The Hedging Footprint

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A large literature studies the motives for risk management and the extent of hedging activity.[1] To date, empirical work relies on snapshots of derivatives positions disclosed in financial-statement footnotes, which offer at best a noisy picture of dynamic hedging patterns and firm hedge policy. As a result, the literature reports mixed findings on the drivers of corporate risk management and its contribution to firm value. We develop an alternative approach that allows us to estimate both the intensity and the maturity of hedging activity from financial accounts rather than footnotes. Thus, we offer a novel empirical method and new insights on the demand for corporate hedging.

Our method capitalizes on the accounting treatment of derivatives, where gains and losses on derivatives used to hedge cash flows are deferred until the underlying transaction is recognized. Hedging activity recorded in this way ("hedge accounting") links a firm's current sales and costs to the hedge positions it initiated in the past: its hedging footprint. We first calibrate our method on a sample of oil refiners by regressing their quarterly sales and costs on lagged energy futures-price changes from 1985 to 2018. We find that these footprint hedging estimates align well with hedging activity reported in financial-statement footnotes. We further validate our method by replicating past empirical associations between hedging activity and firm characteristics, and add to the literature by relating corporate hedging to the state and performance of the futures markets.

Although we test-run our method on the oil-refining industry, where firms face commodity-price risk both on the product-market (heating-oil and gasoline) and the factor-market (crude oil), the method is broadly applicable: Any industry where revenues, costs, or both revenues *and* costs depend on traded risk factors – exchange rates, interest rates, credit spreads, equity prices, etc. – can be studied using this method. For instance, we also apply our method to analyze a stratified random sample of manufacturing firms' exposure to the U.S. dollar index and corroborate its ability to emulate hedging activity reported in these firms' financial-statement footnotes.

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[1] Smith and Stulz (1985) show that hedging can add value by smoothing cash flows when firms face imperfections that cause nonlinear payoffs (e.g., progressive taxation, bankruptcy costs, managerial risk aversion). Their central idea – that nonlinearities justify corporate hedging – was extended to imperfections such as information asymmetry (DeMarzo and Duffie, 1991) and costly external finance (Froot *et al*., 1993, Campello *et al*., 2011). MacKay and Moeller (2007) invoke real-side factors to derive and estimate the value of risk management. See Bessler *et al*. (2018), Bodnar *et al*. (2018), Carter *et al*. (2017), and Geyer-Klingeberg *et al*. (2018) for recent literature reviews.

Before turning to our results, let us illustrate our proposed method with a simple example. Suppose a firm habitually hedges half its sales-price exposure one quarter ahead of delivery.[2] The sales it reports every quarter will reflect two prices: the recent spot price (the unhedged portion) and the futures prices it secured one quarter earlier (the hedged portion). Our method lets the data speak by having the estimation endogenously assign weights ("hedge rates") to the spot price and to the lagged futures prices we consider, i.e., 3, 6, 9, 12, 15, 18, 21, and 24 months.[3] Thus, our method would assign weights of 50% to the current quarter's spot price and 50% to the 3-month futures price observed one quarter earlier, with all other lagged futures prices receiving weights of zero.[4] The resulting decomposition informs us both about the intensity of corporate hedging (the sum of the hedge rates assigned to each of the lagged futures prices) and about the hedging maturity structure (the time-weighted sum of the hedge rates normalized by hedge intensity).[5]

Our results can be summarized as follows. First, under our base specification, which uses up to eight quarters of lagged futures prices (the "discrete model"), the sample median oil refiner hedges about 30% of its sales exposure to refined-product prices and 22% of its costs exposure to the price of crude oil. We then formulate a more parsimonious specification (the "decay model") to avoid multi-collinearity by reducing the number of coefficients to two shape parameters, which also allows us to analyze hedging determinants through interaction terms. Under this specification, the median firm hedges 34% and 22% of output-price and input-price sales and costs exposures.

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[2] Reported income, say for a given quarter, reflects transactions recognized for that period. For instance, Appendix A shows an excerpt from the 2005 10-K for Amerada Hess, which specifies that revenue is recognized when "title passes to the customer". We understand this to happen at the time of delivery and invoicing.

[3] Just to be clear: "spot price" means the average price for nearest-month contracts observed in the current quarter. The "lagged 3-month futures price" means the average price for 3-month contracts observed one quarter prior; the "lagged 6-month futures price" means the average price for 6-month contracts observed two quarters prior, etc. The longest maturity we consider is 24 months, so the "lagged 24-month futures price" means the average price for 24-month contracts observed eight quarters prior to the current quarter. Our price windows map to fiscal-year quarters.

[4] In reality, firms pursue much more complex, time-varying hedging strategies, which introduces estimation error. Our method also assumes that a firm's use of derivatives qualifies for so-called "cash-flow hedge accounting" and that its risk-management program reduces to its use of futures/forward contracts. More on these questions later.

