model and predict that firms are more likely to use financial instruments to hedge short-term risk exposure and rely on operational hedging more heavily to hedge long-term risk exposure. Lim and Wang (2007) develop a model to examine the interaction between financial and operational hedging. They show that financial hedging and operational hedging are more often complementary than substitutive because financial hedging can be used to reduce the common component of profit variability while operational hedging can reduce firm-specific risk exposures. Allayannis, Ihrig and Weston (2001) find that operational hedging is not an effective substitute for financial risk management. Pantzalis, Simkins and Laux (2001) find that the ability to construct operational hedging leads to lower currency exposures for the pooled sample as well as for firms with positive exposure (net importers) and negative exposure (net exporters). Carter, Pantzalis and Simkins (2001) find that the combined use of operational and financial hedges is associated with decreased exchange rate exposure. These results all support the complementary hypothesis.

2.3 Hypotheses

Several authors examined the hedging behavior in the context of a single industry: Tufano (1996) for gold mining, Carter, Rogers and Simkins (2006) for airlines, and Jin and

Jorion (2006) for oil and gas. These industries are similar in that a major source of risk is commodity-based. The commodity risk exposure is relatively easy to identify and hedge by individual investors and also is less subject to information asymmetry. In contrast, information asymmetry is severe in the pharmaceutical and biotech industry due to the essentiality of the R&D investments, which are more difficult to value and the nature of risk is more complex. Also, the novelty and complexity of products under development, as well as the level of product development risk associated with pharmaceutical and biotech companies, suggests the importance of operational hedging such as strategic alliance as a means of mitigating such risk. Allayannis, Ihrig and Weston (2001) and Guay and Kothari (2003) suggest that the exclusion of operation hedging can bias the observed valuation coefficient of financial hedging. At the same time, the high level of information asymmetry makes the pharmaceutical and biotch industry well-suited to test the information asymmetry argument such as Froot, Scharfstein and Stein (1993).

The pharmaceutical and biotech industry is among the largest and fast growing sectors of the economy in terms of the number of companies, innovative products, and contribution to social welfare. The fast innovation pace and fierce competition in this sector creates severe information asymmetries between firms and investors. According to the Lehman Brothers Report in 2003, the estimated total R&D expenses in 2002 were $55 billion, of which at least $37 billion was in drug development. Aboody and Lev (2000) show that higher R&D investment creates more information asymmetry problem between insiders and stockholders. Guo, Lev and Zhou (2004) document that information asymmetry measured by the bid-ask spread is significantly larger for biotech firms than other firms.

Our study revisits the corporate hedging debate by extending the literature to the pharmaceutical and biotech industry where information asymmetry is important due to intangibles and R&D investments. In this paper, we focus on not only the product development risk but also the exchange risk exposure and interest rate risks of firms in pharmaceutical industry, and its management of such risk by financial and operational hedging. As suggested by Froot, Scharfstein and Stein (1993), hedging may help relieve the underinvestment problem, when firms have many growth opportunities and external financing is more expensive than internally generated funds. Information asymmetry in this industry leads to a high cost of external financing. Such an industry is particularly prone to the under-investment problem (Myers, 1977). Therefore hedging would be particularly beneficial for such an industry since reducing uncertainty in internal cash flows would enable firms to finance positive NPV project as external capital is costly.

Based on our discussion above, we develop the following testable hypotheses.

H1: The likelihood of using financial derivatives is positively related to R&D investment in pharmaceutical industry.

H2: The use of financial derivatives is associated with a higher valuation in pharmaceutical industry.

H3: Firms with more severe information asymmetry will experience a greater value enhancement through financial hedging.

H4: Operational hedging is complementary to financial hedging.

3. Sample and Data Description

3.1 Sample Selection

Our initial sample is obtained from COMPUSTAT North America Industrial files. We first select all firms with four digits SIC codes of 2833, 2834, 2835 and 2836. These firms broadly represent the pharmaceutical and biotech industry. We further restrict the sample to those with total assets of $50 million or more. This is partly due to the lack of consistent data on financial and operational hedging for small firms. Large firms are also more likely to engage in hedging activities; for very small firms, setting up a hedging program might be too costly.

Our sample period is 2001 through 2003. We start our sample period in 2001 because beginning in 2001, every firm had fully adopted FASB Statement 133, and had started reporting the fair market values of derivatives rather than notional values as per accounting guidelines laid out in FASB Statement 133 and subsequent related statements 137 and 138. This leads to a final sample of 74 pharmaceutical firms with 221 firm-year observations.[1]

The data on financial hedging activities are hand collected from the 10-K reports and notes of the annual statements from the EDGAR database. Firms report data on the fair value or market value of the derivatives carried and the change in the fair values of such derivatives. We record the total fair value of derivatives and the types of derivatives including futures, forwards, options, and swaps.

Other firm characteristics such as assets, sales, debt, advertising expenditures, R&D investments, dividend payment, net operating losses, and other accounting variables are obtained from the COMPUSTAT annual industrial database. Operational segment data are retrieved from the SEGMENT files of the COMPUSTAT and missing information is hand collected from the annual reports. Stock return data are obtained from the CRSP database. The number of subsidiaries, geographic segments, and strategic alliances is hand collected from the corporate annual reports.

[1] There was only one firm in our sample, Reddy's Laboratories, for which no data are available for the year of 2001.

3.2 Variables Construction

To identify firms that use financial derivatives, we follow the procedure of Allayannis and Weston (2001) and hand collect for each firm in a particular year, the information on forwards, futures, swaps, and options for both interest rate and foreign exchange categories. Financial hedging is measured as a continuous variable that is the absolute value of all the financial derivatives outstanding at the end of the fiscal year scaled by the sales.[2] However, about 51% of firms in our sample do not report the amount of financial derivatives at the end of fiscal year, though they do indicate whether they used derivatives or not. To include these observations in our analysis, we also construct an indicator variable for financial hedging, which takes value of one if a firm uses financial derivatives and zero otherwise.

Table 1 describes various financial derivatives used by a subset of our sample firms that disclose their derivatives positions. This sample of pharmaceutical firms adopts on average $24.34 million (market value) financial derivatives, in the form of forwards, futures, options, and swaps. Nominally, derivative usage in pharmaceutical firms appears lower than other firms. Allayannis and Weston (2001) report that the mean value of foreign currency derivatives is $185.36 million in notional value for a sample of 720 large U.S. nonfinancial firms during 1990 to 1995. Note that the average firm size in our sample is comparable to that in Allayannis and Weston (2001). Kim, Mathur, and Nam (2006) show that in a sample of 212 operationally hedged firms, mean derivatives usage is $1,254 million (notional value). Nevertheless, the

[2] We use the absolute value of all the financial derivatives so as to aggregate derivative positions in both directions.

difference might be driven by the fact that we examine information on the fair market value of financial derivatives while previous studies analyze notional values.[3]

[Insert Table 1 about here]

We construct various measures of operational hedging following Allayannis and Weston (2001) and Pantzalis, Simkins, and Laux (2001). They include the number of operating segments, the number of geographic segments, and the number of foreign subsidiaries. A unique measure of operational hedging for the pharmaceutical industry is the number of strategic alliances that we hand collected from annual reports. The use of strategic alliances is a common method in this industry to mitigate or diversify the risk in product development and research and development (R&D). For alliance activity, we take the natural logarithm of the number of strategic alliances in regressions. To aggregate the impacts of all these four measures of operational hedging, we also use a factor score variable based on all these four measures as a proxy for operational hedging. To compute factor scores, we first perform factor analysis with the four operational hedging variables, and then generate principle factors based on the factor loadings of each variable.

