

## **The Maturity Structure of Corporate Risk Management**

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We examine the maturity structure of corporate hedging activity and its determinants. We estimate hedge maturity as the empirical sensitivity of quarterly firm sales and costs to lagged energy futures prices for a sample of 34 oil refiners. The average firm hedges about a quarter of its exposure, with a significantly shorter hedge maturity for sales (about 7 months) than costs (about 11 months). Maturity first rises then falls with financial distress, consistent with recent theory. Hedge maturity shortens as the maturity of debt shortens and as liquid assets, capital expenditures, risk, and profitability increase. Maturity lengthens with diversification and firm size. Firm value (Tobin's  $q$ ) falls with hedge maturity.

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A large literature studies the motives for risk management and the extent of hedging activity.<sup>1</sup> Most of this literature deals with the *intensity* of hedging; very little has been said on how far ahead firms should hedge and what contracts to use among the several available delivery dates.<sup>2</sup> Yet, managers must make specific decisions when it comes to implementing hedging strategies.<sup>3</sup> Compounding the lack of theoretical guidance, we know nearly nothing about the determinants and value implications of the maturity structure of corporate hedging in practice. Data limitations are largely to blame since even a careful reading of financial-statement footnotes rarely yields more than a coarse measure of hedging activity, let alone details such as contract maturities. This study proposes a way to back out the maturity structure of corporate hedging from limited data, which allows us to investigate this important dimension of corporate risk management.

The paper builds on MacKay and Moeller (2007), where we derive the value of corporate risk management and calibrate the model on a sample of 34 oil refiners (SIC 2911) by regressing quarterly sales and costs on NYMEX energy prices from March 1985 to June 2004. That approach has two useful properties, which we extend here to extract corporate hedge maturity. First, we use standard COMPUSTAT data rather than financial-statement footnotes, proprietary data, or survey results. Second, because reported firm data reflect corporate hedging activity, we let the estimation assign weights to both lagged three-month futures prices (relevant for hedgers) and spot prices (relevant for non-hedgers). The weight assigned to lagged futures prices therefore provides a measure of the level of hedging activity. In this paper, we allow sales and costs to depend on lagged futures prices ranging up to two years in maturity – not just the lagged three-month contract – which yields an empirical measure of corporate maturity structure.

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<sup>1</sup> A seminal paper by Smith and Stulz (1985) lays the ground work for subsequent theory and related empirics. Smith and Stulz show that by stabilizing cash flows, corporate hedging can add value when firms face market imperfections that result in nonlinear payoffs (e.g. progressive taxation, bankruptcy costs). Their central idea – that nonlinearities justify hedging – has since been applied to other financial factors such as costly external finance (Froot, Scharfstein, and Stein, 1993) and information asymmetry (DeMarzo and Duffie, 1991). MacKay and Moeller (2007) apply Smith and Stulz’s model to estimate the value of corporate risk management related to factors affecting the real side of the firm. See MacKay and Moeller (2007) for a review of the empirical literature.

<sup>2</sup> One recent exception is Fehle and Tsyplakov (2005), who model both the optimal hedge intensity and maturity. Neuberger (1999) shows what mix of contract maturities minimizes rollover risk when the desired hedge horizon exceeds the longest-dated futures contract available.

<sup>3</sup> The notorious Metallgesellschaft debacle is a case in point (see Mello and Parsons, 1995).

Before elaborating on our approach, let us first explain what we mean by “lagged futures prices”: The lagged three-month futures price means the average price of a three-month maturity contract in the quarter prior to the current quarter; the lagged six-month futures price means the average price of a six-month maturity contract two quarters prior to the current quarter, etc. The longest maturity we consider is 24 months, so the lagged 24-month futures price means the average price of a 24-month maturity contract eight quarters prior to the current quarter.

Now, suppose a firm hedges half its price exposure one year ahead of delivery. Its current quarter’s sales (or costs) will therefore reflect two price points: the current quarter’s average spot price and the average futures price it contracted a year earlier. Our approach lets the data speak by allowing the estimation to endogenously assign weights to the spot price and any or all of the six lagged futures prices we consider, i.e., 3, 6, 9, 12, 18, and 24 months. Thus, for the firm just described, our approach would assign a weight of 50% to the spot price and 50% to the lagged 12-month futures price; all other lagged futures prices would receive weights of zero.<sup>4</sup> The resulting decomposition tells us about the level of hedging activity (the sum of the weights assigned to the lagged futures prices) as well as the maturity structure of corporate hedging (the distribution of the weights assigned across the lagged futures prices).

Our results can be summarized as follows. First, the average sample firm hedges about a quarter of its exposure. Specifically, our sales (costs) regression assigns 24% (22%) of the weight on the combined set of lagged futures prices and the remaining 76% (78%) on spot prices. This level of hedging activity is higher (but not significantly) than the level obtained if we only include the lagged three-month futures prices (as in MacKay and Moeller, 2007), which shows that including longer-dated contracts improves the specification and helps to correct a downward omitted-variable bias in the estimated level of hedging activity. Thus, we argue that the longer-dated contracts belong in the model on both economic and econometric grounds.

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<sup>4</sup> In reality firms pursue much more complex, time-varying hedge strategies, which will introduce estimation error. Our approach also assumes that the use of futures contracts qualifies for so-called “hedge accounting” and that a firm’s entire risk management program reduces to its use of futures contracts. We return to these questions later.

Second, we find that the average sample firm hedges well beyond the nearest quarter, with a significantly shorter hedge maturity for sales (about 7 months) than costs (about 11 months). However, these results vary considerably when estimated at the firm level, both in comparison to the sample average estimates and across firms. For instance, the median firm-level estimates of hedge intensity are 36% (41%) for sales (costs) and hedge maturity is about 12 (15) months.

Third, our results are somewhat sensitive to what specification is used, in particular, which of the six contract maturities are included in the estimation. For instance, in a regression that includes the lagged futures prices for 3- and 6-month maturities, the lagged 9-month futures prices enter significantly, both economically and statistically (weight of 12% and confidence levels of 5% or higher). However, this weight is shifted away from the 9-month maturity and onto the 12-month maturity once the lagged 12-month futures prices are added to the regression. At this point the model stabilizes, even as we add the 18-month and 24-month maturities.

Fourth, our analysis of which contract maturities belong in the model – which of the six lagged futures prices are assigned significant positive weights – reveals that the average sample firm does not hedge every point along the two-year horizon we consider. For instance, in a regression that includes all six contract maturities, only three enter significantly, namely, three months (with statistically significant weights of 11% for sales and 10% for costs), one year (only sales has a significant weight of 10%), and two years (only costs has a significant weight of 6%). In other words, the average firm exhibits a non-contiguous, asymmetric maturity structure that skips the 6-, 9-, and 18-month maturities and hedges sales up to one year ahead and costs up to two years ahead. Dropping these non-significant contract maturities from the regression places fewer demands on the data without reducing goodness of fit. This model, which only uses spot prices and the 3-, 12-, and 24-month lagged futures prices, is the one we use at the individual firm-level to estimate the hedge intensity and hedge maturity for our 34 oil refiners.

While our approach might seem reasonable, it certainly has its limitations and is subject to estimation error, which may defy its usefulness. We therefore use a variety of strategies to

validate our approach. First, given the small size of the sample, we searched each firm's financial-statement footnotes for clues regarding hedge maturity. In most cases, we were able to tentatively identify the longest contract maturity the firm normally uses. We find that the correlation between our estimated measure of hedge maturity and the one gleaned from footnotes is 21% for our sales-based measure and 37% for our costs-based measure (although only the latter is significant). Second, we are able to replicate key results reported in Fehle and Tsyplakov (2005), where hedge maturity is constructed precisely from detailed data for the gold industry. Finally, we propose a number of determinants of hedge maturity (discussed below) and obtain regression results that conform to our hypotheses, which again helps to validate the approach.

So, what are the determinants of hedge maturity? We first test an empirical prediction from Fehle and Tsyplakov (2005), namely, that hedge maturity should increase then decrease with the probability of financial distress. We regress our measure of hedge maturity on Altman's Z-score, the squared value of Altman's Z-score, and control variables. Then, for robustness, we use financial leverage instead of Altman's Z-score as our measure of the probability of financial distress (Fehle and Tsyplakov only use financial leverage). Regardless of the proxy for financial distress, our results conform to the prediction and reported by Fehle and Tsyplakov: the coefficient on the financial distress proxy is positive and the coefficient on squared term is negative, and both are statistically significant. This result is comforting because it both supports Fehle and Tsyplakov's prediction and validates our approach in that we corroborate their results.

Maturity matching is a common prescription and practice in corporate finance, where firms seek to match the maturities of their assets and liabilities both on and off the balance sheet. We therefore hypothesize a positive relation between hedge maturity and the maturity of a firm's assets as well as the maturity of its financial structure. In other words, we expect that firms with a greater fraction of short-term assets and short-term debt will use hedges of shorter maturity. Our results support these predictions: hedge maturity falls significantly with the ratio of net working capital to total assets and with the ratio of short-term debt to total assets. We find mixed results for to risk: Hedge maturity falls with cash-flow volatility but rises with diversification.

We also investigate the determinants of the level of hedging activity itself. First, we test and support another Fehle and Tsyplakov (2005) prediction, namely, that hedge intensity should first rise then fall with the probability of financial distress. Indeed, we find that the coefficient on Altman's Z-score and its squared value are significant and respectively positive and negative, consistent with Fehle and Tsyplakov and further validating our approach (however, the result does not carry over to the squared value of financial leverage). Second, we test and support standard explanations for hedging, such as the benefit to smoothing cash flow to avoid external finance (the intensity of cost-side hedging increases with the rate of capital expenditure) and that large, profitable, diversified, cash-rich firms hedge less, which supports the idea that firms with better access to external capital markets have less need to hedge.

Finally, we explore the relation between firm value and hedge maturity. Using the market-to-book value of assets as a proxy, we find that firm value decreases with hedge maturity. Without a specific prediction regarding this relation, we simply report the result without tying it down to a particular interpretation. Although we control for many covariates, there remains the possibility that result could stem from an omitted variable, estimation error, or endogeneity. We therefore present the result as noteworthy but exploratory.

This paper makes three contributions. First, we present a straightforward extension of MacKay and Moeller (2007) that extracts the maturity structure of corporate risk management. The approach uses standard COMPUSTAT data rather than the usual, problematic data sources, and therefore represents an important methodological innovation. Our approach clears the way for future research on this important but under-studied dimension of corporate hedging. Second, we provide some of the first descriptive evidence on corporate maturity structure. Although our results are specific to oil refining, the approach can be applied to other industries. Finally, we examine the determinants and value implications of hedge maturity. We corroborate results in Fehle and Tsyplakov (2005), which supports their predictions and validates our approach.

The rest of this paper is structured as follows. Section I extends the MacKay and Moeller (2007) model of the value of corporate risk management to incorporate hedge intensity and maturity. Section II describes the data. Section III presents summary statistics on energy prices, firm characteristics, and derivatives usage. Section IV presents industry- and firm-level estimates of hedge maturity and hedge intensity. Section V examines the determinants and value implications of hedge maturity. Section VI concludes.

## I. The Maturity Structure of Corporate Risk Management

Note to the reviewer or reader: The following sections are being rewritten. For now, please jump to the tables.

This section develops theoretical and empirical models. Our theoretical model uses Jensen's Inequality to derive an analytical expression for how much value risk management can add when revenues and costs are nonlinearly related to risky output and input prices. Our empirical model maps this analytical expression to an empirically testable specification.

### *A. Theoretical Model*

Let  $\Pi(p, w)$  denote a continuous, twice-differentiable profit function. The arguments,  $p$  and  $w$ , are output and input prices with density function  $f(p, w)$  defined over the price space  $\mathbf{P} \subseteq \mathfrak{R}_{++}^2$ . Assume that the profit and density functions are stationary and the discount rate is zero. Thus, firm-value maximization is equivalent to maximizing next-period expected profits:

$$V \equiv E[\Pi(p, w)] = \iint_{\mathbf{P}} \Pi(p, w) f(p, w) dp dw. \quad (1)$$

Expanding the right-hand side as a second-order Taylor series at expected prices  $(\bar{p}, \bar{w})$  yields:

$$\begin{aligned} V \equiv E[\Pi(p, w)] &= \Pi(\bar{p}, \bar{w}) \iint_{\mathbf{P}} f(p, w) dp dw + \\ &\quad \Pi_p(\bar{p}, \bar{w}) \iint_{\mathbf{P}} (p - \bar{p}) f(p, w) dp dw + \end{aligned}$$



$$\begin{aligned}
& \Pi_w(\bar{p}, \bar{w}) \iint_{\mathbf{P}} (w - \bar{w}) f(p, w) dp dw + \\
& \frac{1}{2} \Pi_{pp}(\bar{p}, \bar{w}) \iint_{\mathbf{P}} (p - \bar{p})^2 f(p, w) dp dw + \\
& \frac{1}{2} \Pi_{ww}(\bar{p}, \bar{w}) \iint_{\mathbf{P}} (w - \bar{w})^2 f(p, w) dp dw + \\
& \Pi_{pw}(\bar{p}, \bar{w}) \iint_{\mathbf{P}} (p - \bar{p})(w - \bar{w}) f(p, w) dp dw
\end{aligned}$$

Simplifying and restating the above expansion in terms of the moments of the density function, we obtain:

$$V \equiv E[\Pi(p, w)] = \Pi(\bar{p}, \bar{w}) + \frac{1}{2} \Pi_{pp}(\bar{p}, \bar{w}) \sigma_{pp} + \frac{1}{2} \Pi_{ww}(\bar{p}, \bar{w}) \sigma_{ww} + \Pi_{pw}(\bar{p}, \bar{w}) \sigma_{pw}$$

Because the second- and cross-partial derivatives do not depend on  $(\bar{p}, \bar{w})$ , we can further simplify the above to:<sup>5</sup>

$$V \equiv E[\Pi(p, w)] = \Pi(\bar{p}, \bar{w}) + \frac{1}{2} \Pi_{pp} \sigma_{pp} + \frac{1}{2} \Pi_{ww} \sigma_{ww} + \Pi_{pw} \sigma_{pw}. \quad (2)$$

Suppose the firm's profit function can be broken out into a revenue function and a cost function, that is,

$$\Pi(p, w) = R(p, w) - C(p, w) = p \cdot y(p, w) - w \cdot x(p, w). \quad (3)$$

The right-hand side of expression (3) shows how the revenue and cost functions can be formulated in terms of output price and quantity,  $p$  and  $y$ , and input price and quantity,  $w$  and  $x$ . This formulation also recognizes that, in general, the quantities of output produced and input consumed depend on prices. More specifically,  $y(p, w)$  represents the product-supply function and  $x(p, w)$  the factor-demand function. Our empirical specification uses these relations.