[5] Our method is analogous to "style analysis" (Sharpe, 1988), where risk factors are replaced by lagged futures prices.

Second, we find that the median sample oil refiner hedges well beyond the nearest quarter, hedging slightly further out for sales (11 months) than costs (10 months). Hedge intensity declines nonlinearly with maturity, as indicated by median half-lives of about 7 months for sales and 6 months for costs. This is further evidenced by our finding that energy futures prices beyond 12 months tend to load weakly or statistically insignificantly in the discrete model.[6]

While our method hinges on hedge-accounting principles and yields reasonable estimates, we validate it by relating our footprint estimates to the hedging activity reported in the footnotes to refiners' financial statements. These show a mean hedge intensity of 26% and hedge maturity of 5 months, slightly below our footprint estimates.[7] But there are big methodological differences between our footprint estimates and footnote measures, so such comparisons are only suggestive. As a more reliable concurrence test, we use the decay model to relate bootstrapped firm-cluster robust *footprint* hedging estimates to the *footnote* hedging measures – essentially, non-parametric measures of association. We find economically important effects, attesting to our method's ability to capture an important share of firms' reported hedging activity. For instance, footprint-hedge intensity for sales (costs) increases 20 (33) percentiles as footnote-hedge intensity varies over the sample interquartile range (25th to 75th percentiles).

As a second approach to validating our method, we revisit past empirical tests between hedging activity and firm characteristics. For instance, we corroborate the relations documented in Rampini *et al*. (2014) in that hedge intensity increases in Altman's Z score but decreases in collateral. Some of our findings are more nuanced: We confirm Purnanandam (2008)'s finding that hedge intensity increases in financial leverage. We document a positive relation between

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[6] Interestingly, magnetism appears in that 18- and 24-month (15- and 21-month) maturities load (non)significantly. This might also betray collinearity in the discrete multi-maturity model, which the decay model sidesteps by fitting a *beta*-function decay model across the trail of futures price changes, analogous to a distributed-lagged approach.

[7] These are lower bounds in that missing observations are set to zero. If we exclude missing observations, we find a mean hedge intensity (maturity) of 34% (10.8 months), slightly above our footprint hedging estimates. By way of cursory external validity, both our footprint estimates and the footnote measures are in the vicinity of the percentage of assets hedged reported by Graham and Rogers (2002) and Campello *et al*. (2011) for broader sets of industries.

hedging and CAPEX, as predicted by DeMarzo and Duffie (1991) and Froot *et al*. (1993). But sales and costs hedging decreases in R&D.

Although our reported associations are economically important and statistically significant, they hinge on partialed-variable sorts, where each sorting variable is regressed on the other lagged firm characteristics, and thus do not fully dampen endogeneity bias. So, like most of the referenced studies, these tests of association do not robustly isolate root causes nor the direction of causation. The adoption of FAS 133 in 1998, which more narrowly defined the scope of hedge accounting, does offer another validating clue in that hedging intensity and maturity increased *post* FAS 133. At the firm level, we follow Graham and Rogers (2002) and Campello *et al*. (2011) by estimating firm-year-quarter tax convexity and relating this plausibly-exogenous instrument to our measures.

To illustrate other potential uses of our method, we study how the demand for corporate hedging responds to exogenous factors such as the performance and state of the futures markets. First, we find that corporate hedging depends on <u>realized</u> energy prices, consistent with selective, retrospective decisions where firms condition their hedging activity on simple trend extrapolations. For instance, sales (costs) hedging increases (decreases) when prices are historically high (low), suggesting that refiners seek to lock in (unlock) perceived high (low) prices, i.e., market timing. Sales and costs hedging is inversely related to signed price momentum (past year's price change), again consistent with selective hedging. Second, corporate hedging activity adjusts to prevailing futures-market conditions, consistent with rational, prospective decisions. For instance, hedge intensity, maturity, and half-life vary with the slope, risk, depth, and liquidity of the futures curve.

Two additional variations on the base method further illustrate its versatility and generality. First, our hedging estimates are more sensitive to lagged futures-price *gains* than *loses*, consistent with option-like hedge positions. Thus, our method can detect both *nonlinear* and *linear* hedging strategies. Second, given high correlations among prices along the futures curve, we repeat our analysis using lagged *spot* prices instead of *futures* prices and obtain qualitatively similar results.

Thus, our method can be deployed even without futures data, such as when only spot prices exist or when hedging is through informal markets (OTC or supply contracts – see Almeida *et al*., 2017).

This paper makes several contributions. First, we develop a method to backward-engineer hedging activity based on accounting principles and standard data sources rather than footnotes, which is an important methodological innovation. Aside from sidestepping tedious and unreliable footnote searches, our method focuses on cash-flow hedging rather than generic derivatives usage, and opens up new avenues for empirical corporate risk-management research. Our calibration for oil refining, and external validation for a cross-section of manufacturing firms, produce reasonable results and shows great promise in investigating other industries and risk factors in future work. Second, we revisit firm-level determinants of corporate hedging. Although we corroborate past empirical associations, we also qualify a number of them, which both further validates our method and demonstrates its ability to identify new, more subtle relations. Finally, we find that corporate hedging activity adjusts to performance trends and prevailing conditions in the futures markets and document both retrospective (selective) hedging and prospective (rational) hedging practices.