The primary measure of firm performance is Tobin's Q. Following Jin and Jorion (2006), we compute Tobin's Q as the ratio of the market value of common equity plus the book value of debt and preferred equity to the book value of assets. Alternative measures of firm performance include return on equity (ROE) and return on asset (ROA). ROE is operating income scaled by the market value of equity, and ROA is operating income scaled by total assets.

We employ R&D intensity as a proxy for growth opportunities. R&D intensity is the ratio of R&D expenses to total assets. Geczy, Minton and Schrand (1997) find that the use of currency

[3] In addition, we include all pharmaceutical and biotech firms in excess of $50 million, while they include only multinationals or firms with operational hedging.

derivatives is positively related to the amount of R&D investments. Nance, Smith, and Smithson (1993) has documented that firms with greater investments in R&D are more likely to hedge their foreign exchange exposure.

In the regressions explaining Tobin's Q, we follow existing work (Morck and Yeung, 1991; Lang and Stulz, 1994; and Allayannis and Weston, 2001) and include several control variables, e.g., firm size, profitability, leverage, liquidity, advertising intensity, growth opportunities, and firm risk. Firm size is measured by the natural logarithm of total assets. Profitability is measured by ROA. Leverage is measured as the book value of long-term debt and short term debt scaled by total assets. Liquidity is measured by an indicator variable (Ddividend) that takes a value of one if a firm paid dividends in prior year, and otherwise zero. Advertising intensity is the ratio of advertising expenses to the sales of a firm. We also include the ratio of capital expenditures to total assets as an alternative measure of firm's growth opportunities. Firm risk is proxied by the standard deviation of daily stock returns during previous calendar year. To control for time effect and refined industry effect, we include dummy variables for each calendar year and each 4-digit SIC code in the regression.

3.3 Descriptive Statistics

Table 2 reports descriptive statistics for our sample of pharmaceutical firms. We have about half of all pharmaceutical and biotech firms in the sample using financial derivatives during 2001 through 2003. On average, pharmaceutical and biotech firms use $24.34 millions of financial derivatives, with the maximum being as high as $456.91 millions.

[Insert Table 2 about here]

The average firm in the sample has $7.236 billion in assets and $4.785 billion in sales. We do have a large variation in firm size, given that the minimum and maximum of assets are $71 million and $116.775 billion respectively. Firm size in our sample is comparable to that reported in Allayannis and Weston (2001) and Kim, Mathur, and Nam (2006). The mean Tobin's Q of our sample firms is 2.95, with a maximum of 9.52 and a minimum of 0.42. Since the pharmaceutical and biotech industry is a high growth sector, our sample firms have a much higher Tobin's Q than that is reported in Allayannis and Weston (2001) for all industries.

4. Empirical Results

In this section, we first perform the univariate tests to compare the users and non-users of financial derivatives, and estimate a logit regression to obtain the determinants of the corporate decision to use financial derivatives. We then examine the valuation impacts of financial and operational hedging including their interactions in multiple regressions. Lastly, we examine the hypothesis concerning the impact of information asymmetry and growth opportunities on firm value using detailed data specific to pharmaceutical and biotech firms.

4.1 Univariate Tests for Derivative Users and Non-users

In Table 3, we present results from tests of differences between the means of firm characteristic variables for users and nonusers of financial derivatives. User firms have a significantly better performance (in terms of both Tobin's Q and ROA) than nonusers. Nevertheless, the two groups of firms are no different with respect to variables concerning growth opportunities, including the R&D intensity, the advertising intensity, and the capital expenditure intensity. However, firms using financial derivative have significantly larger number of operating segments, geographic segments, number of subsidiaries, number of foreign subsidiaries, and number of strategic alliances. It suggests a positive association between financial hedging and operational hedging. In addition, user firms appear to be significantly larger in size, with greater analyst coverage, and exhibit lower stock return volatility and ROA volatility than nonusers. These results are sensible since larger firms are more able to afford adopting a financial hedging program, and using derivatives enable firms to reduce the volatility of their stock returns and accounting returns.

[Insert Table 3 about here]

Our evidence from the univariate tests is consistent with our hypothesis *H2* that the use of financial derivatives enhances value. However we have also noticed that other factors such as firm size and the extent of operational hedging are related to financial hedging policy, as well as firm value. Therefore we use a multivariate setting to further test our hypotheses.

4.2 Determinants of the Use of Financial Derivatives

In this subsection, we explore the impact of information asymmetry and operational hedging on the use of financial derivatives. We estimate the following logit regression to examine the determinants of financial hedging:

$$\begin{aligned} Dfinhedge &= \alpha_0 + \alpha_1 * R\&DIntensity + \alpha_2 * AdIntensity + \alpha_3 * Ophedge \\ &+ \sum Control\ Variables + \varepsilon, \end{aligned} \tag{1}$$

where the dependent variable (*Dfinhedge*) is a binary variable that takes a value of one if a firm reports the use of financial derivatives during the year, and zero otherwise. Firm's growth opportunities are proxied by R&D intensity and advertisement intensity. We include several variables measuring operational hedging, such as (a) the number of foreign subsidiaries, (b) the number of geographic segments, (c) the number of strategic alliances, and (d) the number of operating segments. To aggregate the effect of all these variables, we also construct a factor score variable *Fophedge* based on these four proxies. In addition, we include other control variables such as firm size, foreign sales ratio, a dummy variable for dividend payment that takes a value of one if a firm paid dividend during the prior year, and zero otherwise. We also control for capital structure by including leverage in the regressions. To control for tax incentives of loss carry forwards, we include an indicator variable for net operating loss carry-forward, which takes a value of one if a firm reported net operating loss carry forward during the prior year, and zero otherwise. In addition, dummy variables for each calendar year and 4-digit SIC codes are included in the regressions to control for the time and refined industry effects.

The results of the logit regressions are reported in Table 4. As with the evidence documented in prior studies (e.g., Geczy, Minton, and Schrand (1997), Allayannis and Ofek (2001)), the estimated coefficient of R&D intensity and advertising intensity are positive and significant in all the regressions. This result suggests that in the pharmaceutical and biotech industry, firms with ample growth opportunities are more likely to use financial derivatives, so as to minimize their under-investment problem. This supports hypothesis *H1*.