Then, from expression (2), the value of the firm's revenues and costs are given by:

$$R \equiv E[R(p, w)] = R(\bar{p}, \bar{w}) + \frac{1}{2} R_{pp} \sigma_{pp} + \frac{1}{2} R_{ww} \sigma_{ww} + R_{pw} \sigma_{pw}$$

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<sup>5</sup> This is because we assume a second-order expansion for ease of presentation. We consider higher-order expansions in our empirical analysis. However, as we later show, the second-order approximation is preferable.

$$C \equiv E[C(p, w)] = C(\bar{p}, \bar{w}) + \frac{1}{2}C_{ww}\sigma_{ww} + \frac{1}{2}C_{pp}\sigma_{pp} + C_{wp}\sigma_{wp}$$

For simplicity, assume that revenues depend only on the output price,  $p$ , and that costs depend only on the input price,  $w$ . The value of revenues and costs then reduces to

$$R \equiv E[R(p)] = R(\bar{p}) + \frac{1}{2}R_{pp}\sigma_{pp} \quad (4)$$

$$C \equiv E[C(w)] = C(\bar{w}) + \frac{1}{2}C_{ww}\sigma_{ww} \quad (5)$$

Using these expressions, we can restate firm value in terms of the revenue and cost functions:

$$\begin{aligned} V \equiv E[\Pi(p, w)] &= E[R(p)] - E[C(w)] \\ &= R(\bar{p}) - C(\bar{w}) + \frac{1}{2}R_{pp}\sigma_{pp} - \frac{1}{2}C_{ww}\sigma_{ww} \end{aligned} \quad (6)$$

This last expression shows how total firm value derives from two sources. The first source is reflected in the first two terms of equation (6), which correspond to the cash flow the firm earns if expected prices are realized. The second source of value is reflected in the last two terms of equation (6), which correspond to the expected value of the additional gain or loss experienced whenever realized prices depart from expected prices. This source of value formalizes what is often loosely termed “exposure” in the risk management literature. The value of exposure is positive if revenues (costs) are convex (concave) in prices but negative if revenues (costs) are concave (convex) in prices. Note that only in the latter case, when departures from expected prices would destroy value, should exposure be hedged away.

Now suppose that firms can hedge revenues and costs, fixing them at  $R(\bar{p}) = \bar{p} \cdot y(\bar{p})$  and  $C(\bar{w}) = \bar{w} \cdot x(\bar{w})$ .<sup>6</sup> From Jensen’s Inequality, the value of hedging revenues is positive if the

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<sup>6</sup> This is not a trivial assumption because it supposes the firm has access to costless nonlinear hedging strategies that pay out  $p \cdot y(p)$  on the revenue side and  $w \cdot x(w)$  on the cost side. Our purpose here is not to develop such strategies, nor to determine whether they exist, but rather to provide an upper-bound estimate on the real-side value of corporate risk management. Moreover, recent work by Brown and Toft (2002) looks specifically at how firms facing convex costs can hedge correlated price and quantity risks using standard futures and options contracts to construct optimal delta hedges that achieve over 90% of the efficiency of a custom exotic hedge. Brown and Toft assume that both price and quantity are stochastic and explore how a positive or negative correlation between them affects the nature and efficiency of the hedging strategy. Our paper leans more heavily on economic theory by allowing quantity to depend on price via a supply or demand function. This additional structure presumably simplifies and further improves the efficiency of the hedging strategies developed in Brown and Toft (2002). Bakshi and Chen (1997) and Bakshi and Madan (2000) also develop nonlinear payoff hedges.

revenue function is concave in the output price, that is, if  $R(\bar{p}) > E[R(p)]$ , and the value of hedging costs is positive if the cost function is convex in the input price, that is, if  $C(\bar{w}) < E[C(w)]$ . So, in terms of expression (4), the value of hedging revenues is

$$VHR \equiv R(\bar{p}) - E[R(p)] = -\frac{1}{2}R_{pp}\sigma_{pp} > 0 \quad \text{if} \quad R_{pp} < 0. \quad (7)$$

Likewise, we can rewrite expression (5) as

$$C(\bar{w}) - E[C(w)] = -\frac{1}{2}C_{ww}\sigma_{ww}. \quad (8)$$

Multiplying (8) by -1 yields an expression that compares directly to the value of hedging revenues and is positively related to firm value. Thus, we define the value of hedging costs as:

$$VHC \equiv E[C(w)] - C(\bar{w}) = \frac{1}{2}C_{ww}\sigma_{ww} > 0 \quad \text{if} \quad C_{ww} > 0. \quad (9)$$

The value of hedging therefore depends on the second partial derivatives of the revenue and cost functions ( $R_{pp}, C_{ww}$ ) interacted with the variance of output and input prices ( $\sigma_{pp}, \sigma_{ww}$ ). More technically, positive (negative) semi-definiteness of the revenue (cost) function is not a sufficient condition for hedging to add value – it also depends on the volatility of input and output prices. In economic terms, the value of hedging drops as the revenue and cost functions become linear in prices or as price volatility falls. Revenues could be linear in price if the firm faces inelastic demand or is unable to adjust its product supply and, because of technological considerations or contractual obligations, must produce a fixed quantity of output. Similarly, costs could be linear in price if the firm is unable to adjust its factor demand and must consume a set quantity of input.

### *B. Empirical Model*

The previous analysis assumes that the revenue and cost functions are known. In practice, these and the sample moments of the output and input prices must be estimated from available data. This section describes the empirical specification and how we implement the estimation.

Following the production economics literature (e.g., Diewert and Wales (1987, 1992)), and consistent with our theoretical model, our empirical model relies on the popular translog specification of a restricted profit function (all variables are in log-form).<sup>7</sup> This simple flexible functional form places few prior constraints on the firm's production technology and mirrors our theoretical model since it, too, derives from a second-order Taylor series expansion in prices:

$$R(p) = a_p + b_p p + c_p p^2 + f_p x = p \cdot y(p) \quad (10)$$

and

$$C(w) = a_w + b_w w + c_w w^2 + f_w y = w \cdot x(w), \quad (11)$$

$$\text{thus, } \Pi(p, w) = (a_p + b_p p + c_p p^2 + f_p x) - (a_w + b_w w + c_w w^2 + f_w y) = p \cdot y(p) - w \cdot x(w).$$

The regressors include two endogenous variables, namely, input quantity ( $x$ ) and output quantity ( $y$ ), which leads us to use instrumental variable estimation (details discussed later). Including input quantity in the revenue function and output quantity in the cost function is important in keeping with the translog formulation. It is also important because conditioning revenues on input quantity and costs on output quantity allows us to recognize and control for the discretion firms have to adjust their input demand in concert with their supply of output. Adding input and output quantity to the revenue and cost functions allows us to account for this natural hedge within our estimation and to generate a cleaner measure of the value of risk management.

By Shephard's lemma, the optimal output and input quantities ( $y$  and  $x$ ) are given by the first derivatives of the profit function with respect to prices:

$$\Pi_p = b_p + 2c_p p = y(p) = \frac{p \cdot y(p)}{p} = \frac{R(p)}{p} \quad (12)$$

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<sup>7</sup> This follows the so-called "dual approach" favored by production economists over the last 30 years (see Chambers (1994)). One advantage of working with the (dual) profit function over the (primal) production function is that it states the firm's optimization problem in terms of exogenous input and output *prices* rather than endogenous input and output *quantities*. This is important for empirical applications, especially in this paper, where we are interested in the value of managing exposure to price risk. As McFadden (1978) shows, the profit function is a "sufficient statistic" for the technology since all economically relevant information about the technology can be gleaned directly from the profit function.

$$-\Pi_w = b_w + 2c_w w = x(w) = \frac{w \cdot x(w)}{w} = \frac{C(w)}{w} \quad (13)$$

Equations (12) and (13) define the so-called derived output-supply and input-demand equations, and are typically included with the profit function to improve the efficiency of the coefficient estimates. Hence, the system of simultaneous equations we estimate comprises the revenue and cost functions (10) and (11) and the associated output-supply and input-demand equations (12) and (13).

We also control for other determinants of firm revenues and costs besides prices. We include changes in working capital to account for inventories and other short-term balance sheet items that form a firm's first line of defense in managing risk and therefore condition the sensitivity of its revenues and costs to fluctuations in output and input prices.<sup>8</sup> For instance, oil refiners can use inventories of both unrefined input (crude oil) and refined output (heating oil, gasoline) to buffer against variations in the supply and demand conditions for these products and thereby ensure a smoother stream of cash flows than they would otherwise experience.

We also include changes in fixed capital stock (net property, plant, and equipment) since adding or retiring productive capacity clearly affects firm revenues and costs. To account for differences in scale across firms, to mitigate heteroskedasticity, and to control for other determinants of firm revenues and costs, we normalize the firm-level variables (sales and costs, output and input quantities, and changes in net property, plant, and equipment, and working capital) by the lagged book value of assets. Thus, the system of simultaneous equations we estimate is

$$Sales = a_p + b_p p + c_p p^2 + f_p x + i_p \Delta t + k_p \Delta \kappa + \tilde{\mu}_s \quad (14)$$

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<sup>8</sup> A large literature examines the interaction of inventories and production (Ramey (1989, 1991)) and inventories and commodity prices (Pindyck (2001)). As Pindyck (2001) shows, these interactions are particularly important for storable commodities such as those studied here (crude oil, gasoline, and heating oil). Ideally, as in Ramey (1989), we would include finished goods inventories in the revenue function and raw materials and work-in-progress inventories in the cost function. However, data limitations prevent us from doing so: COMPUSTAT coverage for these variables is extremely poor but nearly complete for combined inventories and working capital.

$$Costs = a_w + b_w w + c_w w^2 + f_w y + i_w \Delta t + k_w \Delta \kappa + \tilde{\mu}_c \quad (15)$$

$$y = b_p + 2c_p p + \tilde{\mu}_y \quad (16)$$

$$x = b_w + 2c_w w + \tilde{\mu}_x, \quad (17)$$

where:  $y \equiv \frac{Sales}{p}$ ,  $x \equiv \frac{COGS}{w}$ ,  $\Delta t$  is the change in working capital,  $\Delta \kappa$  is the change in fixed capital stock, and  $\tilde{\mu}_s$ ,  $\tilde{\mu}_c$ ,  $\tilde{\mu}_y$ , and  $\tilde{\mu}_x$  are random error terms.

From our earlier analysis, we obtain an expression for the empirical value of hedging revenues:

$$HR = R(\bar{p}) - E[R(p)] = -\frac{1}{2}R_{pp}\sigma_{pp} = -\frac{1}{2}2c_p\sigma_{pp} = -c_p\sigma_{pp}, \quad (18)$$

and for the empirical value of hedging costs,

$$HC = E[C(w)] - C(\bar{w}) = \frac{1}{2}C_{ww}\sigma_{ww} = \frac{1}{2}2c_w\sigma_{ww} = c_w\sigma_{ww}. \quad (19)$$

Because expressions (7) and (9) do not discriminate between positive and negative hedging values, we refine our measures of the value of hedging to reflect an efficient risk management policy whereby firms hedge when the value of hedging is positive but remain exposed if the value of *not* hedging is positive. In particular, we propose a conditional risk management policy in which the value of conditional hedging is

$$CHR = Max[0, VHR] = Max[0, -c_p\sigma_{pp}] \quad (21)$$

$$CHC = Max[0, VHC] = Max[0, c_w\sigma_{ww}] \quad (22)$$

$$CH = CHR + CHC = Max[0, -c_p\sigma_{pp}] + Max[0, c_w\sigma_{ww}], \quad (23)$$

and the value of conditional exposure is

$$CXR = abs[Min[0, VHR]] = abs[Min[0, -c_p\sigma_{pp}]] \quad (24)$$

$$CXC = abs[Min[0, VHC]] = abs[Min[0, c_w\sigma_{ww}]] \quad (25)$$

$$CX = CXR + CXC = abs[Min[0, -c_p\sigma_{pp}]] + abs[Min[0, c_w\sigma_{ww}]]. \quad (26)$$

Expressions (21) to (23) represent the value of conditionally hedging revenues ( $CHR$ ), costs ( $CHC$ ), and both revenues and costs ( $CH$ ). Expressions (24) to (26) represent the value of conditionally exposing revenues ( $CXR$ ), conditionally exposing costs ( $CXC$ ), and conditionally exposing both revenues and costs ( $CX$ ).

Our empirical implementation of these values proceeds as follows. First, we estimate the set of simultaneous equations given in expressions (14) to (17) using the quarterly firm operating data and energy price series described in Section II. Second, we combine the estimated curvature parameters ( $c_p, c_w$ ) with the sample moments ( $\sigma_{pp}, \sigma_{ww}$ ) to produce estimates for expressions (23) and (26). As we discuss at length in Section V, we estimate that the value of conditional hedging and conditional exposure each represent about 2% or 3% of firm value.

## II. Data

We implement our analysis on a sample of oil refiners. Several reasons make the oil refining industry a good candidate for study. First, energy prices swing widely, and this variation contributes to the empirical fit of the model. This is particularly important here because we use quarterly operating data rather than stock returns. Second, oil refining is a well-defined operation, with highly competitive commodity markets on both the input and output sides of the business where crude oil is the main input, and heating oil and unleaded gasoline are the main outputs. Finally, the petroleum and oil refining industries have been studied in several prior papers (e.g., Gibson and Schwartz (1990), Litzenberger and Rabinowitz (1995), Schwartz (1997), Haushalter (2000), Brown and Toft (2002), Borenstein and Shepard (2002), Haushalter, Heron, and Lie (2002)).