The rest of this paper is organized as follows. Section I motivates the study and develops the method. Section II describes the data. Section III presents summary statistics on energy prices and sample-firm characteristics. Section IV reports discrete and decay versions of our model and corresponding footprint-estimates of corporate hedge activity. Section V presents summary statistics on reported footnote hedging measures. Section VI relates our footprint hedging estimates to reported footnote hedging measures. Section VII presents associations between corporate hedging, firm characteristics, and the futures market. Section VI concludes.

I. Motivation and Methodology

Obtaining precise and accurate data on corporate hedging activity has long eluded financial economists. Researchers generally have resorted to one of three approaches:

1) Estimate an extended market model that includes the return on the risk factor of interest (e.g., Flannery and James, 1984, for interest rates, Jorion, 1990, for foreign exchange rates, Strong, 1991, for oil prices, and Tufano, 1998, for gold prices). Although this approach might interest diversified investors facing priced risk factors, it holds little appeal for corporate finance in that it blurs fundamental risk exposures and the actions taken by corporate risk managers to adjust these exposures (hedge, retain, or speculate) – i.e., stock returns reflect *net* risk exposures.

2) Collect detailed data for a small set of firms, usually for a single industry such as gold mining, through surveys or proprietary data (e.g., Tufano, 1996, 1998, Haushalter, 2000, Brown, 2001, Haushalter *et al.*, 2002, Adam and Fernando, 2006, Carter *et al.*, 2006, Brown *et al.*, 2006, and Jin and Jorion, 2006). But this approach is labor-intensive and the results may not generalize. This approach may be free of estimation error but is prone to judgement and measurement error.

3) Comb through the financial-statement footnotes of a large sample of non-financial firms, a procedure that often yields no more than a "hedge" or "no hedge" dummy variable (e.g., Nance *et al.*, 1993, Mian, 1996, Geczy *et al.*, 1997, Guay, 1999, Allayannis and Weston, 2001, Hentschel and Kothari, 2001). However, firms are now required to report greater detail on their derivatives positions, which some authors have exploited to produce continuous measures of hedging (e.g., Graham and Rogers, 2002, Guay and Kothari, 2003, Bartram *et al.*, 2009, Campello *et al.*, 2011, Hoberg and Moon, 2017, Almeida *et al.*, 2017, Jankensgård, 2017, Hecht and Lampenius, 2018).

Oddly, even with more stringent disclosure rules in recent years, our assessment is that *actual* disclosures remain opaque: Firms may discuss derivatives usage qualitatively (vs quantitatively); reported numbers are often notional amounts rather than position values; and no distinction is made between derivatives used to hedge rather than speculate. Reviewing financial-statement footnotes, we find that transparency has not necessarily improved. For instance, in many cases, *pre*-FAS 133 (1998) hedging disclosures are *more* informative than *post*-FAS 133. A strand of the accounting literature argues that FAS 133 made hedging less attractive and documents reduced usage of "economic hedges" *post*-FAS 133 (e.g., Kalotay and Abreo, 2001, Zhang, 2009, Panaretou *et al*., 2013), consistent with the disclosure-hedging trade-off proposed by DeMarzo and Duffie (1995).

We calibrate our method on a sample of 56 U.S.-listed oil refiners from 1985 to 2018. We choose oil refining because futures contracts are traded both on the output-side (refined-product) and on the input-side (crude oil), which allows for an integrated analysis of hedging activity. We use quarterly financial-account data from COMPUSTAT and daily closing prices from Datastream for NYMEX energy futures contracts, which we volume-weight to form quarterly price time series. The refined-product (output) price "crack weights" heating-oil and gasoline prices (1/3 and 2/3).

Because derivatives positions that do not qualify (or not designated) as "cash-flow hedges" are subject to fair-value accounting, our method isolates *hedging* activity from other derivatives uses, such as speculation and selective hedging (e.g., Adam and Fernando, 2006, Brown *et al*., 2006, Chernenko *et al*., 2011, and Hecht, 2017). But FASB is conservative in defining qualified hedges, and firms may elect not to subject qualified hedges to cash-flow hedge accounting, which means our method tends to understate true corporate hedging activity. We see in this more of a strength than a shortcoming: By focusing only on cash-flow hedges, our method offers a tighter link to theory because most extant models of hedging set out to explain why firms would rationally seek to stabilize cash flow, not why they might engage in fair-value hedges or speculative hedges.