[Insert Table 4 about here]

To examine the relationship between operational hedging and financial hedging, we include each one of the proxies for operational hedging individually in model (1) through (4), and all four proxies together in model (5). The coefficient estimates of the number of foreign subsidiaries and the number of geographic segments are positive and statistically significant. The coefficients of the number of strategic alliances and operating segments are positive but insignificant. If we place all four proxies of operational hedging in one regression in model (5), all of them are positively related to the likelihood of financial hedging, though the result is only statistically significant for geographic segments. In model (5), we also include foreign sales ratio, which is an alternative measure of operational hedging. The significant and positive coefficient on foreign sales reiterates the positive relationship between operational and financial hedging. In model (6), we include a factor score constructed based on all four operational hedging variables. The factor score of operational hedging is positively related to the usage of financial derivatives, and the result is highly significant. Overall, we find a significant positive relationship between operational and financial hedging, thus supporting the complementary nature of these hedging strategies, as stated in our hypothesis *H4*. These results suggest that pharmaceutical and biotech firms that are dispersed in geographic regions do not rely exclusively on their operational dispersion as a means to hedge foreign exchange rate risk. Instead, they tend to complement this dispersion with the use of financial derivatives. Allayannis, Ihrig and Weston (2001) find that operational hedging do not lower the firm's exchange risk, however, on average, firms that are employing operational hedging strategies are more likely to use financial hedging which does reduce exchange rate risk.

The coefficients of other control variables have expected signs. Firm size has a positive and highly significant coefficient across all the models. This result could be explained by the economies of scale involved in establishing a hedging program. The coefficient of dividend dummy variable is positive and significant across all the models. The coefficient estimates of net operating losses indicator variable is negative but insignificant. This is consistent with the findings of Graham and Rogers (2002) who did not find any tax motivations behind use of financial derivatives. The coefficient estimate of leverage is significant in none of the regressions.

Overall, our results suggest that the pattern on the use of financial derivatives in pharmaceutical and biotech industry is consistent with the motivations as suggested by the theory. In the next section, we will investigate whether users of financial derivatives are rewarded with a higher valuation in the capital market than are non-users.

4.3 Financial Hedging and Firm Value

In this subsection we examine the impact of both financial and operational hedging on Tobin's Q. The regression model is as follows:

$$Ln(Tobin's\ Q) = \beta_0 + \beta_1 * Dfinhedge + \beta_2 * Ophedge + \sum Control\ Variables + \varepsilon, \qquad (2)$$

where Tobin's Q is a measure of firm value, *Dfinhedge* is a dummy variable for financial hedging, and *Ophedge* is a proxy variable for operational hedging. In the regressions, we also control for other variables that could have an impact on Tobin's Q, including the return on assets (ROA), firm size, the R&D intensity, the advertising intensity, the capital intensity, foreign sales ratio, a dummy for dividend payment, leverage, and the volatility of stock return. The regression results are reported in Table 5.

[Insert Table 5 about here]

In model (1), the coefficient estimate on the financial hedging dummy is positive and marginally significant at the ten percent level. However, none of the four proxy variables for operational hedging is significant. When we include the factor score based on all these four operational hedging variables in model (2), its coefficient estimate is negative but insignificant.[4] In contrast, financial hedging is positively related to Tobin's Q, and the result remains significant at the ten percent level. These results indicate that while financial hedging is associated with higher market valuation, operational hedging may not increase firm value. In model (3) and (4), we examine the effect of financial hedging ratio (the amount of financial derivatives scaled by

[4] We have also included individual operational hedging variable in each regression in the absence of *Dfinhedge*. The results are similar: none of these operational hedging variables are significantly related to Tobin's Q.

sales) on firm value. The coefficient estimates on financial hedging ratio are positive but insignificant.[5]

The positive relationship between financial hedging and Tobin's Q supports our hypothesis that the use of financial derivatives increases firm value by reducing the volatility of internal cash flows and thereby mitigating the under-investment problem. However, it is possible that this result is driven by a reverse causality: firms with larger Tobin's Q may have more profitable investment opportunities and hence may have a greater incentive to hedge with financial derivatives. To address this endogeneity issue, we estimate a two-step instrumental variable regression.[6] First we estimate a logit model (6) in Table 4, and then estimate equation (2) using the predicted probability of financial hedging (*Pdfinhedge*) derived from the logit model as an explanatory variable. The results are presented in model (5) and (6). Consistent with our earlier findings, the predicted probability of financial hedging is significantly and positively related to firm value. An alternative method to address the reverse causality issue is estimating equation (2) using Tobin's Q of next year (lead Tobin's Q) as a dependent variable, and the result is reported in model (7). The choice of using financial derivatives is also significantly and positively associated with next year's Tobin's Q. Variables measuring operational hedging (individual and factor score) remains insignificant in both sets of estimation.

In summary, our finding supports the hypothesis *H2*. Firms using financial derivatives in pharmaceutical industry are associated with a higher market value than those that do not use financial derivatives. Our findings are consistent with the evidence presented in Allayannis and

[5] Since many firms did not disclose the exact amount or fair value of financial derivatives in their annual reports, we have only 108 observations in model (3) and (4).

[6] Justifying their choice of the oil and gas industry in a hedging study, Jin and Jorion (2006) argue that focusing on a single industry by itself may reduce the endogeneity problem. Rather than dwelling on that notion, we choose to use the instrumental variable approach, along with the lead regression, in this section. In the next section, we also estimate the simultaneous system using the three-stage least square (3SLS) method.

Weston (2001) and Allayannis, Ihrig and Weston (2001) that use all industrial firms. In contrast to Kim, Mathur and Nam (2006), we find no evidence that operational hedge increases firm value. As for the economic magnitude, the use of financial derivatives increases Tobin's Q by a range of 0.136-0.427, which is equivalent to an increase of 4.6%-14.5% in firm value (given that the mean Tobin's Q of our pharmaceutical firms is 2.95). The economic impact of financial hedging on firm value in our pharmaceutical industry firms appears to be larger than those documented in Allayannis and Weston (2001) and Kim, Mathur, and Nam (2006) that report a hedging premium of about 5% in Tobin's Q. This might be due to the fact that we are focusing on an industry in which the under-investment problem is more severe due to the greater extent of information asymmetry problem and higher level of growth opportunities than their samples.

The control variables in the regression have expected signs. The coefficient estimate of ROA is positive and significant across all the models. The coefficient of firm size is insignificant. As expected, the R&D intensity is significantly and positively related to Tobin's Q, consistent with existing work (e.g., Geczy, Minton, and Schrand (1997), Allayannis and Ofek (2001)). However, the advertising intensity and capital intensity are not significant. The coefficient estimates of foreign sales ratios are negative but mostly insignificant. As with Allayannis and Weston (2001), we find a significant negative association between the dividend dummy variable and firm value. Leverage is significantly negatively related to firm value in some models, but insignificant in others. Existing literature provides mixed evidence on the relationship between leverage and Tobin's Q. While Yermack (1996) finds a negative relationship between the leverage and Tobin's Q, Allayannis and Weston (2001) document that leverage is positively related to Tobin's Q.