Our firm-level data for oil refiners (SIC 2911) are from the merged *CRSP-COMPUSTAT* quarterly data set maintained by Wharton Research Data Services (WRDS). The main variables we use are: sales (data item #2), costs (cost of goods sold, item #30, minus depreciation and amortization, item #5), book value of assets (item #44), net property, plant, and equipment (item #42), and working capital (current assets, item #40, minus current liabilities, item #49).

Below we validate our approach by regressing firm value on our risk management values. Our proxy for firm value is Tobin's  $q$ , which we measure as the market-to-book value of assets. We obtain the market value of assets by replacing the book value of equity by its market value (number of common shares outstanding, item #61, times the quarter-end share price, item #14). Following Allayanis and Weston (2001), these cross-sectional regressions include a number of other variables as controls, namely, total debt (short-term debt, item #45, plus long-term debt, item #51), capital expenditures (item #90), dividends (common dividends, item #20, plus preferred dividends, item #24), and research and development (item #4), all divided by the lagged book value of assets (item #44). Some of these control variables have very poor coverage. For instance, research and development is missing for over 75% of the sample. We therefore set missing control variable observations to the industry-year mean to avoid serious sample attrition.

Some of the quarterly data are actually semiannual or annual (*COMPUSTAT* codes these as .S and .A). We identify and treat such cases as follows. For flow variables (sales, costs, etc.), we use the semiannual observation divided by two and the annual observation divided by four. For stock variables (assets, inventories, etc.), we use the most recent observations available. We also try simply deleting such observations. This causes the sample to drop from 34 to 31 firms but does not alter our conclusions.

We use annual *COMPUSTAT* business segment data to construct two additional control variables, namely, vertical integration and diversification. Vertical integration measures a firm's involvement in so-called upstream industries (production and exploration) and downstream industries (chemicals, distribution, marketing, etc.) relative to its core business (oil refining).<sup>9</sup> Diversification measures a firm's involvement in industries unrelated to refining. Using segment

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<sup>9</sup> Specifically, we classify the following segments as upstream industries: two-digit SIC 13 (exploration and production of crude and natural gas) and four-digit SIC 4612 (crude oil pipelines) and 6792 (oil and gas royalties and leases). We classify the following segments as downstream industries: two-digit SIC 28 (chemicals), 30 (plastic products), 46 (pipelines), 49 (natural gas transmission and distribution), 51 (wholesale petroleum-based products distribution), 87 (engineering, management, and consulting services), and four-digit SIC 3533 (oil and gas field machinery), 5541 (gasoline stations), 5984 (propane marketing), and 7549 (fast lube operations).



data, we measure vertical integration as one minus the Herfindahl of a firm's refining-related segments and diversification as one minus the Herfindahl of its nonrefining-related segments.

Input and output prices are constructed as follows. We obtain daily settlement prices, volume, and open interest for all NYMEX-traded futures contracts on light crude oil, heating oil, and unleaded gasoline from *Thompson Financial's Datastream International*. Beginning in March 1985, delivery months for all three commodities have been available for every month of the year going out several months. These commodities represent the main outputs (heating oil and unleaded gasoline) and input (crude oil) for the oil refining industry (SIC 2911).<sup>10</sup>

To simplify our analysis, we exploit a useful feature of the oil refining process, namely, that these inputs and outputs are roughly consumed and produced in the following proportions: three barrels of crude oil yield approximately two barrels of unleaded gasoline plus one barrel of heating oil. The price difference between contracts held in these proportions (3:2:1) is known as the "crack spread," and the contracts traded on NYMEX reflect this ratio (NYMEX (2000)). We combine the prices of heating oil and unleaded gasoline into a single output price, weighting each price according to the crack spread ratio. The resulting price therefore represents two-thirds of the gasoline price plus one-third of the heating oil price. Tracking one output price instead of two makes the analysis more tractable. Figure 1 shows input and output prices and the crack spread from March 1985 to June 2004.

Because our panel runs from March 1985 through June 2004 we need a deflator to make firm variables and prices comparable across time. We use the monthly consumer price index #SA0L1E (All items less food and energy) produced by the *U.S. Bureau of Labor Statistics (BLS)*. We use a deflator that excludes energy prices because we want to remove the effect of general inflation without removing the effect of energy price changes. We scale the deflator and the input and output prices relative to their March 1985 levels, the first month of our panel.

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<sup>10</sup> Following Litzenberger and Rabinowitz (1995), we use the nearest-month futures contract to construct our time series of spot prices. Datastream uses the previous business day's settlement price for holidays (when reported volume is zero). We therefore exclude these and any other zero-volume daily observations.

Because our firm-level data are quarterly, the next step is to convert our input and output price series from daily to quarterly series. We consider three weighting schemes to aggregate the daily data into quarterly observations. First, we use a volume-weighted average to guard against stale data and to avoid giving equal importance to prices associated with unusually low or high trade volume. Second, as a variant on this scheme, we also try weighting prices by the daily level of open interest. Third, and simplest, we equally weight the daily observations. Although the three weighting schemes produce similar results, we retain the volume-weighted scheme because it seems most suitable. Weighting by volume also accounts for times when trade volume in the futures contracts differs substantially from the level of trade in the nearest-month (spot) contract.

We match the firm-level quarterly data to the price data by mapping fiscal year-quarters to the appropriate calendar year-quarters. Because fiscal year-ends can occur in any month of the year, we match firm data to quarterly price averages constructed for each month of the year.

### **III. Summary Statistics**

Figure 1 shows nominal quarterly spot and three-month futures prices from March 1985 to June 2004. The graph shows that input and output prices vary widely, fluctuating between roughly 13 and 48 dollars per barrel and that the difference between the output and input price – the crack spread – understandably trades in a much smaller range of 2 to 10 dollars. Although the magnitude of the crack spread is much smaller than the output and input price, each penny change in the spread translates into millions of dollars for the average oil refiner. A back-of-the-envelope calculation shows that for the mean firm in our sample, a one-cent change in the crack spread causes a \$2.5 million change in quarterly operating cash flow in 1985 dollars.

*Insert Figure 1 around here.*

Table I shows summary statistics for the 78 quarterly spot and futures energy prices in our sample period. The mean nominal output and input spot prices are 26.43 and 21.87 dollars per barrel while the mean crack spread is 4.56 dollars. Figure 1 and Table I show that the futures prices are generally below the spot prices, indicating backwardation both in the price of crude oil

(as in Litzenberger and Robonowitz (1995)) and in the output prices (gasoline and heating oil). Input and output prices are highly correlated (0.99 for both spot and futures), as are spot and futures prices (0.99 for both input prices and output prices but only 0.71 for the crack spread).

*Insert Table I around here.*

Figure 2 shows aggregate statistics for the U.S. refining industry. These include annual production and consumption of refined petroleum products and refinery capacity utilization rates. Using a price index of refined petroleum products from the *Bureau of Labor Statistics* from 1977 to 2003, we estimate that the price elasticity of demand (consumption) is -10%.

*Insert Figure 2 around here.*

Table II, Panel A reports summary statistics on the operating characteristics of our sample of 34 oil refiners obtained from quarterly *COMPUSTAT* data. The data show that oil refining is a large-scale, capital-intensive activity (mean assets near \$12 billion, net plant, property, and equipment nearly 50% of assets, capital expenditures nearly 5% of assets per year), that operates on thin margins (mean operating cash flow is 5.4%), and is characterized by relatively low market-to-book value of assets (mean Tobin's  $q$  is 1.26).

*Insert Table II around here.*

We later use the hedging activity reflected in the data to estimate hedge rates. To put those estimates into perspective, Table II, Panel B reports summary statistics on derivatives usage by our 34 sample firms. Following previous studies (e.g., Geczy, Minton, and Schrand (1997), Allayanis and Weston (2001)), we conduct a systematic search of our sample firms' annual reports for all discussions of risk management policy and practice. Specifically, we search for the words risk, hedge, forward, futures, derivative, swap, option, and index. We find that hedging policies and derivatives usage are barely mentioned prior to 1996. Discussion of these subjects

has become more detailed as disclosure requirements have increased.<sup>11</sup> From this search we construct two measures of derivatives usage, one measuring the level of derivatives usage, the other measuring the type of derivatives used.<sup>12</sup>

The first measure classifies firms according to whether they *rarely* hedge, *sometimes* hedge, or *usually* hedge. We find that twenty oil refiners usually hedge while seven sometimes hedge and seven others rarely hedge. All sample firms report using derivatives except for one, Imperial Oil, which explicitly states that its policy is not to use derivatives. Two firms, ConocoPhillips and ExxonMobil, report some derivatives usage even though they have a stated policy of remaining exposed to price fluctuations or relying on diversification to manage risk.<sup>13</sup>

The second measure sorts firms based on the type of derivatives they use. Firms that use energy-related derivatives we classify as *operating*. Firms that use financial derivatives (e.g. interest rates, foreign exchange rates) we classify as *financial*. We find that eight firms use operating derivatives only, four firms use financial derivatives only, and 22 firms use both. Intersecting these two measures of derivatives usage, we find that the largest subgroup in our sample consists of the 15 firms that usually hedge and that use both operating and financial derivatives.

It is important to recognize that the FASB rules regarding the treatment of derivatives apply to conventional definitions of derivatives (futures, options, swaps) and do not necessarily include nonderivatives-based hedges such as long-term arrangements refiners make with clients. For instance, in its 2002 annual report Amoco explains that it enters into “fixed-price agreements for marketing purposes with its clients” and may use derivatives to offset these contracts if the

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<sup>11</sup> The Financial Accounting Standards Board (FASB) issued a series of statements intended to improve the transparency of derivatives usage. A review of these statements is available from the authors.

<sup>12</sup> Although we would prefer to use a *continuous* measure of derivatives usage, the data disclosed by our sample firms on their derivatives positions are too sporadic and inconsistent to construct a meaningful continuous measure. We therefore fall back on the categorical variables presented here and commonly used in prior studies.

<sup>13</sup> The results of our annual report search, including the lack of a meaningful continuous measure, that only one firm does not use derivatives, and that a few firms indicate they rely on integration to manage risk, are independently confirmed by the U.S. Energy Information Administration in “Derivatives and Risk Management in the Petroleum, Natural Gas and Electricity Industries.”

associated cost basis has not been hedged or otherwise fixed. This example points to a limitation of “derivatives usage” as a proxy for risk management. The hedge rates we present later help to overcome this limitation of the derivatives usage measures. Recent work on “selective hedging” (e.g., Brown, Crabb, and Haushalter (2003), Adam and Fernando (2005)) illustrates another way in which observed (or stated) use of derivatives does not tell the whole risk management story.

#### **IV. Regression Model Estimation**

##### *A. Econometric Approach*

Table III presents General Method of Moments (GMM) coefficient estimates for the set of simultaneous equations represented by expressions (14) to (17) for a pooled sample of oil refiners. These equations represent the revenue and cost functions and their associated derived output-supply and input-demand equations. The dependent variables for these equations are, respectively sales, costs, output quantity (sales divided by output price), and input quantity (costs divided by input price). The table presents various specifications of the model to examine the effect of including second and higher powers of the output and input prices (Models 1 to 4). No separate column appears for the input and output equations because the sales and costs equations already reflect all the model coefficients. We include the input and output equations in the estimation because the added structure reflects the firm’s first-order conditions and the flux of its product and factor markets. They also improve the efficiency of the coefficient estimates.

In contrast to Ordinary Least Squares (OLS), GMM allows for simultaneity among the dependent variables by incorporating the correlation of residuals across the four equations. This improves the efficiency and consistency of the estimates. As an instrumental variable estimation method, GMM mitigates simultaneity bias caused by endogenous explanatory variables by using predicted (instrumented) values rather than realized values of the endogenous variables. We instrument the endogenous variables (all variables except prices) by the first to fourth powers of the spot, futures, and lagged futures prices for inputs and outputs (24 instruments).

We use Hansen's (1982) J-statistic to jointly test whether the model is well specified and the instruments are valid. We also use the J-statistic to assess the gain or loss in overall fit across model specifications. For every model in Table III we find J-statistics significantly different than zero, which represents a rejection of the overidentifying restrictions and implies that the model is not fully specified, the instruments are correlated with the residuals, or both. Comparing models one through four, we observe that simply adding powers of the input and output prices substantially lowers the J-statistics, suggesting that, as Leamer (1983) shows, large-sample specification tests are sensitive to even small departures from the "true" model. However, even in the fullest specification we consider (Model 4), where the J-statistics are lowest, the overidentifying restrictions are still rejected, suggesting that some simultaneity bias remains.<sup>14</sup> The chosen instrument set reflects a best-efforts balance between validity (instruments uncorrelated with residuals) and relevance (instruments correlated with the endogenous variables).

Although we address heteroskedasticity by normalizing the firm-level variables by the lagged book value of assets, this might still pose a problem. Additionally, sales, costs, and prices all exhibit autocorrelation (see Tables I and II). Heteroskedasticity and autocorrelation can bias the standard errors and over- or understate both the statistical significance of the variables and the precision of our estimates of the value of risk management. We therefore use a first-order autocorrelated Newey-West (1987) procedure to correct for these econometric problems. Our regressions also include unreported fiscal-quarter dummy variables to adjust for seasonality.

*Insert Table III around here.*

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<sup>14</sup> Excluding the two most obvious endogenous variables from the model, namely, the input and output quantities, causes a substantial drop in the J-statistics (from 277 to 202 for Model 2) but not enough to avoid rejecting overidentifying restrictions. However, omitting these variables means we no longer control for the discretion firms have to coordinate their input and output decisions. Doing so overstates the value of risk management by about 5%. Models 5 through 8 presented in Table IV further address endogeneity and misspecification by considering additional control variables and alternate formulations.

## *B. Regression Results: Base Specification*

Table III reports regression results for four variants of our empirical model. Model 2 is the base specification developed in Section I and includes the first and second powers of the energy prices. Model 1 is a simple linear model that excludes the second and higher price powers. This model is useful in benchmarking our approach against the linear specification traditionally used in empirical studies, where risk factor returns are routinely added to the market model. Models 3 and 4 extend Model 2 by adding the third and fourth powers of the energy prices. These extensions allows us to examine whether adding flexibility to the functional form linking prices to revenues and costs improves the fit of the model and thereby our understanding of corporate risk management.