A. Description of the Proposed Method

Our proposed method is simple to implement and uses nothing but standard financial-accounting data, such as those found in COMPUSTAT, and plausibly-exogenous market-traded derivatives prices, such as those found on Thomson Reuters' DATASTREAM. The main insight is that the accounting treatment of derivatives used to hedge cash flows ("cash-flow hedges") leaves a traceable footprint. We first explain how cash-flow hedge accounting works then how it leads to a straightforward way to detect corporate hedging activity using readily-available data.

Our approach rests on two features of cash-flow hedge accounting.[8] First, gains and losses on derivatives designated as cash-flow hedges are reflected in sales or costs rather than "other comprehensive income", where non-designated derivatives gains and losses are reported.[9] Second, such designated gains and losses only pass through the income statement in the period when the underlying risky transaction is recognized (until then, unrealized gains and losses are carried on the balance sheet under "other current assets" and "accumulated other comprehensive income").

As a consequence of cash-flow hedge accounting, a hedger's reported sales and costs are an amalgam of past hedging decisions: Products (supplies) delivered (received) this quarter might have been hedged one, two, or many quarters ago – or not at all, if a firm does not hedge or does not use hedge accounting. Thus, we can decompose sales and costs as follows (in months):

$$Sales = b_p p_0 + \beta_1 \dot{p}_{L1} + \beta_2 \dot{p}_{L2} + \cdots + \beta_7 \dot{p}_{L7} + \beta_8 \dot{p}_{L8} \tag{1}$$

$$Costs = b_w w_0 + \theta_1 \dot{w}_{L1} + \theta_2 \dot{w}_{L2} + \cdots + \theta_7 \dot{w}_{L7} + \theta_8 \dot{w}_{L8}, \tag{2}$$

where p_0 and w_0 denote output and input spot prices, and $\dot{p}_{L\tau}$ and $\dot{w}_{L\tau}$ are τ-lagged futures-price difference operators. For instance, $\dot{p}_{L1}$ is the current-quarter's spot price minus the 3-month futures price observed one quarter ago; $\dot{p}_{L2}$ is the 3-month futures price observed one quarter ago minus the 6-month futures price observed two quarters ago, and $\dot{p}_{L8}$ is the 21-month futures price observed seven quarters ago minus the 24-month futures price observed eights quarters ago. In other words, $\dot{p}_{L\tau}$ and $\dot{w}_{L\tau}$ represent mark-to-market operators.

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[8] The development we provide here follows Kieso *et al*., 2019, a widely-used financial-accounting textbook. The related FASB and IASB directives are FAS 133 (1998), FAS 157 (2006), FAS 161 (2008), and IFRS 9 (2018).

[9] Derivatives positions used to hedge balance-sheet accounts, rather than sales or costs, are called fair-value hedges (e.g., interest rates swaps used to fix borrowing costs). Fair-value hedges and all other uses of derivatives that do not qualify as cash-flow hedges follow normal GAAP (e.g., hedges meant to protect a competitive position, time the market, or speculate). Unrealized gains or losses on such non-qualifying derivatives positions are carried on the balance sheet and reported in the statement of comprehensive income (see Amerada-Hess in Appendix A).

Thus, $\dot{p}_{L1}$, $\dot{p}_{L2}$, …, $\dot{p}_{L8}$ form the set of adjacent (non-overlapping) price gains or losses on hedge positions a firm might have initiated in each of the eight lagged quarters we track. Aside from cleanly stratifying the hedging footprint, the adjacency of the price differences is important econometrically as it avoids the multicollinearity and variance-dampening issues often associated with overlapping price series. These lagged futures-price *differences* should not be confused with concurrent quarterly price *changes*, say as the futures curve evolves from one period to the next. Put differently, futures-price *differences* are changes both along the futures curve *and* over time, i.e., how the value of a given contract evolves as its maturity shortens with the passage of time.

Finally, $\beta_1, \beta_2, \ldots \beta_8$ and $\theta_1, \theta_2, \ldots \theta_8$ are the hedge rates associated with the τ-lagged futures-price differences (for τ = 1, 2, …, 8) *versus* spot (nearest-month) prices (b_p and b_w).[10]

Estimated hedge rates can be combined to measure hedge intensity, maturity, and half-life:

Sales Hedge Intensity: $$HI_S = \sum_\tau \hat{\beta}_\tau = \hat{\beta}_1 + \hat{\beta}_2 + \cdots + \hat{\beta}_8 \quad (3)$$

Costs Hedge Intensity: $$HI_C = \sum_\tau \hat{\theta}_\tau = \hat{\theta}_1 + \hat{\theta}_2 + \cdots + \hat{\theta}_8 \quad (4)$$

We measure a firm's estimated hedge maturity as the time-weighted sum of the hedge rates (similar to duration under a discount rate of zero) normalized by hedge intensity:

Sales Hedge Maturity: $$HM_S = \left[\sum_\tau \tau\hat{\beta}_\tau\right] \div HI_S \quad (5)$$

Costs Hedge Maturity: $$HM_C = \left[\sum_\tau \tau\hat{\theta}_\tau\right] \div HI_C \quad (6)$$