4.4 Interaction between Financial Hedging and Operational Hedging

Our results above suggest that operational hedging is not an effective substitute for financial risk management. Instead operational hedging is often used in conjunction with financial derivatives. Chowdhry and Howe (1999) develop a model and predict that operational and financial hedging strategies are used for managing different types of risk exposures, that is, operational hedging for long-term exposure (economic exposure) and financial hedging for short-term exposure (transaction exposure). Therefore, we expect that there is a synergy between financial and operational hedging, and the use of both hedging strategies would create a higher firm value. To test the interactive effect of the two types of hedging strategies, we estimate the following regression model:

$$\begin{aligned} Tobin's\ Q &= \delta_0 + \delta_1 * Dfinhedge + \delta_2 * Ophedge + \delta_3 * (Dfinhedge * Ophedge) \\ &+ \sum Control\ Variables + \varepsilon, \end{aligned} \tag{3}$$

and the results are reported in Table 6. The interaction term ($Dfinhedge * Ophedge$) is included to capture the synergy effect of operational and financial hedging for firms that use both of these strategies. In model (1) and (2), we use a dummy variable to measure financial hedging. In model (3) and (4), we measure financial hedging as the predicted probability of using financial derivatives estimated from the logit model in regression (6) of Table 4.

[Insert Table 6 about here]

The coefficient estimates of operational hedging variables (*Nforgsubs* and *Fophedge*) are all negative and mostly significant, suggesting that operational hedging alone reduces firm value. However, the coefficients of the interaction term ($Dfinhedge * Ophedge$) are positive in all the regressions and also statistically significant in three out of four models. These results suggest that the combined use of both types of hedging is particularly important as a value enhancement strategy, and that there is some synergy between financial and operational hedging strategies. Thus an integration of both hedging strategies enables pharmaceutical firms to better manage their short-term and long-term risk exposures simultaneously, thereby mitigating the under-investment problem more effectively. These results support hypothesis *H4*.

4.5 Further Analysis of Information Asymmetry and Growth Opportunities

In the above section, we find that the use of financial derivatives enhances firm value in the pharmaceutical and biotech industry. If the value increase arises from the fact that financial hedging mitigates the under-investment problem as suggested by Froot, Scharfstein and Stein (1993), we would expect that the extent of value added will differ across firms with different levels of information asymmetries and growth opportunities. Our hypothesis *H3* suggests that firms with more severe information asymmetry are subject to greater under-investment problem (unable to exploit its growth opportunities), therefore would benefit more from financial hedging. To examine this hypothesis, we construct proxy variables for information asymmetry (such as the number of analyst following and analyst earnings forecast error) and for growth opportunities specific to the pharmaceutical industry (such as the number of products in pipeline and the number of patents). While all pharmaceutical and biotech firms invest heavily in R&D, they differ significantly in the number of products in pipeline and the number of patents. These unique measures from the pharmaceutical industry allow us to better gauge the growth opportunities of these firms.

In Table 7 for the regression explaining Tobin's Q, we include an interaction term of the financial hedging variable and the variables proxy for information asymmetry and growth opportunities. In model (1), while the coefficient estimate of *Dfinhedge* is positive and significant, the interaction term *Dfinhedge*Nanalyst* is negative and marginally significant. These results imply that the greater the analyst coverage (less information asymmetry), the less financial hedging increases firm value. In model (2), the coefficient estimate on *Dfinhedge*Forecast error* is significantly positive, and *Dfinhedge* itself is positive but insignificant. It suggests that firms with greater forecast error (more information asymmetry) experience greater increase in firm value from financial hedging. In model (3) and (4), we observe significant positive coefficient estimate on *Dfinhedge*Nproduct-pipeline* and *Dfinhedge*Npatent.* These results indicate that the larger the number of product in pipeline (or number of patents), the greater extent financial hedging enhances firm value. Models (5) through (8) are similar to models (1) through (4), except we use the predicted probability of financial hedging (*Pdfinhedge*), and we find similar results. In summary, our findings lend strong support to our hypothesis *H3*: firms with more severe information asymmetries and higher growth opportunities benefit more in valuation from financial hedging.

[Insert Table 7 about here]

5. Robustness Tests

To examine the robustness of our results, we conduct additional work using accounting measures of firm performance rather than Tobin's Q. To provide additional evidence in addressing the endogeneity problem, we estimate the simultaneous system of firm value and hedging using the three-stage least square (3SLS) method.

5.1 Alternative Measure of Firm Performance

While we find financial hedging increases Tobin's Q, a forward-looking market-based firm performance measure, it would be interesting to examine whether financial hedging affects short-term accounting performance as well. In Panel A of Table 8, we investigate the relationship between financial hedging and the contemporaneous or lead ROE and ROA. We find a strong and consistent positive relationship between the use of financial derivatives and these accounting performance measures. The coefficient estimates on *Dfinhedge* are positive and significant in all the regressions. It substantiates our finding that financial hedging enhances firm performance. Interestingly, the dummy for biotech firms is negative, indicating that accounting performance is lower for biotech firms than pharmaceutical firms.

[Insert Table 8 about here]

5.2 Simultaneous Equation Models

As we discuss above, the decision on the use of financial derivative is endogeneous. Firms with high Tobin's Q face ample growth opportunities and therefore are more likely to engage in financial hedging. To further account for the endogeneity of using financial derivatives and potential bidirectional impact between Tobin's Q and financial hedging, we introduce a simultaneous equation model of both Tobin's Q and *Dfinhedge*, and estimate it using the 3SLS technique as follows:

$$\begin{aligned} Dfinhedge &= \alpha_0 + \alpha_1 * Ln(Tobin's\ Q) + \alpha_2 * Ophedge + \alpha_3 * R\&DIntensity \\ &+ \alpha_4 * AdIntensity + \sum Control\ Variables + \varepsilon_1, \end{aligned} \tag{4}$$

$$\begin{aligned} Ln(Tobin's\ Q) &= \beta_0 + \beta_1 * Dfinhedge + \beta_2 * Dfinhedge * InfoAsym\ (Growth\ Opportunities) \\ &+ \beta_3 * Ophedge + \sum Control\ Variables + \varepsilon_2. \end{aligned} \tag{5}$$

To explore the direction of potential causality between financial hedging and Tobin's Q, in equation (4) we examine the influence of Tobin's Q on the choice of financial hedging, and in equation (5) we examine the influence of financial hedging choice on Tobin's Q. Results are reported in Panel B of Table 8.

Regression result in model (1) corresponds to equation (4) where the dependent variable is *Dfinhedge*. After controlling for operational hedging, firm size, R&D intensity, advertising intensity, and other firm characteristics, Tobin's Q is not significantly related to the likelihood of using financial derivatives, suggesting that the causality does not run from Tobin's Q to financial hedging. Model (2) corresponds to equation (5) where the dependent variable is Tobin's Q. In a simultaneous system equation model where we allow potential bidirectional impact between financial hedging and Tobin's Q, we still find that financial hedging leads to higher firm value. We estimate additional simultaneous equation models by including an interaction term between *Dfinhedge* and proxy variables for information asymmetry or for growth opportunities, and results are reported in models (3) through (6). To save space, we only report the results for equation (5) that explains Tobin's Q.[7] Consistent with our results in Table 7, the coefficient estimate on *Dfinhedge*Nanalyst* is significantly negative, and the coefficient of interaction terms, *Dfinhedge*Forecast error, Dfinhedge*Nproduct-pipeline* and *Dfinhedge*Npatent,* are all positive and significant. These results confirm our earlier results, suggesting that financial hedging enhances firm value, and firms with more severe information asymmetry and greater growth opportunities benefit more from financial hedging. And the causality between financial hedging and Tobin's Q appears unidirectional – from financial hedging to Tobin's Q not the reverse.