The four models share common controls, namely, changes in working capital and capital stocks. Also, the sales (costs) equation in each model controls for input (output) quantity. The models are in log-form, which means the coefficient estimates can be interpreted directly as elasticities. In addition to adjusted- $R^2$ s, we present incremental J-statistics to test whether augmenting the specification with higher powers of the price series improves the fit of the model.

Model 1 shows that a 1% change in output price ( $p$ ) causes a 0.48% change in revenue and that a 1% change in input price ( $w$ ) causes a 0.39% change in costs. Our first nonlinear specification, Model 2, exhibits several differences relative to the linear specification of Model 1. First, squared output and input prices enter the sales and costs equations with highly significant negative signs, indicating that both revenues and costs are concave in prices. Second, the overall statistical fit of the model is significantly improved: The J-statistic drops from 453 in Model 1 to 313 in Model 2. Thus, simply adding squared output and input prices markedly improves model fit and points to the importance of nonlinearity.

We should also point out that the magnitudes of the price coefficients themselves are substantially different than those that obtain in Model 1. Specifically, Model 2 yields coefficients of 0.71 and 0.58 (compared to 0.48 and 0.39 in Model 1) for the *direct* effect of output price on

sales and input price on costs. What Model 2 makes clear, however, is that revenues and costs are also *indirectly* related to prices, as reflected in the negative coefficients on squared energy prices. One simple interpretation of this result is that oil refiners face price-elastic demand for their products. Thus, an increase in the output price has a positive *direct* effect on revenues (higher price per barrel sold) but a negative *indirect* effect on quantity demanded (fewer barrels sold). This decrease in output demand leads oil refiners to cut their supply of product and lower their own demand for crude oil. This linkage in supply and demand causes output and input prices to be correlated and could explain why we also observe cost concavity.

Models 3 and 4 extend Model 2 by adding the third and fourth powers of energy prices. We add these because even though adding squared energy prices significantly improves the model, Model 2 maintains a strong assumption, namely, that revenues and costs are globally concave (or convex, as the case may be). Also, we have no reason to believe that the second-order Taylor series expansion represented by the translog specification in Model 2 cannot be improved by adding higher powers of the price series. Our results show that both these concerns were founded.

The cubic model (Model 3) significantly improves model fit relative to the quadratic model (Model 2). The coefficients for prices cubed are significant and positive, indicating that revenues (and costs) are actually concavo-convex in prices. In other words, global concavity is rejected in favor of local concavity and local convexity. Since the value of hedging is positive if revenues (costs) are concave (convex) in prices, adding convexity to the revenue (cost) function may lower (raise) the value of hedging revenues (costs). However, as we noted earlier, adding another power of the price series allows for more flexibility in the functional form. This is true in Model 3 where we find that adding prices cubed alters the magnitude of the coefficients for the first and second powers of energy prices. Thus, we cannot surmise from the coefficients alone whether Model 3 will yield higher or lower risk management value estimates than Model 2.



Taking the experiment one step further, the quartic model (Model 4) includes the first through fourth powers of energy prices. The basic message from Model 4 is similar to what we learn from Model 3: Revenues and costs are concavo-convex, and including quartic prices adds flexibility to the estimation that alters the magnitude of the other price coefficients. For reasons we develop in Section V, we do not consider higher-order specifications than the quartic model.

### C. Regression Results: Hedge Rates, Adjustment Costs, Market Power, and Real Optionality

One limitation to our approach is that we have implicitly assumed that reported sales and costs do not reflect corporate hedging activity. Table IV acknowledges this possibility by restating Model 2 (Table III) to encompass both lagged three-month futures prices and spot prices. The idea is that past hedging decisions (at then prevailing futures prices) will be reflected in the current quarter's numbers.<sup>15</sup> If no hedging took place, then a firm's numbers should mainly reflect current-quarter spot prices. We therefore reformulate expressions (14) to (17) as follows:

$$Sales = a_p + (1 - HR) \cdot [b_p p_0 + c_p p_0^2] + HR \cdot [b_p \bar{p}_{-3} + c_p \bar{p}_{-3}^2] + f_p x + i_p \Delta t + k_p \Delta \kappa + \tilde{\mu}_s \quad (27)$$

$$COGS = a_w + (1 - HC) \cdot [b_w w_0 + c_w w_0^2] + HC \cdot [b_w \bar{w}_{-3} + c_w \bar{w}_{-3}^2] + f_w y + i_w \Delta t + k_w \Delta \kappa + \tilde{\mu}_c \quad (28)$$

$$y = (1 - HR) \cdot [b_p + 2c_p p_0] + HR \cdot [b_p + 2c_p \bar{p}_{-3}] + \tilde{\mu}_y \quad (29)$$

$$x = (1 - HC) \cdot [b_w + 2c_w w_0] + HC \cdot [b_w + 2c_w \bar{w}_{-3}] + \tilde{\mu}_x, \quad (30)$$

where  $\bar{p}_{-3}$  and  $\bar{w}_{-3}$  are the lagged three-month output and input futures prices and  $p_0$  and  $w_0$  are the corresponding current-quarter spot prices.<sup>16</sup> This regression is nonlinear in the parameters, and the estimated weights associated with the lagged futures prices ( $HR$  and  $HC$ ) give an

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<sup>15</sup> This approach is predicated on how firms account for derivatives. The FASB rules distinguish between so-called hedge-qualifying and nonqualifying derivatives positions. Gains and losses on hedge-qualifying positions are recognized in sales and costs in the quarter in which the associated product deliveries (and prices) are realized. Non-derivatives-based hedges, such as long-term contracts refiners establish with customers and suppliers, are treated similarly and thus also are reflected in sales and costs. Nonqualifying derivatives positions are marked to market and carried on the balance sheet in "other comprehensive income" until a gain or loss is realized and then are recognized in that quarter's non-operating income. Because nonqualifying derivatives positions are excluded from sales and costs they also escape our proposed hedge rates. However, since most of our sample firms indicate that they use derivatives primarily for hedging purposes, it seems likely that our approach captures most hedging activity.

<sup>16</sup> Using other contract maturities, such as six-month lagged futures prices, yields similar risk management values.

indication of how much a firm did hedge. Thus, in addition to addressing the accounting problem, this approach offers a useful by-product, namely, endogenously estimated hedge rates. A hedge rate of one (zero) indicates that a firm has hedged all (none) of its spot price exposure using three-month contracts. In other words, these hedge rates tell us whether firms use hedging to shift the price-sensitive portion of their revenue and cost functions intertemporally.

*Insert Table IV around here.*

Table IV presents four variants of this formulation. The first version (Model 5) is a direct extension of Model 2 that simply adds the hedge rates as per expressions (27) to (30). Borenstein and Shepard (2002) report that the oil refining industry exhibits adjustment costs and market power, either of which could explain, or at least contribute to, the observed nonlinear price relations. Models 6 and 7 examine these factors. First, following Whited (1992) and MacKay (2003), Model 6 incorporates a quadratic adjustment cost function by including the squared quarterly change in output and input quantities ( $\Delta^2y$  and  $\Delta^2x$ ) in the sales and cost equations. Second, as noted earlier, our finding that revenues are concave in price is consistent with imperfect competition. Thus, Model 7 allows for market power by adding market share and market share squared. For the sales (cost) equation we measure market share in a given quarter as own-firm sales (costs) divided by total industry sales (costs).

Comparing results for Model 5 (Table IV) and Model 2 (Table III), we note a significant improvement in overall model fit (Hansen J-statistic of 242 Model 5 versus 313 for Model 2). The estimated hedge rates take on plausible values of 0.27 for sales and 0.25 for costs. While they are precisely estimated (standard errors of 0.02), they vary across the four models presented in Table IV. The magnitude of the squared price coefficients increases (-0.30 and -0.25 for sales and costs in Model 5 versus -0.27 and -0.22 in Model 2). This suggests that the hedging activity concealed in the data masks even greater nonlinearity than the spot-price-only models reveal.

Models 6 and 7 examine how adjustment costs and market power affect our results. In each of these models, the indirect price effects, that is, the squared prices coefficients, are statistically

greater than in Model 5, which points to greater price nonlinearity than when the proxies for adjustment costs and market power are excluded. Thus, although these proxies substantially improve the overall fit of the model, they do not remove the observed nonlinearity in price.

As a final extension we model the role of real optionality in shaping the nonlinearities we detect in oil refiners' revenue and cost functions. For instance, suppose a one-plant refiner buys a second refining plant. A two-plant operation provides more flexibility by enabling the refiner to deal more efficiently with changes in the level or mix of product demand by allowing each plant to specialize its product line or shut down marginal operations when prices fall. This type of real optionality suggests an inverse relation between capital investment and nonlinearity.

Model 8 considers the scope firms have to change the degree of nonlinearity they face. We capture this real optionality by including the interaction between investment (change in net plant, property, and equipment) and prices squared. As it turns out, this interaction term enters the sales and costs regressions with a highly significant positive sign and further contributes to the overall fit of the model (Hansen J-statistic of 95 versus 111 for Model 7). The positive sign of these interaction coefficients indicates that capacity expansion (contraction) lowers (raises) the degree of nonlinearity in oil refiners' revenue and cost functions, as predicted.

## **V. The Value of Risk Management: Empirical Estimates**

This section explains how we combine the regression estimates from Tables III and IV and the sample moments of the energy price series to compute the value of risk management derived in Section I. We begin with industry-wide estimates computed from the regression estimates of Section IV. Next, we check for time aggregation bias by replicating the analysis on semiannual data and examine the role of firm heterogeneity by parsing the sample by vertical integration and diversification levels. We then report firm-level estimates and close the section by examining the relation between our endogenously estimated hedge rate and measures of derivatives usage.

### *A. Industry-Level Estimates*

Table V reports point estimates and confidence intervals of the value of corporate risk management corresponding to the hedging policy presented in expressions (23) and (26), namely, the value of conditional hedging (*CH*) and the value of conditional exposure (*CX*). The legend to Table V gives expressions for the value of risk management for the cubic and quartic models that are not presented elsewhere in the paper. Although the formulations are more involved, these expressions are simply derived by extending the second-order expansion presented in Section I. Reported values are a percentage of fitted operating cash flow (fitted sales minus fitted costs).<sup>17</sup>

*Insert Table V around here.*

It should be noted that our results are fairly aggregate because of the nature of the data at hand: Quarterly firm-level data are such that a wealth of operational data is packed into firm-level observations, and daily energy prices must be collapsed into quarterly averages. These data constraints also mean that our results reflect *average* economic relations from 1985 to 2004 rather than the evolution or the latest state of the oil refining business.

The regression coefficients in Tables III and IV provide the second and higher partial derivatives needed to compute expressions (23) and (26). These expressions also require estimates of the second (and higher) moments of the energy prices. We estimate these as the sample moments of the futures prices over the empirical period (March 1985 to June 2004). More specifically, because some firms only appear for part of the sample period, we compute firm-specific estimates of the sample moments based solely on the quarters the firm appears in the sample.

Using quarterly data on the simplest specification (the quadratic model, Model 2), our point estimates [confidence intervals] for the value of conditional hedging and conditional exposure

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<sup>17</sup> We can also interpret these estimates as a percentage of firm value. This is because both the numerator (value of hedging or exposure) and the denominator (operating cash flow) would have to be capitalized by the same factor.

are 2.29% [2.15%, 2.44%] and 2.07% [1.94%, 2.21%] of fitted operating cash flow. Note that although a simple “natural hedge” strategy of letting revenue and cost exposures offset each other might appear effective, it is not particularly astute because it squanders the expected gain from leaving concave costs exposed on the expected loss from leaving concave revenues exposed. A better strategy is to hedge revenues and leave costs exposed. Of course, this strategy ignores the usual financial motives for managing risk (tax convexities, bankruptcy cost, etc.). Section VI.C further discusses the trade-off between real and financial hedging motives.

Adding the third and fourth powers of energy prices changes the point estimates somewhat. The value of conditional hedging (exposure) is 2.16% (2.12%) in the cubic model and 2.01% (1.83%) in the quartic model. Although none of these estimates differ statistically, they do support our earlier conjecture that by adding local convexity, Models 3 and 4 could alter the value of risk management estimated from the globally concave function in Model 2. Indeed, Models 3 and 4 show that adding flexibility leads us to revise the estimates downwards.

The problem with Models 3 and 4 is that the confidence intervals become very wide. Precision drops as terms are added because more coefficients are involved in calculating the value of risk management. For instance, the 95% joint *Bonferroni* confidence interval for the value of conditional hedging is [0.35%, 3.97%] for Model 3 and [-12.95%, 19.11%] for Model 4. In short, greater accuracy comes at the cost of lower precision; we dismiss Models 3 and 4 because they are simply too imprecise to draw reliable inferences.<sup>18</sup> Figure 3 plots the revenue and cost functions for Model 1s through 4. Consistent with our point estimates, the plots show that there is little to distinguish Models 3 and 4 from Model 2 within the relevant price range.

Models 5 through 8 build on Model 2 by adding endogenously estimated hedge rates and allowing for adjustment costs, market power, and real optionality. These models perform considerably better than Models 1 through 4 in explaining the data; Table V shows they also

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<sup>18</sup> Another reason to discount Models 3 and 4 is that the inflection points fall outside the historical price ranges. The 1985-dollars inflection point for the revenue (cost) function in Model 3 is \$42.28 (\$40.45); the highest output (input) price from March 1985 to June 2004 was \$35.11 (\$31.65). Inflection points for Model 4 are undefined.

produce higher estimates of the value of risk management. This is expected since these models consistently show greater concavity in the relation between sales and the output price and between costs and the input price. Thus, according to Model 5, the value of conditional hedging (exposure) is 2.59% (2.34%). Although adding hedge rates alone does not significantly raise our estimates of the value of managing risk, further controlling for adjustment costs, market power, or real optimality does. For instance, based on Model 8, the value of conditional hedging (exposure) is 3.53% (3.24%). Thus, failing to account for these confounding factors can significantly understate the value of risk management.

### *B. Time Aggregation*

By relying on quarterly data, our analysis so far assumes that price behavior and firm decisions fit neatly into quarterly brackets and are independent of past prices and past decisions. Yet, the autocorrelation we document in both prices (Table I) and firm data (Table II) shows that we must relax this assumption. Autocorrelation in prices means that sample moments are sensitive to the frequency of the data. Autocorrelation in the firm variables can arise because production time, seasonality, adjustment costs, and real optionality create intertemporal linkages between successive firm decisions. In short, estimated price properties and firm behavior are subject to time-aggregation bias. Our various model specifications and econometrics already account for many of these complications. This section examines whether remaining time-related factors affect our estimates by replicating the analysis on semiannual rather than quarterly data.