Hedge half-life summarizes the shape of the hedging program over its time horizon: It is the time needed (in years) for the hedge rates to sum to half the hedge intensity:

Sales Hedge Half-life: $$HL_S = \hat{\phi} \ni \sum_\tau^\phi \hat{\beta}_t = \tfrac{1}{2} HI_S \quad (7)$$

Costs Hedge Half-life: $$HL_C = \hat{\varphi} \ni \sum_\tau^\varphi \hat{\theta}_t = \tfrac{1}{2} HI_C \quad (8)$$

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[10] Because all firm-level variables and prices are logged, $\beta_1, \beta_2, \ldots \beta_8$ and $\theta_1, \theta_2, \ldots \theta_8$ are actually price elasticities.

Bringing together the hedge intensities and hedge maturities for sales and costs allows us to analyze both sides of the business model in ways that have not been examined before: Is the hedge intensity the same for sales and costs? If it is different, why? Is the hedge maturity the same for sales and costs? If it is different, why? What is the scope for natural hedging (the degree to which output and input prices correlate)? Etc. In other words, our proposed method allows us to explore several related dimensions of hedging policy and determinants of corporate-risk management.

B. Empirical Specification and Econometrics

We use nonlinear Generalized Method-of-Moments (GMM) to estimate the following simultaneous-equation specification, which contains equations for sales, costs, and the derived output-supply and input-demand equations:

$$Sales_{ti} = a_p + b_p p_{t0} + c_p p_{t0}^2 + \beta_1 \dot{p}_{tL1} + \ldots + \beta_8 \dot{p}_{tL8} + d_p q_{ti} + controls_{ti} + \tilde{\mu}_{sti} \tag{9}$$

$$Costs_{ti} = a_w + b_w w_{t0} + c_w w_{t0}^2 + \theta_1 \dot{w}_{tL1} + \ldots + \theta_8 \dot{w}_{tL8} + d_w y_{ti} + controls_{ti} + \tilde{\mu}_{cti} \tag{10}$$

$$y_{ti} = b_p + 2c_p p_{t0} + \tilde{\mu}_{yti} \tag{11}$$

$$q_{ti} = b_w + 2c_w w_{t0} + \tilde{\mu}_{qti}, \tag{12}$$

where p_{t0} and w_{t0} are quarter-t averages of daily output and input nearest-month prices, y_{ti} is $Sales_{ti} \div p_{t0}$, q_{ti} is $Costs_{ti} \div w_{t0}$, $\tilde{\mu}_{.ti}$ are the error terms associated with each equation, $\dot{p}_{tL\tau}$ and $\dot{w}_{tL\tau}$ are the τ-lag futures-price differences at quarter t, $\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_8$ and $\hat{\theta}_1, \hat{\theta}_2, \ldots, \hat{\theta}_8$ are the estimated hedge rates for sales and costs to be used in the hedging measures equations (3-8).

As in MacKay and Moeller (2007), we include squared values of the prices to capture the curvature of the sales and cost functions and to estimate the value of corporate risk management. The number of contracts we examine (from 3 to 24 months, in quarterly increments) reflects the availability of contracts over the empirical time period, which varies from as few as ten months (1980 to 1985) to as many as seven years recently.[11] The control variables are the change in

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[11] In order to retain the entire empirical sample period (1985 through 2018), we use adjacent contracts to interpolate or extrapolate prices for the 12-month, 18-month, and 24-month contracts when these are unavailable.

inventories, and both the level and change in net property, plant, and equipment (Net PPE). We include quarter dummies (fourth fiscal quarter omitted) to adjust for seasonality in real activity or accounting. Sales, costs, output, and input are normalized by Net PPE. Firm-level balance sheet variables are lagged once and normalized by assets or Net PPE. Finally, all variables are logged.

C. Empirical Specification: Time Decay Models

The discrete model presented above raises some econometric issues. First, the lagged price differences, although non-overlapping, are correlated enough empirically to produce collinearity. This is apparent in Table III.B, where maturities that load significantly on a standalone basis (Table III.A) may fail to load significantly when other maturities are included. This issue mainly afflicts maturities over 12 months, which we are certainly interested in detecting. Second, the set of maturities to keep or drop to avoid collinearity is arbitrary, which is also problematic.