6. Conclusion

The pharmaceutical industry provides us with a unique sample to test the value implications of hedging predicted by Froot, Scharfstein and Stein (1993). Heavy investment in

[7] In any regressions explaining the choice of financial hedging corresponding to model (3) through (6), Tobin's Q is not significantly related to *Dfinhedge*. This reiterates the result of model (1).

R&D, unique product development risk, and fierce competition endow the pharmaceutical industry with high growth opportunities and severe information asymmetries. Therefore, the pharmaceutical industry is particularly prone to the under-investment problem.

In this study, we investigate the interrelationship between the use of financial derivatives, operational hedging, and the firm value in pharmaceutical and biotech industry. We find that R&D and advertising intensive firms are more likely to use financial derivatives. Firms using financial derivatives are valued significantly higher than those not engaging in financial hedging. We estimate a hedging premium of about 5 to 15%, which compares with no hedging premium for the oil and gas industry reported by Jin and Jorion (2006) and 2% for oil refiners by MacKay and Moeller (2007), and which appears to be larger than the hedging premium documented for 720 large multinationals by Allayannis and Weston (2001). This is consistent with our argument that pharmaceutical and biotech firms are more prone to information asymmetry and the under-investment problem, thereby incurring greater benefit from financial hedging.[8] In addition, operational hedging has little significant effect on firm value; however, operational hedging is complementary to financial hedging in that firm value is enhanced only when financial hedging is used in conjunction with operational hedging. Furthermore, we find that firms with more severe under-investment problem, i.e., those with greater information asymmetry and larger growth opportunities, experience the more value enhancement through financial hedging. Our results are consistent with Froot, Scharfstein and Stein (1993) and suggest that the source of value enhancement derives from the fact that hedging helps relieve the under-investment

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[8] Our estimation of 5-15% hedging premium for pharmaceutical firms is also consistent with Carter, Rogers and Simkins (2006) who report a hedging premium of about 14% for airline firms. Compared to the pharmaceutical industry, the airline industry may not have much information asymmetry but under-investment is believed to be severe as well.

problem and allows firms to take advantage of positive NPV projects at times when external financing is costly.

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Table 1
Descriptive Statistics of Financial Derivatives Used by Hedging Firms
This table presents summary statistics for the fair market value of financial derivative used by pharmaceutical and biotech firms. Financial derivatives include both interest rate and foreign exchange derivatives as reported by the firm as of the end of each fiscal year. They are broken down into three types of derivative contracts, including forward/futures, options, and swaps. The market value for each type of contracts is reported below. About 49% of our sample firms report the exact amount of financial derivatives.

Variables	Mean	Median	Max	Min	Std. dev.	NOBS	% Firms
Financial Derivatives ($ mill)	46.872	7.425	456.910	0.010	85.542	108	48.869
Forward/Future ($ mill)	21.568	2.600	265.000	0.000	48.109	108	48.869
Option ($ mill)	21.817	3.725	311.550	0.000	49.738	108	48.869
Swaps ($ mill)	21.568	0.950	223.000	0.000	42.638	108	48.869

NOBS = number of observations

Table 2
Descriptive Statistics of Our Sample

This table provides summary statistics of our sample used in the analysis. The sample includes 74 firms in pharmaceutical and biotech industries (SIC codes of 2833, 2834, 2835, and 2836) for the period of 2001 through 2003. Financial derivative is the sum of fair market value of all the financial derivatives reported by a firm, including interest rate derivatives and exchange rate derivatives. Tobin's Q is the ratio of market value of assets to book value of assets. Foreign sales is the ratio of foreign sales to net sales. Nopseg is the number of operating segments. Ngeoseg is the number of geographical segments. Nsubsidiaries is the number of all the subsidiaries of a firm. Nforgsub is the number of foreign subsidiaries of a firm. Nalliance is the number of strategic alliances. Nproduct-pipeline is the number of products under development. Npatent is the number of patents. Nanalyst is the number of analysts following a firm in a given year. Forecast-error is the absolute value of the difference between the actual earnings and the median of analyst earnings forecasts scaled by stock price. R&D intensity is the ratio of total R&D expense to total assets. Capital intensity is the ratio of capital expenditures to total assets. Advertising intensity is the ratio of advertising expenditures to sales. Ddividend is a dummy variable that equals one for firms paying dividends, and zero otherwise. Leverage is the ratio of book value of long term and short term debts to total assets. ROA is net income scaled by total assets. RET Volatility is the standard deviation of daily stock returns during previous calendar year. ROA volatility is the standard deviation of quarterly returns on assets during the previous twenty quarters.

Variable	Mean	Median	Max	Min	Std. dev.	NOBS
Financial Derivatives ($ mill)	24.338	0.065	456.910	0.000	65.829	208
Assets ($ mill)	7236.883	1389.656	116775.000	71.072	14177.650	215
Sales ($ mill)	4785.528	648.597	51790.300	0.419	9770.279	215
Tobin's Q	2.948	2.594	9.515	0.421	1.790	215
Foreign sales	0.395	0.372	1.000	0.000	0.288	212
Nopseg	1.977	1.000	8.000	1.000	1.314	217
Ngeoseg	3.505	3.000	10.000	1.000	1.639	204
Nsubsidiaries	47.015	16.000	533.000	1.000	79.784	202
Nforgsub	31.817	10.000	438.000	0.000	58.969	202
Nalliance	9.688	3.000	300.000	0.000	37.123	221
Nproduct-pipeline	10.326	4.000	201.000	0.000	21.000	221
Npatent	33.756	0.000	683.000	0.000	89.595	205
Nanalyst	10.645	7.000	32.000	1.000	8.550	170
Forecast-error	0.094	0.062	0.899	0.000	0.118	169
R&D intensity	0.102	0.087	0.605	0.000	0.085	215
Capital intensity	0.282	0.068	17.245	0.000	1.452	211
Advertising intensity	0.017	0.000	0.457	0.000	0.049	213
Ddividend	0.362	0.000	1.000	0.000	0.482	218
Leverage	0.162	0.047	3.277	0.000	0.374	212
ROA	0.020	0.063	0.337	-0.766	0.161	215
RET Volatility	0.033	0.031	0.091	0.013	0.014	200
ROA Volatility	0.057	0.038	0.267	0.004	0.049	180