The bottom panel of Table V reports risk management values based on semiannual data. For every model considered (Models 2 through 8), we find that semiannual data produce lower estimates of the value of risk management. Disregarding Models 3 and 4 due to their lack of precision, we find that the value of conditional hedging estimated from semiannual data is statistically lower than when estimated from quarterly data. For instance, the semiannual point estimates for Models 2, 5, and 8 are 1.83%, 1.91%, and 2.14% compared to 2.29%, 2.59%, and

3.53% when estimated from quarterly data. The estimates of the value of conditional exposure are also lower when estimated from semiannual data, but not significantly so.

These data frequency-related differences confirm that time aggregation is a valid concern. Whether the differences stem from aggregating firm data, price series, or both is hard to say. However, the observed pattern seems consistent with the conventional economic view that firms are better able to adjust in the medium or long run than in the short run. For instance, as refiners reach the point at which firm agreements and production schedules must be set, their revenues and costs become particularly vulnerable to price shocks going forward. This suggests greater nonlinearity, and risk management value, for quarterly horizons than semiannual horizons.

### *C. Vertical Integration and Diversification*

Our analysis so far assumes that the sample firms are relatively homogeneous oil refiners. In reality, these firms vary substantially in the focus and scope of their operations: Some are small specialized oil refiners (e.g., Huntway Refining) while others are large integrated oil companies (e.g., ConocoPhillips); some derive income from energy-related operations alone (e.g., Amerada Hess) while others are diversified conglomerates (e.g., USX). This section examines whether and how differences in vertical integration and diversification levels affect our results.

Table VI presents risk management values and hedge rates for Models 2, 5, and 8 arrayed by level of vertical integration and diversification. We measure vertical integration (diversification) as one minus the Herfindahl of a firm's business segments related (unrelated) to oil refining. We find that vertically integrated firms (above the sample median) derive less value from risk management than firms with low vertical integration levels (at or below the sample median). Similar results obtain for diversification but the differences are mostly insignificant. Significant differences do emerge when we compare firms with low vertical integration and diversification levels against firms that are vertically integrated and diversified.

*Insert Table VI around here.*

These findings are consistent with the notion that vertical integration and diversification create natural hedges that substitute for other risk management strategies.<sup>19</sup> This interpretation is bolstered by the fact that the hedge rates from Model 5 are economically and statistically lower for firms that are both vertically integrated and diversified. Thus, vertical integration and diversification appear to substitute for derivatives usage. Given this apparent substitutability, the *q*-regressions we report in Section VI to validate our approach not only include our risk management values and hedge rates, but also control for vertical integration and diversification.

#### *D. Firm-Level Estimates*

The values we discuss so far are derived from the entire sample of oil refiners; they therefore represent industry-wide averages. We also run the model and compute risk management values and hedge rates for each sample firm. These values appear in Table VII. For robustness, we report risk management measures based on Models 2, 5, and 8, with similar results.

*Insert Table VII around here.*

We find considerable variation across firms. Focusing on the value of conditional hedging (exposure) for Model 5, we find estimates ranging from 0.8% (0.0%) to 15.8% (16.1%) of fitted operating cash flow. However, the mean and median are quite close and similar to the industry-level estimates. Finally, in only four out of 34 cases are the estimates over 10%. Results for Models 2 and 8 are similar in every respect and highly correlated with those of Model 5.

Table VII also shows the estimated revenue and cost hedge rates for each firm. We find hedge rates generally near the industry-level estimates reported in Table IV. Based on Model 5, the mean [median] hedge rate is 39% [32%] for revenues and 31% [26%] for costs. Model 8 produces slightly higher estimates: 42% [32%] for revenues and 38% [27%] for costs. In a few

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<sup>19</sup> In its 2002 annual report, Exxon Mobil states: “The corporation’s size, geographic diversity and the complementary nature of the upstream, downstream, and chemicals businesses mitigate the corporation’s risk from changes in interest rates, currency rates and commodity prices. [...] As a result, the corporation makes limited use of derivatives to offset exposures arising from existing transactions.”



cases, we find hedge rates over 100% (Huntway, Murphy, Ultramar, Valero) and under 0% (Atlantic Richfield, Chevron, Diamond Shamrock, Holly, Quaker State). Taking these results at face value, this suggests that these firms are leveraging their hedge positions or price exposures.

Do firms hedge when they should and remain exposed when they should? Yes and no. Just as we document for the pooled sample, we find that for every firm in the sample the value of conditional hedging derives from revenue concavity (rather than cost convexity) and the value of conditional exposure derives from cost concavity (rather than revenue convexity). Thus, oil refiners should hedge revenues but leave costs exposed. Consistent with this prediction, Table VII shows positive correlations between the value of conditional hedging and the revenue hedge rates. However, contrary to the prediction, we also note positive correlations between the value of conditional exposure and the cost hedge rates. In Section VI we investigate whether the market can discriminate between these efficient and inefficient risk management practices.

#### *E. Hedge Rates, Derivatives Usage, and the Measurement of Hedging Activity*

Our hedge rates and the derivatives usage measures each tell part of the hedging story. The hedge rates measure both derivatives-based and nonderivatives-based hedging activity, although only for operating risks (energy prices) of a specific maturity (three months). The derivatives usage measures reflect hedging activity across all maturities, financial and operating risks alike, but ignore nonderivatives-based hedges and only offer a broad indication of hedging policy.

Given the overlap between these measures of hedging activity, we expect them to correlate positively, making them informational substitutes. Given their differences, however, we also do not expect these measures to correlate perfectly, thus making them informational complements. Even if the measures did not overlap, they might still correlate positively if the underlying motives for risk management lead firms to use both derivatives or nonderivatives hedges.

We confirm that our hedge rates are consistent with firms' reported derivatives usage. The median sales-based hedge rates for firms that rarely, sometimes, or usually hedge increase monotonically: 22.7%, 29.3%, and 35.9% (the cost-based ratios are 24.5%, 18.3%, and 28.7%).

However, the difference between firms that rarely hedge and firms that usually hedge is not statistically significant ( $p$ -value of 0.152). Since our hedge rates focus on operating risks (energy prices), we drop the four sample firms that only use financial derivatives. The sales-based hedge rates still increase monotonically (21.4%, 22.6%, and 35.9%) but the difference between firms that rarely and usually hedge is now significant ( $p$ -value of 0.038). The difference between the corresponding cost-based hedge rates (25.5%, 22.8%, and 28.7%) is insignificant.

## VI. Cross-Sectional Analysis of the Value of Corporate Risk Management

While suggestive, our analysis so far cannot tell us whether the risk management values we derive analytically and estimate empirically matter to the market value of the firm. An important assumption in Smith and Stulz (1985), which underpins our analysis as well, is that firms have access to costless hedging, that is, financial markets are complete and frictionless. Departures from these ideal-market conditions create hedging costs that lower or even outweigh the value of corporate risk management. Thus, even if our risk management values were entirely accurate, we might still fail to find a relation with firm market value.

One problem with regressing firm market value on our risk management measures is that the null hypothesis speaks as much to market perfection as to the validity of our measures. Therefore, failure to reject the null does not allow us to say whether our measures are invalid. Another difficulty is that our measures are estimated with error and the sample size is small.

Setting aside these difficulties, Table VIII reports GMM regressions of Tobin's  $q$  (using the market-to-book value of assets as a proxy) on the estimated risk management values and hedge rates derived from Model 8.<sup>20</sup> As noted earlier, the sales-based and cost-based risk management values are highly correlated, which poses an econometric difficulty. Indeed, including the value of conditional hedging and exposure ( $CH$  and  $CX$ ) in the same regression produces unstable

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<sup>20</sup> To overcome our small sample size, Table VIII reports pooled cross-sectional regressions in which the same set of hedging proxies (hedge rates, hedging intensity, financial hedging) is repeated for every quarter a firm appears in the sample. Note that the risk management values for a given firm *do* vary over time because these include an interaction between investment and price squared. Thus, each quarter's estimate of the value of risk management is shifted up or down depending on a firm's investment in that quarter and its firm-specific interaction coefficient.

results and greatly inflated standard errors. We avoid this multicollinearity problem by examining the sales-based and cost-based measures in separate regressions. We present standardized regression coefficients to facilitate the interpretation of results (this is also why no intercept term is included in these regressions). The reported coefficients thus show how a one-standard deviation variation in each regressor affects the dependent variable.

*Insert Table VIII around here.*

Most of the regressions in Table VIII include indicators of hedging activity derived from the derivatives usage measures presented earlier. We term the first of these indicators “hedging intensity,” a binary variable that is set to one if the firm usually hedges and zero if the firm rarely or sometimes hedges. The second indicator we term “financial hedging,” a binary variable that is set to one if the firm only hedges financial risks (exchange rates and interest rates) and zero if the firm hedges operating risks (energy prices) alone or both operating and financial risks. Section VI.B discusses the regression results that pertain to these indicators of hedging activity.

Our regressions include other well-known determinants of firm value, specifically, most of the controls used by Allayannis and Weston (2001) in their analysis of firm market value and corporate hedging activity. We also control for vertical integration, diversification, and a measure of real optionality derived from Model 8, namely, the absolute value of the coefficient estimate for the interaction of investment and price squared (set to zero if insignificant).

#### *A. Firm Value and the Value of Risk Management*

We find statistically significant positive relations between firm value (Tobin’s  $q$ ) and the value of conditional hedging ( $CH$ ) and conditional exposure ( $CX$ ) in every specification of Table VIII (Models A to G). To verify whether these results are specific to the use of risk management measures derived from Model 8 we also examine results based on Model 2 and Model 5 – all with very similar results. Thus, although our risk management estimates are affected by hedging activity (Model 5), adjustment costs, market power, and real optionality (Model 8), these factors do not materially change our conclusions on how risk management affects firm value.

Because our regression coefficients are standardized, we can compare the magnitude of the coefficients to get a sense of the relative economic importance of each regressor. For instance, the coefficient for the value of conditional hedging averages 0.14 (Models A to G), indicating that a one-standard deviation increase in the value of conditional hedging coincides with a 14%-standard deviation increase in Tobin's  $q$ . Based on the sample statistics reported in Table II, this translates into 4.4% of firm value, in line with our estimates of the value of risk management. To put this in perspective, note that the corresponding averages for fitted operating cash flow and firm size are 7.6% and 7.0% of firm value. The value of conditional exposure is somewhat less important (averaging 0.09 or 2.9% of firm value), but collectively the value of our risk management variables account for a nontrivial fraction of explained variance in firm value.

We find significant inverse relations between firm value and both the sales-based and cost-based hedge rates ( $HR$  and  $HC$ ). The inverse relation between firm value and the cost-based hedge rate is consistent with our finding that costs are convex in input price and should not be hedged. However, the inverse relation between firm value and the sales-based hedge rate is inconsistent with our finding that sales are concave in output price and should be hedged. Thus, on the surface, this finding conflicts with the findings in Allayannis and Weston (2001) and Jin and Jorion (2006) that firm value is either positively or insignificantly related to corporate hedging. We obtain similar results for hedging intensity, indicating that these findings are not artifacts of our estimation method as they extend to external measures of corporate hedging activity.

We find that adding the interaction of the hedge rates and the value of risk management to the regressions goes a long way toward uniting the normative and positive sides of the analysis. These interactions effectively benchmark observed hedging activity against its potential value. Specifically, we find that hedging revenues (costs) significantly raises (lowers) firm value once interacted with the value of conditional hedging (exposure). As argued earlier, refiners should hedge revenues but leave costs exposed. The market appears to make this distinction by bidding up firms that hedge revenues when the value of revenue hedging is high and bidding down firms

that hedge costs when the value of cost exposure is high. In short, the market rewards firms that hedge when hedging creates value and penalizes firms that hedge when hedging destroys value.

What do these findings mean? First, they provide some assurance that our analysis and its empirical implementation are not without merit. Second, our findings suggest that potential risk management gains (and losses) are recognized and valued by the market. This evidence is consistent with past empirical studies that find that factors other than market risk are priced (e.g., Jorion (1990), Strong (1991), Tufano (1998), Haushalter, Heron, and Lie (2002), that total risk matters (e.g., Minton and Schrand (1999), Goyal and Santa-Clara (2003), and that firm value is positively related to corporate hedging activity (e.g., Cassidy, Constand, and Corbett (1990), Allayannis and Weston (2001)).

We run a number of robustness checks because our risk management measures are subject to estimation error that might bias our results. For instance, we screen out firms for which the net value of hedging ( $CH - CX$ ) is greater than the sample mean plus one standard deviation and find qualitatively similar results. A less arbitrary way to mitigate the role of influential observations is to take the rank transforms of the variables before running the regression. This, too, produces similar results. Our results are also robust to the inclusion or exclusion of the control variables.

### *B. Firm Value and Derivatives Usage*

Results for the external measures of corporate hedging activity, namely, derivatives usage, offer additional insights. First, including or excluding the hedging intensity or financial hedging variables does not change our conclusions regarding the relation between firm value and the value of risk management. Second, as noted earlier, the inverse relation between the hedge rates and the value of risk management also obtain for hedging intensity. Third, in contrast, we find a significant *positive* relation between firm value and financial hedging.

This last result offers an important clue to the mixed findings in the literature regarding the relation between firm value and corporate hedging. Allayannis and Weston (2001) document a positive relation between firm value and the use of foreign currency derivatives, and Carter,

Rogers, and Simkins (2006) estimate that the hedging premium for U.S. airlines is about 14%. Yet Jin and Jorion (2006) find that hedging has no value implications for oil and gas producers and Guay and Kothari (2003) estimate that the risk exposure of 234 nonfinancial firms is small relative to their investment needs and market capitalization. Indeed, Guay and Kothari argue that corporate derivatives usage is but a small piece of nonfinancial firms' overall risk profile and call for a rethinking of the design of empirical research on corporate hedging.