We therefore propose a more parsimonious specification, a time decay model, analogous to a distributed-lags model, where rather than compete for econometric bandwidth, the information spanned by the lagged price differences is used to estimate one or two shape parameters (*versus* up to 8 separate hedge-rate parameters), such as initial hedge intensity and hedging time decay. In contrast to a standard distributed-lags approach, which exploits the time-series variation, we use the pooled cross-sections of the lagged price differences to estimate these shape parameters. Thus, the discrete-time model specification is modified as follows:

$$Sales_{ti} = a_p + b_p p_{t0} + c_p p_{t0}^2 + f[\beta,\lambda|\dot{p}_{tL1}\dots\dot{p}_{tL8}] + d_p q_{ti} + controls_{ti} + \tilde{\mu}_{sti} \tag{13}$$

$$Costs_{ti} = a_w + b_w w_{t0} + c_w w_{t0}^2 + g[\theta,\gamma|\dot{w}_{tL1}\dots\dot{w}_{tL8}] + d_w y_{ti} + controls_{ti} + \tilde{\mu}_{cti} \tag{14}$$

$$y_{ti} = b_p + 2c_p p_{t0} + \tilde{\mu}_{yti} \tag{15}$$

$$q_{ti} = b_w + 2c_w w_{t0} + \tilde{\mu}_{qti}, \tag{16}$$

where p_{t0}, w_{t0}, $\dot{p}_{tL\tau}$, $\dot{w}_{tL\tau}$ are the spot and τ-lagged price differences defined earlier, and β, θ, λ, γ are the shape parameters of time-decay functions $f\left[\beta,\lambda|\dot{p}_{tL\tau}\right]$ and $g[\theta,\gamma|\dot{w}_{tL\tau}]$. We consider four functional forms, namely, the uniform, exponential, gamma, and beta functions:

Uniform: $$f[\beta,\lambda|\dot{p}_{tL\tau}] \equiv \beta\dot{p}_{tL1} + \cdots + \beta\dot{p}_{tL4} + \lambda\dot{p}_{tL5} + \cdots + \lambda\dot{p}_{tL8}\ , \tag{17}$$
$$g[\theta,\gamma|\dot{w}_{tL\tau}] \equiv \theta\dot{w}_{tL1} + \cdots + \theta\dot{w}_{tL4} + \gamma\dot{w}_{tL5} + \cdots + \gamma\dot{w}_{tL8} \tag{18}$$

Exponential: $$f[\beta,\lambda|\dot{p}_{tL\tau}] \equiv \beta\left[e^{-0\lambda}\dot{p}_{tL1} + e^{-1\lambda}\dot{p}_{tL2} + \ldots + e^{-7\lambda}\dot{p}_{tL8}\right]\ , \tag{19}$$
$$g[\theta,\gamma|\dot{w}_{tL\tau}] \equiv \theta[e^{-0\gamma}\dot{w}_{tL1} + e^{-1\gamma}\dot{w}_{tL2} + \ldots + e^{-7\gamma}\dot{w}_{tL8}] \tag{20}$$

Gamma: $$f[\beta,\lambda|\dot{p}_{tL\tau}] \equiv \beta^{\lambda}\left[x_1^{\lambda-1}e^{-\beta x_1}\dot{p}_{tL1} + \cdots + x_8^{\lambda-1}e^{-\beta x_8}\dot{p}_{tL8}\right]\ , \tag{21}$$
$$g[\theta,\gamma|\dot{w}_{tL\tau}] \equiv \theta^{\gamma}\left[x_1^{\gamma-1}e^{-\theta x_1}\dot{w}_{tL1} + \cdots + x_8^{\gamma-1}e^{-\theta x_8}\dot{w}_{tL8}\right] \tag{22}$$

Beta: $$f[\beta,\lambda|\dot{p}_{tL\tau}] \equiv x_1^{\beta-1}z_1^{\lambda-1}\dot{p}_{tL1} + \ldots + x_8^{\beta-1}z_8^{\lambda-1}\dot{p}_{tL8}\ , \tag{23}$$
$$g[\theta,\gamma|\dot{w}_{tL\tau}] \equiv x_1^{\theta-1}z_1^{\gamma-1}\dot{p}_{tL1} + \ldots + x_8^{\theta-1}z_8^{\gamma-1}\dot{p}_{tL8}\ , \tag{24}$$

where $x_1 \ldots x_8 \equiv \left\{\frac{1}{9},\ldots,\frac{8}{9}\right\}$ and $z_1 \ldots z_8 \equiv \left\{\frac{8}{9},\ldots,\frac{1}{9}\right\}$ span the unit interval.

Each of these functional forms is permuted twice by retaining one or two shape parameters, i.e., setting $\beta = \lambda$ or $\beta \neq \lambda$ and $\theta = \gamma$ or $\theta \neq \lambda$, resulting in the eight specifications in Table III.C. We use Hansen's J-statistic to pick the best-fit specification to use in our ensuing tests.

II. Data

We implement our analysis on a sample of US-listed oil refiners. Several reasons make the oil refining industry a good candidate for study. First, energy prices swing widely (see Figure 1), and this variation contributes statistical power. This is particularly important here because we use quarterly accounts 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 refining industries are used 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 *et al*., 2002, MacKay and Moeller, 2007).