Table 3
Difference-of-Means Tests of Users and Non-users of Financial Derivatives
This table reports the mean values of various characteristic variables for firms that use financial derivatives and those that do not use any financial derivatives. Firm size is the natural logarithm of sales. All other variables are as defined in Table 1. T-tests are used to examine the null hypothesis that the mean of each variable is the same between the two groups. T-statistics are reported in the last column, and *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Variable	Financial Derivative Users	Financial Derivative Non-users	Difference	T-stat
Tobin's Q	0.975	0.814	0.161	2.020**
R&D intensity	0.107	0.094	0.013	1.050
Advertising intensity	0.018	0.012	0.006	0.870
Capital intensity	0.044	0.046	-0.002	-0.320
Ngeoseg	4.140	2.785	1.355	6.50***
Nopseg	2.291	1.620	0.671	3.830***
Nsubsidiaries	66.800	12.394	54.406	7.010***
Nforgsub	43.257	8.096	35.161	6.970***
Nalliance	15.035	4.150	10.885	2.270**
Nproduct-pipeline	0.023	0.359	-0.336	-2.260**
Npatent	0.162	3.041	-2.879	-1.780*
Nanalyst	13.385	7.068	6.317	5.290***
Forecast-error	0.007	0.008	0.001	0.530
ROA	0.042	-0.015	0.057	2.57***
Firm size	7.532	4.863	2.669	10.300***
Foreign sales	0.478	0.326	0.152	3.720***
Leverage	0.130	0.209	-0.079	-1.420
RET Volatility	0.029	0.040	-0.011	-5.290***
ROA Volatility	0.043	0.076	-0.033	-4.390***

Table 4
Logistic Regressions Explaining the Use of Financial Derivatives
This table presents the results of logistic models in which the dependent variable is a binary variable equal to one for firms using financial derivatives (users) and zero for those not using financial derivatives (non-users). DNOL is a dummy variable for tax incentives of net operating loss and is equals to one if a firm incurs a net operating loss and zero otherwise. Fophedge is a factor score variable based on all four proxies of operational hedging, including Nforsubs, Ngeoseg, Nalliance, and Nopseg. To compute factor scores, we first perform factor analysis with the four operational hedging variables, and then principle factors were generated based on the factor loadings of each variable. All other explanatory variables are as defined in Table 1. All the regressions include intercept, dummy variables for each calendar year and each 4-digit SIC code to control for time effect and refined industry effect. P-values in parentheses below are computed based on Huber-White-sandwich estimator of variance, and are reported in parentheses below each coefficient estimate. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Variable	1	2	3	4	5	6
R&D intensity	10.577***	12.726***	7.607***	9.331***	12.759***	12.909***
	(0.000)	(0.000)	(0.003)	(0.001)	(0.000)	(0.000)
Advertising intensity	9.667***	12.559***	8.595**	7.622*	17.099***	14.586***
	(0.007)	(0.001)	(0.028)	(0.055)	(0.000)	(0.001)
Nforgsub	0.492**				0.117	
	(0.029)				(0.748)	
Ngeoseg		0.839***			0.666***	
		(0.000)			(0.010)	
Nalliance			0.292		0.363	
			(0.227)		(0.331)	
Nopseg				0.040	0.117	
				(0.810)	(0.524)	
Fophedge						1.173**
						(0.004)
Foreign sales					2.581**	2.995***
					(0.046)	(0.003)
Firm size	0.832***	0.945***	0.885***	0.926***	0.979***	0.928***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ddividend	1.425***	1.192**	1.976***	1.728***	1.414**	1.340**
	(0.010)	(0.038)	(0.000)	(0.000)	(0.038)	(0.010)
DNOL	-0.108	-0.614	0.014	0.032	-0.512	-0.408
	(0.806)	(0.213)	(0.973)	(0.938)	(0.338)	(0.389)
Leverage	-0.083	-0.282	0.556	0.688	-0.427	-0.351
	(0.852)	(0.655)	(0.611)	(0.532)	(0.471)	(0.504)
Intercept, SIC & Yr. Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	187	187	204	200	177	177
Pseudo R^2	0.455	0.466	0.4406	0.4266	0.518	0.499

Table 5
Financial Hedging and Firm Value
This table reports the results of the pooled cross-sectional time-series OLS regressions of the impact of financial hedging on firm value. Lead Tobin's Q is the Tobin's Q of a firm in year t+1. Dfinhedge is a dummy variable that takes a value of 1 if a firm uses financial derivatives, and otherwise zero. Pdfinhedge is the predicted financial hedging probability using Model 6 of Table 4. Finhedge Ratio is the fair market value of all the financial derivatives used by the firm scaled by sales. All other explanatory variables are as defined in Table 1 and Table 4. All the regressions include intercept, dummy variables for each calendar year and each 4-digit SIC code to control for time effect and refined industry effect. White's corrected t-statistics are reported in parentheses below each coefficient estimate, and *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Ln(Tobin's Q)						Lead Ln(Tobin's Q)
Variable	1	2	3	4	5	6	7
Dfinhedge	0.136*	0.147*					0.204**
	(1.710)	(1.900)					(2.400)
Finhedge Ratio			4.610	4.436			
			(1.510)	(1.500)			
Pdfinhedge					0.329*	0.427**	
					(1.840)	(2.280)	
Nforgsubs	-0.029		-0.052		-0.035		
	(-1.010)		(-1.580)		(-1.210)		
Ngeoseg	0.015		0.018		0.001		
	(0.730)		(0.780)		(0.070)		
Nalliance	0.013		0.024		0.015	0.002	
	(0.440)		(0.750)		(0.490)	(0.080)	
Nopseg	-0.017		-0.029		-0.042	-0.025	
	(-0.720)		(-1.160)		(-1.640)	(-1.110)	
Fophedge		-0.004		-0.009		-0.019	0.029
		(-0.150)		(-0.290)		(-0.590)	(0.960)
ROA	1.677***	1.730***	1.967***	2.049***	2.171***	2.214***	1.285***
	(3.920)	(4.110)	(4.730)	(5.000)	(5.480)	(5.540)	(3.300)
Firm size	0.021	0.015	0.027	0.016	-0.018	-0.019	-0.001
	(0.740)	(0.550)	(1.000)	(0.620)	(-0.650)	(-0.690)	(-0.040)
R&D intensity	2.658***	2.776***	3.361***	3.579***	3.097***	3.390***	1.770***
	(4.880)	(5.610)	(6.300)	(7.160)	(5.090)	(5.970)	(3.280)
Advertising intensity	0.943	0.949	-0.292	-0.246	-0.322	-0.160	1.572***
	(1.360)	(1.480)	(-0.280)	(-0.250)	(-0.300)	(-0.160)	(3.060)
Capital intensity	1.092	1.060	1.208	1.161	1.359	1.313	1.204
	(1.140)	(1.120)	(1.250)	(1.210)	(1.380)	(1.340)	(1.560)
Foreign sales	-0.190	-0.195	-0.150	-0.158	-0.226*	-0.209	-0.205*
	(-1.460)	(-1.510)	(-1.240)	(-1.310)	(-1.720)	(-1.580)	(-1.750)
Ddividend	-0.139*	-0.173**	-0.172*	-0.222**	-0.194**	-0.218**	-0.084
	(-1.720)	(-2.200)	(-1.850)	(-2.370)	(-2.040)	(-2.310)	(-0.980)
Leverage	-0.506***	-0.523***	0.215	0.181	0.140	0.129	-0.392**
	(-2.830)	(-3.010)	(0.980)	(0.810)	(0.650)	(0.580)	(-2.290)
RET Volatility	0.317	1.486	-5.030	-3.298	-3.025	-1.941	5.418
	(0.080)	(0.390)	(-1.200)	(-0.800)	(-0.750)	(-0.470)	(1.180)
Intercept, SIC & Yr. Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	167	167	108	108	170	170	167
Adj. R^2	0.498	0.503	0.478	0.476	0.480	0.479	0.314