Our study contributes to this debate in three ways. First, in response to Guay and Kothari's (2003) concern, our model draws a direct link between product market prices, operations, and the value of risk management. Second, we show that the valuation effects of corporate hedging must be gauged against a benchmark of how much value hedging activity can potentially add. This point rests on our finding that the *interaction* of the hedge rates and the risk management values – not the hedge rates themselves – are pivotal relations in our regressions of firm value.

Finally, we find that hedging operating and financial risks has distinct value implications. This idea is foreshadowed in Jin and Jorion (2006) who conjecture that Allayannis and Weston (2001) find a positive relation between firm value and the use of foreign currency derivatives because firms might have a comparative advantage over investors in the financial derivatives markets but not in the commodity derivatives markets. Our finding that firms that hedge financial risks create value while firms that hedge operating risks or both financial and operating risks destroy value corroborates Jin and Jorion's conjecture.

### *C. Financial Factors and Corporate Hedging*

In developing our real-side story for risk management, we have conveniently ignored the usual financial factors associated with corporate hedging (tax convexities, bankruptcy cost, etc.). A simple strategy of hedging revenues and leaving convex costs exposed ignores such factors. Because this strategy raises both the level and the variance of operating cash flow, the value of risk management that we trace to real-side factors might carry a cost in terms of financial factors.

In other words, a trade-off arises between the value of lowering cash flow volatility in the face of financial nonlinearities and the value of risk management related to real-side nonlinearities.

To examine this trade-off we would need to know the cost function describing financial distress, tax convexities, information asymmetry, etc. Since this cost function is unknown, we cannot estimate the value of risk management related to these financial factors. We can partially examine their relevance by testing whether the market rewards hedging more as the probability of financial distress rises. Specifically, Model G in Table VIII includes the interaction of hedging intensity and financial leverage. This interaction term is positive and significant, indicating that the value of hedging does rise with the risk of financial distress.<sup>21</sup> This result supports the financial motives for hedging. However, the fact that our risk management estimates enter the regression significantly even after controlling for financial leverage (and its interaction with hedging intensity) suggests that the real-side story we develop is not swamped by financial factors.

## **VII. Out-of-Sample Analysis and General Applicability**

Although our results appear reasonable, they are specific to a single industry. We therefore examine the applicability of our approach to other industries by testing whether our results can be generalized out of sample. The availability of futures prices puts an important constraint on such an extension. In particular, very few industries have futures contracts for both the input and output sides of their operations. For this reason, and to truly generalize the analysis, we propose a limited but simple extension that relies on our existing set of energy futures prices.

We use data from the National Bureau of Economic Research to rank all manufacturing industries except oil refining by mean energy intensity (energy consumed divided by operating

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<sup>21</sup> Alternatively, the increased value associated with leverage and hedging intensity could reflect the greater debt interest tax shield firms can realize if risk management allows for increased leverage, as Graham and Rogers (2002) document. To the extent that an empirical estimate of the probability of bankruptcy controls for this possibility, in unreported regressions we include Altman's Z-score as an additional proxy for financial distress. This yields qualitatively similar results, indicating that risk management may create value through both these financial channels. We thank the reviewer for pointing out this possibility to us.

cash flow) for the period 1985 to 1996 (the data set ends in 1996). The lowest energy-intensity decile is 2% and the highest decile is 21%, which suggests that firms in most manufacturing industries should exhibit some energy price sensitivity. We then estimate Model 8 for these deciles using quarterly firm data from March 1985 to June 2004. We find significant conditional hedging (exposure) values of 1.44% (1.12%) for the lowest decile and statistically greater values of 3.09% (2.61%) for the highest decile.<sup>22</sup> Comparable values for oil refining are 3.53% (3.24%).

Despite their limitations, these results suggest that our approach holds its own in a broader setting and produces plausible out-of-sample estimates, particularly by assigning higher risk management values to firms in energy-intensive industries. Additionally, just as for oil refiners, we find that firm value is positively related to the value of risk management in the broader sample, further validating our approach. This out-of-sample check suggests that applying our approach to analyze other individual industries or other price factors holds promise.

### **VIII. Conclusions**

In this paper, we derive and estimate a model of the value of corporate risk management. Our approach is inspired by Smith and Stulz (1985) who use Jensen's Inequality to show that cash flow volatility should be managed if the firm faces convex financial costs. We apply this basic idea to the real side of the firm and show that corporate risk management can also add value if revenues and costs are nonlinearly related to risk factors such as energy prices.

Our base approach is subject to an important caveat, namely, that reported firm data might well reflect corporate hedging activity that could skew our results. We address this accounting problem by restating our model in terms of lagged futures prices and spot prices rather than spot prices alone. This refinement produces endogenously estimated hedge rates as a by-product.

We estimate our model using quarterly operating data for a sample of oil refiners. We find that the value of hedging concave revenues and leaving concave costs exposed each represent

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<sup>22</sup> Comparable estimates for the middle eight energy-intensity deciles combined are 2.65% (2.04%). These estimates are statistically greater than the lowest-decile estimates and statistically lower than the highest-decile estimates.

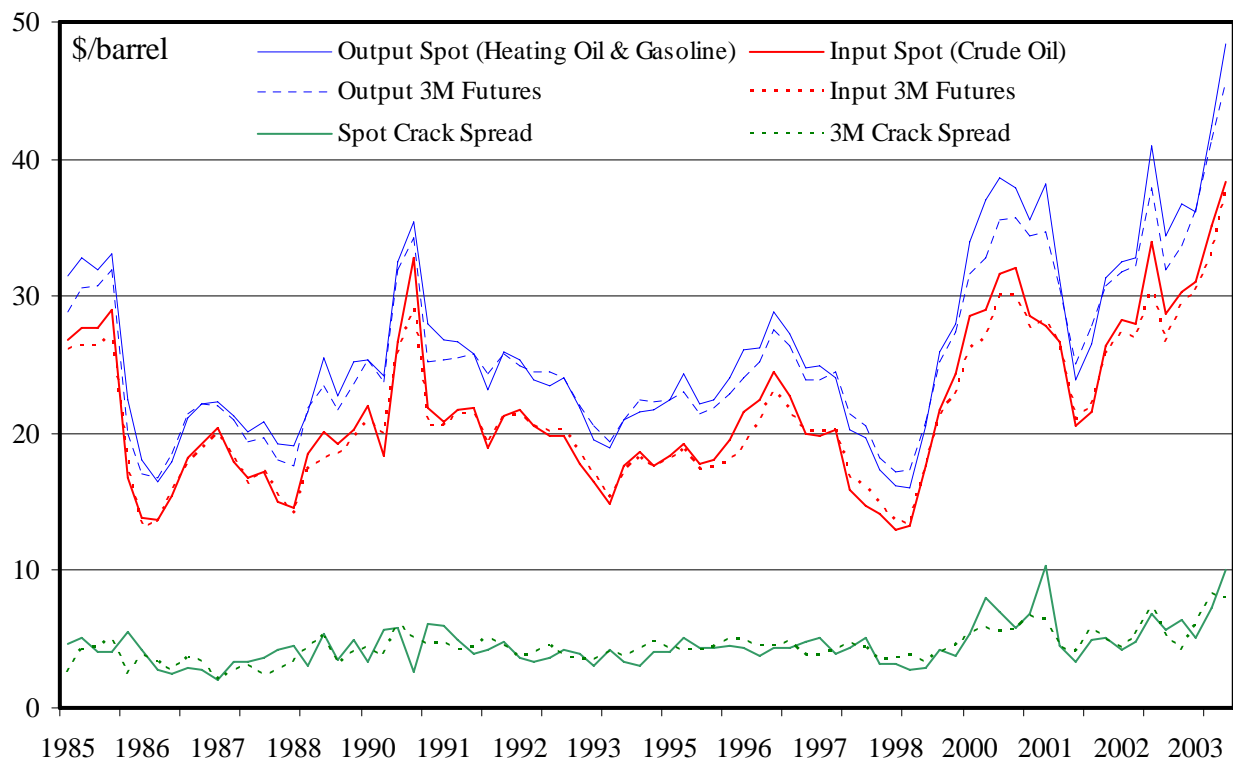


about 2% of firm value under the base approach and 3% once we account for the hedging activity reflected in the data. We validate our approach by regressing firm value on our risk management values and find statistically and economically significant relations that are robust to the inclusion of proxies for alternative risk management techniques such as real optionality, vertical integration, and diversification. We show that the market rewards firms that hedge when hedging creates value and penalizes firms that hedge when hedging destroys value.

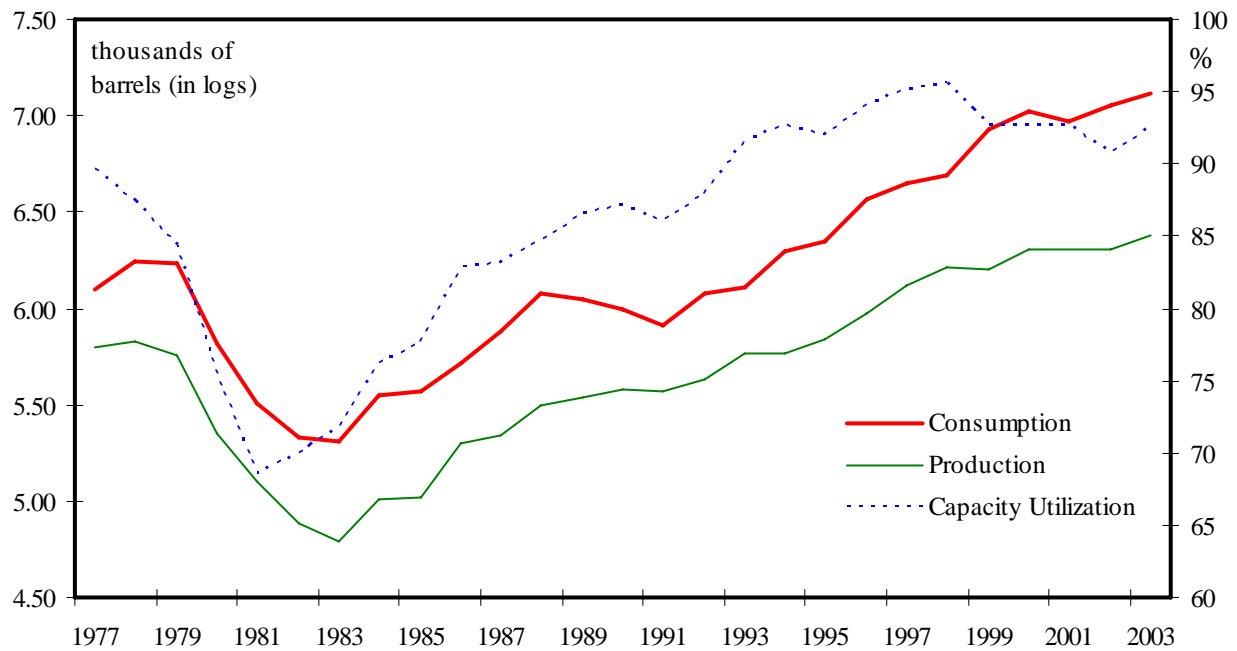
We find a positive relation between our endogenously estimated hedge rates and external measures of derivatives usage, which validates our approach and suggests that hedging activity can be inferred from conventional firm data and either supplement or replace the proprietary, survey, or footnote-based measures of derivatives usage traditionally used in the literature.

Our analysis points to a source of risk management value that has been overlooked. Our approach, which directly relates revenues and costs to output and input prices, avoids many of the pitfalls associated with returns-based analyses of risk factor exposure and provides a tight link between the proposed analytical framework and its estimation. By making explicit how risk factors affect revenues and costs, our approach offers more specific guidance to corporate risk managers than past studies on what risks to hedge to maximize firm value.