Our firm-level data for oil refiners (SIC 2911) are from the merged *CRSP-COMPUSTAT* quarterly data set maintained by Wharton Research Data Services, including: sales (var #338), costs (cost of goods sold, var #119), assets (var #98), operating income (sales *minus* costs), cash and equivalents (var #108), inventories (var #217), LIFO reserve (var #286), collateral (net property, plant, and equipment, var #293), capital expenditures (var #451), research and development (var #453), 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, var #120, times the quarter-end share price, var #679)), total debt (short-term debt, var #139, plus long-term debt, var #140), S&P long-term debt credit rating, and dividends (common dividends, var #677, plus preferred dividends, var #153). Some control variables have poor coverage. For instance, research and development is missing for over 75% of the sample. We set missing control-variable observations to the industry-year mean to avoid serious 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 use *COMPUSTAT* annual business-segment data to construct three additional variables: vertical integration, industrial diversification, and geographic diversification. Vertical integration measures a firm's oil-refining related activities, both upstream (exploration and production) and downstream (chemicals, distribution, marketing, etc.).[12] Industrial diversification measures a firm's activities *unrelated* to oil refining or upstream and downstream industries. We measure vertical integration (industrial diversification) as one minus the Hirshman-Herfindahl Index (HHI) of a firm's segment sales that are related (unrelated) to oil refining. Finally, we measure geographic diversification as one minus the HHI of a firm's geographic segment sales.

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[12] 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).

Input and output prices are constructed as follows. We obtain daily closing prices, volume, and closing open interest for all NYMEX-traded futures contracts on light crude oil, heating oil, and unleaded or reformulated gasoline from *Thompson Financial's Datastream International*.[13] From March 1985, delivery months for all three commodities have been available for every month of the year going out several months, often years. These commodities represent the main outputs (heating oil and unleaded gasoline) and input (crude oil) for the oil refining industry (SIC 2911).[14]

To simplify our analysis, we exploit a convenient 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)). For tractability, 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 output price represents two-thirds of the gasoline price plus one-third of the heating oil price. Figure 1 shows spot and 3-month futures input and output prices and the crack spread from March 1985 to December 2018.

Because our panel runs from March 1985 to December 2018, 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.

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

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[13] In 2006, reformulated gasoline replaced unleaded gasoline as the basis for the futures contract. We use contract trading volumes during that transition period to smooth-paste this change in the gasoline futures price time series.

[14] 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.

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, we equally weight the daily observations. Although the three schemes yield similar results, we use volume-weighted prices because this seems closest in spirit to representative prices. 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. This fact is illustrated quite dramatically in Figures 3a and 3b for all three energy price series.

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 plots nominal quarterly spot and 3-month futures prices from March 1985 to December 2018. The graph shows that input and output prices vary widely, fluctuating between roughly 13 and 138 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 33 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 136 quarterly spot and futures energy prices in our sample period. The mean (median) nominal output and input spot prices are $52.56 ($34.95) and $43.03 ($28.76) per barrel while the mean (median) crack spread is $9.53 ($5.93) per barrel. Figure 1 and median values in Table I show that futures prices are generally below 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, and slightly less for the crack spread, 0.96).

Insert Table I around here.

Figure 2 shows aggregate statistics for the U.S. oil 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 2018, we estimate the price elasticity of demand (consumption) to be -20%. Referring to the coefficient associated with squared spot prices in Table III, which roughly embed the inverse demand function facing refiners' (sales-side) and refiners' own demand for crude oil (cost-side), we obtain corresponding elasticity estimates of about -18% (sales) and -14% (costs).

Insert Figure 2 around here.

Table II, Panel A reports summary statistics on the operating characteristics of our sample of 56 oil refiners obtained from quarterly *COMPUSTAT* data. The data show that oil refining is a large-scale, capital-intensive activity (mean assets of about $16 billion, net plant, property, and equipment (Net PPE) nearly 50% of assets, capital expenditures nearly 9% of Net PPE per year), that operates on thin margins (mean operating income 6% of Net PPE).

In order to validate our method and ground our hedging estimates against reported practice, Table IV shows summary statistics on derivatives usage by our sample firms collected from their financial-statement footnotes. Following past practice (Campello *et al*., 2011, Hoberg and Moon, 2017, etc.), we conduct a systematic search of our sample firms' 10-K filings and annual reports for the terms: risk, hedge, hedging, derivatives, risk management, and hedge accounting. Figures 4a, 4b, and 4c show the number of oil refiners whose 10-K or annual reports we checked each year, how many of these firm-years disclosed hedging-related information, and the sample means and standard deviations for hedge accounting, hedge intensity, and hedge maturity. Table IV presents the corresponding summary statistics, along with a breakdown by maturity bracket.

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 non-derivatives-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 associated cost basis has not been hedged or otherwise fixed. Recent work by Almeida *et al.* (2017) on the substitutability of derivatives and supply contracts drives this point home.