Table 6
Interaction between Financial Hedging and Operational Hedging
This table reports the results of the pooled cross-sectional time-series OLS regressions of the joint impact of financial hedging and operational hedging on firm value. Dfinhedge is a dummy variable that takes a value of one if a firm uses financial derivatives, and zero otherwise. Pdfinhedge is the predicted probability of financial hedging using Model 6 of Table 4. All other explanatory variables are as defined in Table 1 and Table 4. All the regressions include intercept, dummy variables for each calendar year and each 4-digit SIC code to control for time effect and refined industry effect. White's corrected t-statistic are reported in parentheses below each coefficient estimate, and *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Ln (Tobin's Q)				
Variable	1	2		3	4
Dfinhedge	-0.063	0.200**	Pdfinhedge	-0.054	0.563***
	(-0.420)	(2.020)		(-0.220)	(2.830)
Nforgsubs*Dfinhedge	0.099**		Nforgsubs*Pdfinhedge	0.195***	
	(2.070)			(3.620)	
Nforgsubs	-0.105**		Nforgsubs	-0.169***	
	(-2.400)			(-3.620)	
Fophedge*Dfinhedge		0.126	Fophedge*Pdfinhedge		0.297**
		(1.010)			(1.950)
Fophedge		-0.117	Fophedge		-0.287*
		(-0.950)			(-1.940)
ROA	2.100***	1.719***	ROA	2.102***	2.238***
	(5.100)	(4.100)		(5.210)	(5.710)
Firm size	0.012	0.015	Firm size	-0.008	-0.029
	(0.440)	(0.550)		(-0.270)	(-1.040)
R&D intensity	3.422***	2.718***	R&D intensity	3.117***	3.128***
	(7.040)	(5.520)		(5.980)	(5.520)
Capital intensity	1.410	0.851	Capital intensity	1.369	1.096
	(1.560)	(0.920)		(1.490)	(1.160)
Foreign sales	-0.053	-0.185	Foreign sales	-0.155	-0.223*
	(-0.420)	(-1.410)		(-1.140)	(-1.650)
Ddividend	-0.190**	-0.174**	Ddividend	0.278	0.118
	(-2.200)	(-2.140)		(1.250)	(0.550)
Leverage	0.309	-0.521***	Leverage	-0.259***	-0.250***
	(1.410)	(2.950)		(-2.750)	(-2.630)
Advertising intensity	-0.116	0.951	Advertising intensity	-0.240	-0.286
	(-0.110)	(1.420)		(-0.230)	(-0.280)
RET volatility	-4.817	1.008	RET volatility	-4.371	-2.261
	(-1.170)	(0.260)		(-1.010)	(-0.550)
Intercept, SIC & Yr. Dummies	Yes	Yes	Intercept, SIC & Yr. Dummies	Yes	Yes
No. of Obs.	173	170	No. of Obs.	170	170
Adj. R^2	0.488	0.505	Adj. R^2	0.506	0.489

Table 7: Information Asymmetry, Growth Opportunities, and the Effect of Financial Hedging on Firm Value

This table reports the results of the pooled cross-sectional time-series OLS regressions of the impact of financial hedging on firm value conditional on the degree of information asymmetry and firms' growth opportunities. Dfinhedge is a dummy variable that takes a value of one if a firm uses financial derivatives, and zero otherwise. Nanalyst is the number of analysts following a firm in a given year. Forecast-error is the absolute value of the difference between the actual earnings and the median of analyst earnings forecasts scaled by stock price. Nalliance is the number of strategic alliances scaled by sales. Nproduct-pipeline is the number of products under development scaled by sales. Npatent is the number of patents scaled by sales. All other explanatory variables are as defined in Table 1 and Table 4. All the regressions include intercept, dummy variables for each calendar year and each 4-digit SIC code to control for time effect and refined industry effect. White's corrected t-statistic are reported in parentheses below each coefficient estimate, and *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Ln (Tobin's Q)								
	1	2	3	4		5	6	7	8
Dfinhedge	0.284***	0.101	0.062	0.097	Pdfinhedge	0.344	0.158	0.312	0.328
	(2.620)	(1.090)	(0.710)	(1.160)		(1.540)	(0.720)	(1.440)	(1.430)
Dfinhedge*Nanalyst	-0.019*				Pdfinhedge*Nanalysts	-0.021			
	(-1.880)					(-1.600)			
Nanalyst	0.029***				Nanalysts	0.030***			
	(2.770)					(2.580)			
Dfinhedge*Forecast error		8.751***			Pdfinhedge*Forecast-error		10.597***		
		(3.270)					(3.120)		
Forecast-error		-4.852***			Forecast-error		-5.619***		
		(-2.700)					(-2.450)		
Dfinhedge*Nproduct-pipeline			0.989**		Pdfinhedge*Nproduct-pipeline			1.933***	
			(2.530)					(2.810)	
Nproduct-pipeline			0.038**		Nproduct-pipeline			0.026	
			(2.140)					(1.180)	
Dfinhedge*Npatent				0.108***	Pdfinhedge*Npatents				0.114
				(2.650)					(1.310)
Npatent				0.004**	Npatents				0.002
				(2.200)					(0.650)
Nopseg	0.008	-0.020	-0.035	-0.056**	Nopseg	0.014	-0.016	-0.039	-0.059**
	(0.340)	(-0.820)	(-1.640)	(-2.330)		(0.540)	(-0.580)	(-1.630)	(-2.100)
ROA	2.301***	2.586***	2.145***	2.114***	ROA	2.328***	2.515***	2.334***	2.156***
	(5.440)	(4.750)	(5.240)	(4.930)		(5.520)	(4.700)	(5.440)	(5.070)
Firm Size	-0.042	-0.015	0.039	0.037	Firm Size	-0.055**	-0.027	0.008	-0.003
	(-1.480)	(-0.590)	(1.270)	(1.180)		(-1.990)	(-0.980)	(0.230)	(-0.070)
R&D Intensity	3.691***	4.132***	3.511***	3.439***	R&D Intensity	3.680***	4.071***	3.144***	3.184***
	(6.790)	(6.460)	(6.890)	(6.550)		(6.080)	(5.530)	(5.460)	(5.020)
Capital Intensity	1.812	1.643	1.504	1.538	Capital Intensity	1.569	1.293	1.324	1.306