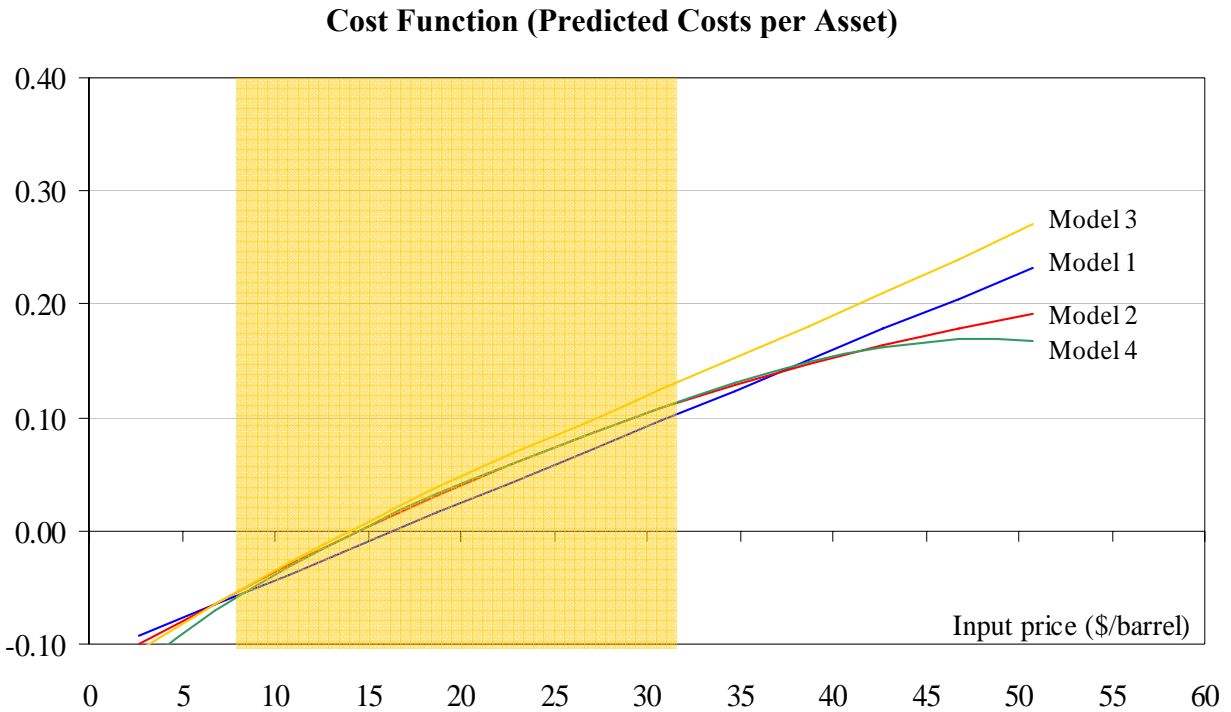
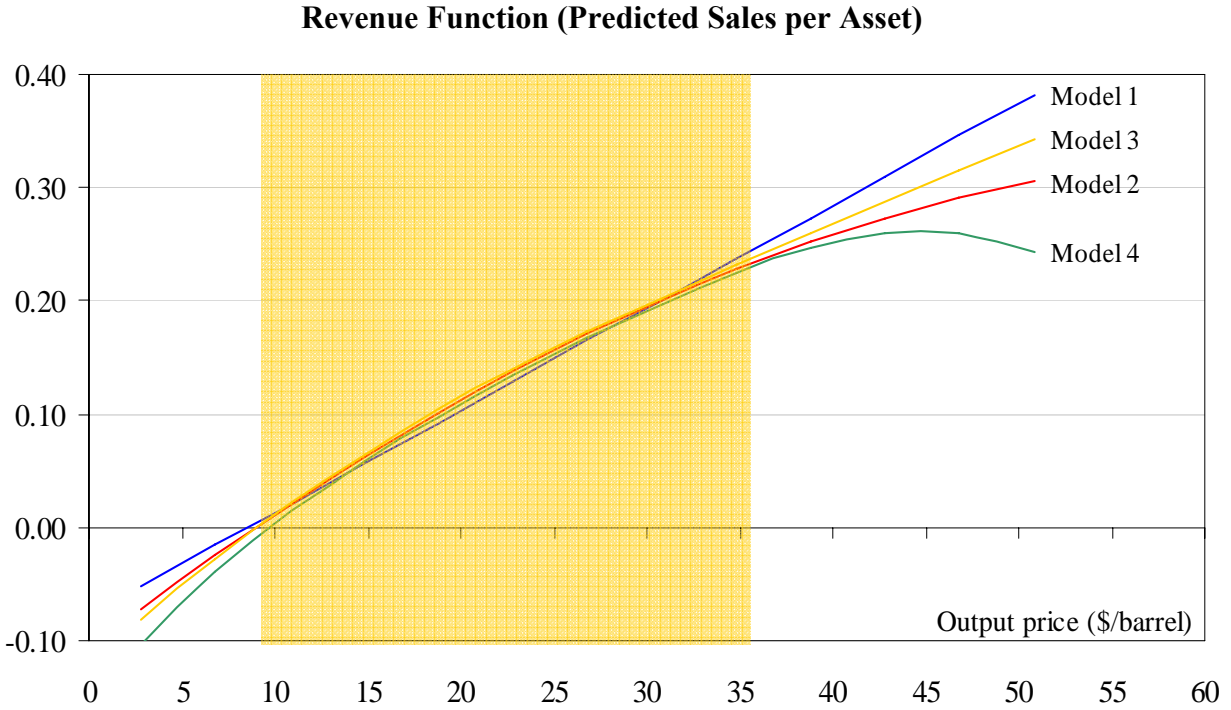
In developing our real-side story for risk management, we have conveniently ignored the usual financial factors associated with corporate hedging (tax convexities, bankruptcy cost, etc.). Although the cost function describing these financial factors is unknown, we find that the market does bid up firms that hedge more as the risk of financial distress rises. This indicates that a trade-off arises between the real-side value of risk management and the usual financial motives. Future research should strive to balance the real and financial factors to form an integrated model of corporate risk management. We leave this avenue as a promising direction for future research.



**Figure 1. Quarterly energy prices from march 1985 to june 2004.** Quarterly energy spot (nearest-month) and three-month futures prices constructed from daily NYMEX-traded futures contracts on light-crude oil, heating oil, and unleaded gasoline from Datastream. We construct quarterly price series from trade-volume weighted averages of daily closing prices. The output price,  $p$ , is one-third of the price of heating oil plus two-thirds of the price of unleaded gasoline. The input price,  $w$ , is the price of light crude oil. The crack spread,  $s$ , is the difference between the output price and the input price.



**Figure 2. Annual oil refining statistics 1977 to 2003.** Annual data on U.S. production and consumption of refined petroleum products and refinery capacity utilization. Based on a refined petroleum product price index from *the Bureau of Labor Statistics*, the estimated price elasticity of demand (consumption) is -10%. *Source: U. S. Department of Energy (Energy Information Administration).*



**Figure 3. Estimated revenue and cost functions.** Estimated revenue functions (predicted sales per asset) and cost functions (predicted costs per asset) as a function of output and input prices using the coefficient estimates reported in Table III. Model 1 is linear, Model 2 is quadratic, Model 3 is cubic, and Model 4 is quartic. The shaded areas correspond to the realized historical spot output and input prices (in 1985 dollars) over the period March 1985 through June 2004.

**Table I**  
**Summary Statistics: Quarterly Energy Prices**

Quarterly energy spot (nearest-month) and three-month futures prices constructed from daily NYMEX-traded futures contracts on light crude oil, heating oil, and unleaded gasoline from Datastream for March 1985 through June 2004. We construct quarterly price series from trade-volume weighted averages of daily closing prices. The output price,  $p$ , is one-third of the price of heating oil plus two-thirds of the price of unleaded gasoline. The input price,  $w$ , is the price of light crude oil. The crack spread,  $s$ , is the difference between the output price and the input price.

	Spot (Nearest-Month) Prices			3-Month Futures Prices		
	Output Price, $p$	Input Price, $w$	Crack Spread, $s$	Output Price, $p$	Input Price, $w$	Crack Spread, $s$
Observations (quarters)	78	78	78	78	78	78
Mean	26.43	21.87	4.56	25.70	21.29	4.41
Median	24.87	20.32	4.32	24.39	20.17	4.33
Standard Deviation	6.80	5.77	1.50	6.05	5.14	1.18
Skewness	0.89	0.73	1.55	0.90	0.76	0.91
Kurtosis	0.42	-0.11	3.82	0.59	0.17	1.79
Minimum	16.03	12.96	2.00	16.73	13.33	2.00
Maximum	48.45	38.41	10.33	45.58	37.58	8.35
Correlations ( $p$ & $w$ )	0.99			0.99		
Correlations (Spot & 3M)	0.99	0.99	0.71	0.99	0.99	0.71
ARMA ( $p,q$ )	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)
1 <sup>st</sup> -order autocorrelation	0.87	0.84	0.51	0.88	0.87	0.66

**Table II****Summary Statistics: Quarterly Firm Operating Data and Derivatives Usage**

Panel A shows summary statistics for a sample of 34 oil refining firms (SIC 2911) from 1985 to 2004. Quarterly *COMPUSTAT* data definitions: sales (item #2), costs (cost of goods sold, item #30, minus depreciation and amortization, item #5), book value of assets (item #44), fixed-capital (net property, plant, and equipment, item #42), working capital (current assets, item #40, minus current liabilities, item #49), Tobin's  $q$  (market-to-book value of assets, where the market value of assets is obtained by replacing the book value of equity by its market value (common shares outstanding, item #61, times the quarter-end share price, item #14)), total debt (short-term debt, item #45, plus long-term debt, item #51), capital expenditures (item #90), dividends (common dividends, item #20, plus preferred dividends, item #24), and research and development (item #4). All normalized variables are divided by the lagged book value of assets. Some of these variables have very poor coverage so we set missing values of control variables (namely, total debt, capital expenditures, dividends, and research and development) to the industry-year mean to mitigate sample attrition. Vertical integration measures a firm's involvement in upstream industries (production and exploration) and downstream industries (chemicals, distribution, and marketing) relative to oil refining. Diversification measures its involvement in industries unrelated to oil refining. Using *COMPUSTAT* business-segment data, we measure vertical integration (diversification) as one minus the Herfindahl of a firm's oil-related (unrelated) business segments. Panel B shows derivatives usage derived from annual reports, classified by hedging level (*rarely, sometimes, and usually*) and type of risks hedged (*operational, financial, and both*).

Panel A. Quarterly Firm Operating Data							
	Mean	Median	St. Dev.	Within Firm Variation	Min	Max	1 <sup>st</sup> Order Auto-correlation
Sales (in million \$)	3,492	1,081	5,330	13%	2.16	35,769	83%
Costs (in million \$)	2,543	768	3,955	16%	-2.24	29,857	81%
Size (in million \$)	12,088	3,539	17,033	3%	20.27	96,916	95%
Operating Cash Flow / Assets	5.40%	5.47%	2.34%	56%	-9.70%	42.06%	40%
Fixed Capital / Assets	48.55%	49.42%	7.66%	40%	17.62%	64.62%	83%
Working Capital / Assets	3.84%	4.27%	11.69%	45%	-167%	25.62%	77%
Tobin's $q$	1.26	1.22	0.40	54%	0.36	3.28	84%
Total Debt / Assets	26.48%	24.37%	13.40%	31%	0.00%	92.46%	85%
Capital Expenditures / Assets	5.13%	4.21%	3.89%	83%	0.00%	27.49%	13%
Dividends / Assets	0.06%	0.01%	0.19%	61%	0.00%	2.01%	86%
R&D / Assets	0.12%	0.12%	0.04%	67%	0.00%	0.28%	91%
Vertical Integration	26.55%	27.95%	20.39%	36%	0.00%	74.58%	89%
Diversification	5.45%	0.00%	11.65%	25%	0.00%	54.89%	87%
Observations (firm-quarters)	2,145						

Panel B. Derivatives Usage				
Risks Hedged	Hedging Level			Total
	Rarely	Sometimes	Usually	
Operational	1	2	5	8
Financial	3	1	-	4
Both	3	4	15	22
Total	7	7	20	34



3 months: <i>HR3, HC3</i>	0.18 <sup>a</sup>	0.18 <sup>a</sup>	0.20 <sup>a</sup>	0.20 <sup>a</sup>	0.12 <sup>a</sup>	0.10 <sup>c</sup>	0.13 <sup>a</sup>	0.11 <sup>b</sup>	0.12 <sup>a</sup>	0.11 <sup>c</sup>	0.11 <sup>b</sup>	0.10 <sup>c</sup>	0.12 <sup>a</sup>	0.11 <sup>b</sup>
	0.03	0.03	0.03	0.03	0.04	0.06	0.04	0.05	0.04	0.05	0.04	0.05	0.04	0.05
6 months: <i>HR6, HC6</i>			0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00		
			n/a	n/a	n/a	0.05	n/a	n/a	n/a	n/a	n/a	n/a		
9 months: <i>HR9, HC9</i>					0.12 <sup>a</sup>	0.12 <sup>b</sup>	0.00	0.04	0.00	0.04	0.00	0.03		
					0.04	0.05	n/a	0.05	n/a	0.06	n/a	0.06		
12 months: <i>HR12, HC12</i>							0.12 <sup>a</sup>	0.10 <sup>a</sup>	0.11 <sup>a</sup>	0.06	0.10 <sup>a</sup>	0.05	0.10 <sup>a</sup>	0.07 <sup>c</sup>
							0.03	0.04	0.03	0.05	0.03	0.05	0.03	0.04
18 months: <i>HR18, HC18</i>									0.00	0.04	0.00	0.00		
									n/a	0.03	n/a	n/a		
24 months: <i>HR24, HC24</i>											0.00	0.06 <sup>a</sup>	0.00	0.06 <sup>a</sup>
											n/a	0.02	n/a	0.02
Degrees of Freedom	2136	2136	2135	2135	2135	2135	2135	2135	2135	2135	2135	2135	2135	2135
Hansen's J-Statistic ( <i>p</i> -val)	149 <sup>a</sup>	0.00	132 <sup>a</sup>	0.00	127 <sup>a</sup>	0.00	126 <sup>a</sup>	0.00	129 <sup>a</sup>	0.00	128 <sup>a</sup>	0.00	121 <sup>a</sup>	0.00
Incremental J-Statistic ( <i>p</i> -val)	-17 <sup>a</sup>	0.00	-5 <sup>c</sup>	0.08	-1	0.61	3	0.22	-1	0.61	-7 <sup>b</sup>	0.03	-3	0.22
Hedge Intensity (Sales different than Costs?)	0.18	0.18	0.20	0.20	0.24	0.24	0.25	0.25	0.23	0.25	0.21	0.24	0.22	0.24
Hedge Maturity (Sales different than Costs?)	0.25	0.25	0.25	0.25	0.50	0.52	0.61	0.63	0.61	0.71	0.61	0.91	0.59	0.91 <sup>b</sup>



**Table IV**  
**The Maturity Structure of Corporate Risk Management: Firm-Level Estimates**

Estimates of the value of risk management, hedge intensity, and hedge maturity computed from firm-level regressions corresponding to Model 8 in Table III. The value of risk management reflects a *conditional* hedging policy whereby the firm hedges if hedging is valuable (*CH*) and does not hedge if exposure is valuable (*CX*). Hedge intensity (*HR* for sales, *HC* for costs) is the sum of the weights the estimation assigns to the lagged futures prices (3, 12, and 24-month maturities) *versus* the spot prices (*I-HR* and *I-HC*). Hedge maturity (*MS* for sales, *MC* for costs) is the time-weighted sum of the coefficients associated with the lagged futures prices divided by hedge intensity (expressed in years). We also present measures of hedge intensity (*HD*, where 0 means no hedging, 1 means some hedging, and 2 means hedging) and hedge maturity (*MT*, in months) obtained from financial-statement footnotes. The last four columns are from MacKay and Moeller (2007), where only the lagged three-month futures prices are used. We present these for comparison with the estimates obtained using the extended model developed in this study (the correlations below these columns give a formal measure of how close the estimates are across the two studies). Estimates for each firm are specific to the subperiod it appears in the sample period (minimum 34 quarters, maximum 75 quarters between March 1985 and June 2004).