	(1.430)	(1.400)	(1.530)	(1.550)		(1.200)	(1.070)	(1.360)	(1.300)
Foreign Sales	-0.043	-0.135	-0.126	-0.130	Foreign Sales	-0.019	-0.138	-0.186	-0.193
	(-0.330)	(-1.040)	(-1.060)	(-1.090)		(-0.120)	(-0.920)	(-1.280)	(-1.300)
Ddividend	-0.092	-0.185**	-0.203***	-0.198**\	Ddividend	-0.064	-0.168*	-0.234**	-0.202**
	(-1.140)	(-2.380)	(-2.600)	(-2.450)		(-0.630)	(-1.670)	(-2.490)	(-2.110)
Leverage	0.190	0.217	0.267	0.233	Leverage	0.077	0.106	0.187	0.111
	(0.960)	(1.010)	(1.320)	(1.150)		(0.350)	(0.430)	(0.820)	(0.480)
Advertising Intensity	0.097	-0.048	-0.949	-0.843	Advertising Intensity	0.289	0.062	-1.146	-0.534
	(0.110)	(-0.050)	(-1.270)	(-0.990)		(0.290)	(0.060)	(-1.440)	(-0.510)
RET Volatility	-1.098	-5.070	-3.221	-3.648	RET Volatility	0.238	-4.307	-0.979	-2.659
	(-0.260)	(-1.180)	(-0.810)	(-0.880)		(0.050)	(-0.930)	(-0.230)	(-0.620)
Intercept, SIC & Yr. Dummies	Yes	Yes	Yes	Yes	Intercept, SIC & Yr. Dummies	Yes	Yes	Yes	Yes
No. of Obs.	161	160	182	169	No. of Obs.	150	149	170	157
Adj. R^2	0.528	0.511	0.500	0.507	Adj. R^2	0.517	0.500	0.498	0.490

Table 8: Robustness Tests

This table reports the results of additional robustness tests. In Panel A, we employ ROE, lead ROE, ROA, and lead ROA as alternative measures of firm performance. ROE is operating income scaled by the market value of equity. Lead ROE is the ROE of a firm in year t+1. ROA is operating income scaled by total assets. Lead ROA is the ROA of a firm in year t+1. Dfinhedge is a dummy variable that takes a value of one if a firm uses financial derivatives, and zero otherwise. Dbiotech is a dummy variable equal to one for biotech firms and zero otherwise. All other explanatory variables are as defined in Table 1 and Table 4. All the regressions include intercept, dummy variables for each calendar year and each 4-digit SIC code to control for time effect and refined industry effect. White's corrected t-statistic are reported in parentheses below each coefficient estimate, and *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively. In Panel B, we report the results of simultaneous equation models (3SLS procedure), where both Ln(Tobin's Q) and Dfinhedge are treated as endogeneous variables. Nanalyst is the number of analysts following a firm in a given year. Forecast-error is the absolute value of the difference between the actual earnings and the median of analyst earnings forecasts scaled by stock price. Nproduct-pipeline is the number of products under development scaled by sales. Npatent is the number of patents scaled by sales. All other explanatory variables are as defined in Table 1 and Table 4. All the regressions include intercept, dummy variables for each calendar year and each 4-digit SIC code to control for time effect and refined industry effect. Model (1) corresponds to equation explaining the choice of hedging (Dfinhedge), and model (2) corresponds to equation explaining firm performance. To save space, we only report the results of the equation explaining firm performance in model (3) through (6). White's corrected t-statistic are reported in parentheses below each coefficient estimate, and *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A. Alternative Measure of Firm Performance

Variable	**ROE**	**Lead ROE**	**ROA**	**Lead ROA**
Dfinhedge	0.023*	0.026**	0.044**	0.051***
	(1.880)	(2.390)	(2.530)	(2.670)
Ln(Assets)	-0.008**	-0.006**	0.006	-0.004
	(-2.180)	(-2.050)	(0.950)	(-0.670)
Nopseg	0.003	0.006**	0.001	0.002
	(1.010)	(2.210)	(0.998)	(0.410)
R&D Intensity	-0.400***	-0.358***	-0.516***	-0.379**
	(-3.010)	(-3.190)	(-2.800)	(-2.390)
Capital Investment	0.266**	0.197	0.484**	0.552***
	(2.040)	(1.460)	(2.340)	(2.610)
Leverage	0.045	0.043	-0.122***	-0.062
	(1.190)	(1.230)	(-2.700)	(-1.200)
RET Volatility	-3.810***	-3.008***	-5.122***	-5.973***
	(-4.970)	(-4.730)	-(5.080)	(-5.520)
Dbiotech	-0.033**	-0.025**	-0.035*	-0.028
	(-2.220)	(-1.990)	(-1.890)	(-1.440)
Intercept & Yr. Dummies	Yes	Yes	Yes	Yes
No. of Obs.	182	182	182	182
Adj. R^2	0.441	0.444	0.589	0.526

Panel B. Simultaneous Equation Models (3SLS procedure)

	Dependent Variable					
	1	2	3	4	5	6
Variable	Dfinhedge	Ln(Tobin's Q)	Ln(Tobin's Q)	Ln(Tobin's Q)	Ln(Tobin's Q)	Ln(Tobin's Q)
Dfinhedge		0.147*	0.284**	0.101	0.062	0.097
		(1.720)	(2.370)	(1.060)	(0.700)	(1.100)
Ln(Tobin's Q)	0.052					
	(0.720)					
Dfinhedge*Nanalyst			-0.019**			
			(-2.100)			
Nanalyst			0.029***			
			(3.340)			
Dfinhedge*Forecast-error				8.751**		
				(2.360)		
Forecast-error				-4.852		
				(-1.490)		
Dfinhedge*Nproduct-pipeline					0.989**	
					(2.110)	
Nproduct-pipeline					0.038	
					(1.140)	
Dfinhedge*Npatent						0.108**
						(2.110)
Npatent						0.004
						(1.260)
Fophedge	0.047	-0.004				
	(1.210)	(-0.110)				
DNOL	0.045					
	(0.700)					
Nopseg			0.008	-0.020	-0.035	-0.056**
			(0.270)	(-0.690)	(-1.410)	(-2.100)
ROA		1.730***	2.301***	2.586***	2.145***	2.114***
		(5.560)	(7.090)	(6.760)	(7.260)	(6.830)
Firm Size	0.096***	0.015	-0.042	-0.015	0.039	0.037
	(4.790)	(0.580)	(-1.430)	(-0.540)	(1.380)	(1.330)
R&D Intensity	0.953***	2.776***	3.691***	4.132***	3.511***	3.439***
	(2.610)	(5.810)	(7.840)	(8.110)	(7.960)	(7.510)
Capital Intensity		1.060	1.812**	1.643*	1.504*	1.538*
		(1.280)	(2.060)	(1.820)	(1.840)	(1.850)
Foreign Sales	0.384***	-0.195*	-0.043	-0.135	-0.126	-0.130
	(3.420)	(-1.650)	(-0.350)	(-1.050)	(-1.110)	(-1.110)
Ddividend	0.248***	-0.173*	-0.092	-0.185**	-0.203**	-0.198**
	(2.880)	(-1.870)	(-0.940)	(-1.950)	(-2.260)	(-2.130)
Leverage	0.153	-0.523***	0.190	0.217	0.267	0.233
	(1.080)	(-3.350)	(1.050)	(1.170)	(1.520)	(1.310)
Advertising Intensity	1.157*	0.949	0.097	-0.048	-0.949	-0.843
	(1.900)	(1.480)	(0.150)	-(0.070)	(-1.270)	(-1.040)
RET Volatility		1.486	-1.098	-5.070	-3.221	-3.648
		(0.400)	(-0.280)	(-1.240)	(-0.920)	(-1.000)
Intercept, SIC & Yr. Dummies	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	167	167	161	160	182	169
Adj. R^2	0.490	0.551	0.581	0.560	0.549	0.562