Firm Name	Model 8								Footnotes		MacKay & Moeller (2007)			
	<i>N</i>	<i>CH</i>	<i>CX</i>	<i>HR</i>	<i>HC</i>	<i>MS</i>	<i>MC</i>	<i>MT</i>	<i>HD</i>	<i>CH</i>	<i>CX</i>	<i>HR</i>	<i>HC</i>	
AMERADA HESS CORP	75	2.1%	1.6%	61%	67%	1.5	1.7	24	2	1.6%	0.9%	63%	8%	
AMOCO CORP	53	2.7%	2.5%	22%	33%	1.2	1.3	22	2	2.7%	2.4%	23%	33%	
ARABIAN AMERICAN DEVELOPMENT	63	6.4%	5.9%	68%	84%	1.3	1.8	12	1	4.0%	1.4%	51%	18%	
ATLANTIC RICHFIELD CO	59	0.7%	0.0%	0%	16%	0.0	0.3	12	2	0.7%	0.0%	-13%	12%	
BP PLC -ADS	66	4.7%	4.9%	28%	47%	1.2	1.5	72	1	4.3%	3.9%	8%	27%	
CHEVRONTEXACO CORP	75	2.1%	2.1%	61%	70%	1.9	2.0	36	1	0.9%	0.7%	16%	14%	
CONOCOPHILLIPS	75	3.2%	2.7%	34%	41%	1.3	1.3	0	0	2.9%	2.4%	35%	40%	
CROWN CENTRAL PETROL -CL B	61	4.6%	5.4%	30%	29%	1.3	1.8	12	1	4.5%	4.9%	29%	18%	
DIAMOND SHAMROCK INC	41	1.6%	1.8%	24%	5%	1.0	2.0	24	2	1.1%	1.4%	-7%	-16%	
EXXON MOBIL CORP	75	4.6%	4.5%	19%	28%	1.3	1.0	0	0	4.7%	4.5%	20%	24%	
FINA INC -CL A	52	5.2%	5.1%	42%	32%	0.6	0.9	12	2	5.4%	5.1%	40%	28%	
FRONTIER OIL CORP	75	12.9%	12.8%	66%	74%	1.2	1.3	12	2	10.2%	9.7%	73%	72%	
GIANT INDUSTRIES INC	63	2.4%	3.2%	81%	106%	0.7	1.5	24	2	1.7%	0.9%	76%	63%	
HOLLY CORP	73	2.9%	2.8%	5%	6%	0.8	1.1	10	2	2.1%	1.7%	-1%	-1%	
HUNTWAY REFINING CO	37	11.0%	9.3%	100%	132%	0.9	0.9	9	1	5.4%	4.2%	139%	183%	
IMPERIAL OIL LTD	75	3.5%	3.2%	60%	52%	0.8	1.2	0	0	2.8%	2.5%	62%	48%	
MAPCO INC	50	4.7%	5.0%	26%	31%	2.0	2.0	24	1	5.0%	5.0%	16%	17%	
MARATHON OIL CORP	60	5.2%	6.2%	70%	84%	1.6	1.8	12	2	1.9%	1.4%	38%	39%	
MOBIL CORP	57	3.9%	3.7%	26%	29%	1.5	1.3	0	0	4.0%	3.6%	23%	26%	
MURPHY OIL CORP	75	2.6%	2.3%	87%	90%	0.9	1.3	24	2	1.9%	1.4%	101%	101%	
PETRO-CANADA	55	1.8%	2.4%	30%	21%	0.5	0.8	24	2	1.9%	2.1%	43%	19%	
PREMCO REFINING GROUP INC	59	9.5%	13.3%	29%	41%	0.9	0.7	6	2	7.6%	10.4%	21%	35%	
QUAKER STATE CORP	53	2.4%	1.7%	6%	0%	0.3	0.0	0	0	2.8%	1.7%	3%	-9%	

**Table IV (Continued)**  
**The Maturity Structure of Corporate Risk Management: Firm-Level Estimates**

Firm Name	Model 8							Footnotes		MacKay & Moeller (2007)			
	<i>N</i>	<i>CH</i>	<i>CX</i>	<i>HR</i>	<i>HC</i>	<i>MS</i>	<i>MC</i>	<i>MT</i>	<i>HD</i>	<i>CH</i>	<i>CX</i>	<i>HR</i>	<i>HC</i>
ROYAL DUTCH PETROLEUM -ADR	74	2.0%	1.6%	31%	33%	1.0	1.5	12	2	1.9%	1.3%	31%	26%
SHELL CANADA LTD -CL A	55	3.5%	4.9%	59%	74%	1.1	1.3	12	2	2.2%	2.4%	42%	47%
SHELL TRAN&TRADE -ADR	74	2.1%	1.6%	32%	32%	0.8	1.5	12	2	1.9%	1.3%	34%	29%
SUNCOR ENERGY INC	59	1.8%	1.8%	22%	37%	0.3	0.9	12	2	1.8%	1.4%	21%	29%
SUNOCO INC	75	7.7%	7.8%	64%	72%	1.1	1.2	12	1	6.2%	6.0%	79%	77%
TESORO PETROLEUM CORP	74	5.8%	5.7%	29%	31%	0.9	1.0	12	0	4.3%	3.6%	16%	16%
TEXACO INC	64	5.4%	5.7%	38%	43%	1.8	1.9	12	0	4.7%	4.6%	29%	24%
TOSCO CORP	62	16.5%	17.1%	41%	36%	0.9	0.7	12	2	15.2%	15.3%	33%	27%
ULTRAMAR DIAMOND SHAMROCK	41	12.5%	15.7%	105%	107%	1.0	1.2	24	2	6.7%	7.0%	120%	95%
USX CORP-CONSOLIDATED	65	6.8%	6.9%	39%	40%	1.8	1.8	24	2	5.8%	5.8%	27%	24%
VALERO ENERGY CORP	75	13.5%	13.8%	87%	82%	1.1	1.4	12	2	9.7%	10.2%	121%	88%
Average	63	5.2%	5.4%	45%	50 %	1.1	1.3	15.5	1.4	4.1%	3.9%	42%	38%
Median	63	4.2%	4.7%	36%	41%	1.0	1.3	12.0	2.0	3.4%	2.5%	32%	27%
Standard deviation	11	3.9%	4.4%	27%	32%	0.5	0.5	13.2	0.8	3.1%	3.4%	37%	38%
Minimum	37	0.7%	0.0%	0%	0%	0.0	0.0	0.0	0.0	0.7%	0.0%	-13%	-16%
Maximum	75	16.5%	17.1%	105%	132%	2.0	2.0	72.0	2.0	15.2%	15.3%	139%	183%
Correlation Matrix (Spearman \ Pearson)	<i>CH</i>	1.00	0.98	0.48	0.42	0.12	-0.10	-0.09	0.11				
Correlation Matrix (Spearman \ Pearson)	<i>CX</i>	0.97	1.00	0.47	0.40	0.12	-0.09	-0.06	0.16	93%	91%	91%	81%
Correlation Matrix (Spearman \ Pearson)	<i>HR</i>	0.48	0.48	1.00	0.95	0.20	0.27	0.12	0.19				
Correlation Matrix (Spearman \ Pearson)	<i>HC</i>	0.45	0.45	0.89	1.00	0.19	0.23	0.16	0.16				
Correlation Matrix (Spearman \ Pearson)	<i>MS</i>	0.32	0.25	0.19	0.23	1.00	0.79	0.17	-0.24				
Correlation Matrix (Spearman \ Pearson)	<i>MC</i>	-0.04	-0.07	0.24	0.20	0.72	1.00	0.35	0.05				
Correlation Matrix (Spearman \ Pearson)	<i>MT</i>	-0.19	-0.15	0.24	0.24	0.14	0.42	1.00	0.36				
Correlation Matrix (Spearman \ Pearson)	<i>HD</i>	-0.14	-0.07	0.17	0.14	-0.31	-0.06	0.54	1.00				

**Table V**  
**Determinants of Hedge Maturity, Hedge Intensity, and Firm Value**

Fama-MacBeth regressions of hedge maturity, hedge intensity, and firm value on their determinants and control variables. Reported are the average standardized regression coefficients and adjusted R-squared of 75 quarterly cross-sectional regressions estimated from the third quarter of 1985 through the first quarter of 2004 (75 quarters). The firm-level values for hedge maturity and hedge intensity (for sales and costs) are reported in Table IV. We use Tobin's  $q$  (measured as the end-of-period market-to-book value of assets) as a proxy for firm value. Altman's Z score is computed using the weights and variable (leverage, etc) published in Altman (1968). The standardized regression coefficients reported show how a one-standard deviation variation in each regressor affects the dependent variable. All other control variables are defined in Table II. We use the Newey-West (1987) procedure to correct for heteroskedasticity and first-order autocorrelation. Asymptotic standard errors in parentheses. a, b, c denote statistical significance at the 1%, 5%, and 10% confidence levels.

	Hedge Maturity				Hedge Intensity				Firm Value					
	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Q	Q		
Hedge Maturity													-0.14 <sup>a</sup>	-0.18 <sup>a</sup>
													(0.03)	(0.02)
Altman's Z-score	0.21 <sup>a</sup>	0.21 <sup>a</sup>	0.19 <sup>a</sup>	0.21 <sup>a</sup>	0.21 <sup>a</sup>	0.22 <sup>a</sup>	0.06 <sup>a</sup>	0.07 <sup>a</sup>	0.05 <sup>a</sup>	0.04 <sup>b</sup>	0.06 <sup>a</sup>	0.06 <sup>b</sup>	0.09 <sup>a</sup>	0.08 <sup>b</sup>
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
Altman's Z-score Squared			-0.06 <sup>a</sup>	-0.04 <sup>a</sup>					-0.06 <sup>a</sup>	-0.08 <sup>a</sup>				
			(0.01)	(0.01)					(0.01)	(0.01)				
Leverage: Total Debt / Assets	0.12 <sup>a</sup>	0.04 <sup>b</sup>	0.12 <sup>a</sup>	0.04 <sup>b</sup>	0.14 <sup>a</sup>	0.06 <sup>a</sup>	0.14 <sup>a</sup>	0.23 <sup>a</sup>	0.12 <sup>a</sup>	0.21 <sup>a</sup>	0.13 <sup>a</sup>	0.22 <sup>a</sup>	0.04 <sup>c</sup>	0.04 <sup>b</sup>
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Leverage Squared					-0.04 <sup>a</sup>	-0.06 <sup>a</sup>					0.01	0.02 <sup>c</sup>		
					(0.01)	(0.01)					(0.01)	(0.01)		
Short-term Debt / Assets	-0.25 <sup>a</sup>	-0.15 <sup>a</sup>	-0.24 <sup>a</sup>	-0.15 <sup>a</sup>	-0.24 <sup>a</sup>	-0.13 <sup>a</sup>	-0.25 <sup>a</sup>	-0.18 <sup>a</sup>	-0.24 <sup>a</sup>	-0.17 <sup>a</sup>	-0.25 <sup>a</sup>	-0.19 <sup>a</sup>	-0.10 <sup>a</sup>	-0.12 <sup>a</sup>
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)
Net Working Capital / Assets	-0.52 <sup>a</sup>	-0.45 <sup>a</sup>	-0.52 <sup>a</sup>	-0.45 <sup>a</sup>	-0.50 <sup>a</sup>	-0.43 <sup>a</sup>	-0.40 <sup>a</sup>	-0.46 <sup>a</sup>	-0.40 <sup>a</sup>	-0.46 <sup>a</sup>	-0.39 <sup>a</sup>	-0.46 <sup>a</sup>	-0.43 <sup>a</sup>	-0.44 <sup>a</sup>
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Capital Expenditures / Assets	-0.03 <sup>c</sup>	0.01	-0.04 <sup>c</sup>	0.00	-0.04 <sup>b</sup>	-0.01	0.03	0.05 <sup>b</sup>	0.02	0.04 <sup>b</sup>	0.02	0.04 <sup>b</sup>	0.06 <sup>b</sup>	0.08 <sup>a</sup>
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Cash Flow-Volatility / Assets	-0.17 <sup>a</sup>	-0.14 <sup>a</sup>	-0.17 <sup>a</sup>	-0.14 <sup>a</sup>	-0.17 <sup>a</sup>	-0.13 <sup>a</sup>	-0.10 <sup>a</sup>	-0.02	-0.09 <sup>a</sup>	-0.02	-0.10 <sup>a</sup>	-0.03 <sup>c</sup>	0.03 <sup>b</sup>	0.04 <sup>b</sup>
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Diversification	0.17 <sup>a</sup>	0.10 <sup>a</sup>	0.17 <sup>a</sup>	0.10 <sup>a</sup>	0.16 <sup>a</sup>	0.10 <sup>a</sup>	-0.13 <sup>a</sup>	-0.12 <sup>a</sup>	-0.13 <sup>a</sup>	-0.13 <sup>a</sup>	-0.13 <sup>a</sup>	-0.12 <sup>a</sup>	-0.04 <sup>b</sup>	-0.04 <sup>b</sup>
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Operating Cash Flow / Assets	-0.31 <sup>a</sup>	-0.10 <sup>a</sup>	-0.32 <sup>a</sup>	-0.09 <sup>a</sup>	-0.30 <sup>a</sup>	-0.07 <sup>b</sup>	-0.05 <sup>b</sup>	0.08 <sup>a</sup>	-0.06 <sup>b</sup>	0.07 <sup>a</sup>	-0.05 <sup>b</sup>	0.07 <sup>a</sup>	0.17 <sup>a</sup>	0.18 <sup>a</sup>
	(0.01)	(0.04)	(0.01)	(0.04)	(0.02)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Size (log of Assets)	0.44 <sup>a</sup>	0.18 <sup>a</sup>	0.43 <sup>a</sup>	0.16 <sup>a</sup>	0.43 <sup>a</sup>	0.16 <sup>a</sup>	-0.24 <sup>a</sup>	-0.19 <sup>a</sup>	-0.25 <sup>a</sup>	-0.21 <sup>a</sup>	-0.23 <sup>a</sup>	-0.18 <sup>a</sup>	0.21 <sup>a</sup>	0.18 <sup>a</sup>
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.05)
Average Adjusted R-squared	0.21 <sup>a</sup>	0.06 <sup>a</sup>	0.18 <sup>a</sup>	0.02	0.18 <sup>a</sup>	0.03 <sup>c</sup>	-0.01	0.10 <sup>a</sup>	-0.03 <sup>b</sup>	0.08 <sup>a</sup>	-0.05 <sup>a</sup>	0.07 <sup>a</sup>	0.26 <sup>a</sup>	0.27 <sup>a</sup>

(0.01) (0.01) (0.01) (0.02) (0.01) (0.02) (0.02) (0.02) (0.02) (0.02) (0.02) (0.02) (0.02) (0.03) (0.03)

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