This example points to a limitation of footnote-based measure of "derivatives usage" as a proxy for "risk management". The footprint hedging estimates we present later help to overcome this limitation of footnote-based measures. Recent work on selective hedging (e.g., Brown, *et al.*, 2003, Adam and Fernando, 2005) illustrates another way in which observed (or stated) use of derivatives does not tell the whole risk management story. We will have more to say on selective hedging, evidence of which our proposed method is able to detect (see Table VII).

IV. Regression Model Estimation

A. Econometric Approach

Table III reports GMM coefficient estimates for our unbalanced pooled sample of refiners for the set of simultaneous equations in expressions (4) to (7) for the discrete model (Tables III.A and III.B) and in expressions (8) to (11) for the time-decay models (Table III.C). These equations systems represent the revenue and cost functions and their associated derived output-supply and input-demand equations. The dependent variables for these equations are: sales, costs, output quantity (sales divided by current output price), and input quantity (costs divided by current input price). Table III presents univariate (III.A) and staggered (III.B) versions of the discrete model to show the effect of adding progressively-more lagged futures contracts (Models 1 to 8). Similarly, Table III.C presents variations of the time-decay model. No separate columns appear for the input and output equations because the sales and costs equations contain all the model coefficients. We include the input and output equations in the estimation because the added structure mirrors the firm's first-order conditions and the state of its product and factor markets. These equations also improve the efficiency of the 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 and lagged futures price differences for inputs and outputs (40 instruments).

We use Hansen's (1982) J-statistic to jointly test whether the model is well specified and the instruments are valid. For every model in Table III we find J-statistics significantly different than zero, which represents a rejection of the over-identifying restrictions and implies that the model is not fully specified, the instruments are correlated with the residuals, or both. Comparing models one and two, we find that adding even a single lagged futures price (e.g., the 3-month contract) substantially lowers the J-statistic, suggesting that, as Leamer (1983) shows, large-sample specification tests are sensitive to even small departures from the "true" model. However, even in our preferred specification (Model 8), where the J-statistics are lowest, the over-identifying restrictions are still rejected, indicating residual simultaneity and/or misspecification. The chosen instrument set reflects a balance between the exclusion and inclusion restrictions (instruments uncorrelated with the residuals but correlated with the endogenous variables).

We employ firm-cluster robust bootstrapping (as *per* Cameron *et al.*, 2008) to circumvent econometric issues surrounding the calculation of standard errors. First, because the pooled panel nature of our sample entails repeated year-quarter price data and recurring firms over time, the usual problem of inconsistent standard errors and over rejection arises. Parametric clustering correction methods exist to correct for this, although these are not valid with interactions and for nonlinear estimation (Ai and Norton, 2003, Greene, 2010). Second, our footprint-hedging measures are constructed by combining the estimated hedge rates, which renders the computation of robust standard errors intractable. Structured bootstrapping is a simple, reliable way to avoid these problems. It also allows us to run paired-differences tests, which we use to investigate associations between hedging, footnote hedging measures, firm characteristics, futures-market conditions, and other variables of interest.

B. Discussion of Results (forthcoming – apologies that tables need revisions)

V. Conclusion

We propose a new method to measure corporate hedging activity and study its determinants. The method shadows cash-flow hedge accounting, which means derivatives positions can be traced by regressing sales or costs on lagged futures prices. Calibration for oil-refining and manufacturing firms yields estimated hedge intensities and maturities in line with positions disclosed in financial-statement footnotes. Replication of past empirical relations and hedging patterns that depend on the state and flux of the futures markets lend credence to the method and its general applicability.

Our method holds promise for future studies of corporate risk management but also for asset-pricing studies, especially where micro-foundations are linked to risk premia since a firm's risk-management activity determines its net risk-factor exposure profile and equilibrium stock returns.

Appendix A

Excerpts from 10K Filings on the Accounting Treatment of Key Variables

Cash-flow hedge Accounting, Fair-value Accounting, and Treatment of Gains/Losses

"Hedging: The Corporation may use futures, forwards, options and swaps, individually or in combination, to reduce the effects of fluctuations in crude oil, natural gas and refined product selling prices. Related hedge gains or losses are an integral part of the selling or purchase prices. Generally, these derivatives are designated as hedges of expected future cash flows or forecasted transactions (cash flow hedges), and the changes in fair value are recorded in accumulated other comprehensive income. These transactions meet the requirements for hedge accounting, including correlation. The Corporation reclassifies hedging gains and losses included in accumulated other comprehensive income to earnings at the time the hedged transactions are recognized. The ineffective portion of hedges is included in current earnings. The Corporation's remaining derivatives, including foreign currency contracts, are not designated as hedges and the change in fair value is included in income currently." *Source*: Amerada Hess 2005 10K (p 33-34)

FIFO, LIFO, and Treatment of Inventories

*"**Inventories***: Crude oil and refined product inventories are valued at the lower of cost or market. For inventories valued at cost, the Corporation uses principally the last-in, first-out (LIFO) inventory method. Inventories of merchandise, materials and supplies are valued at the lower of average cost or market. […] During 2005 and 2004, the Corporation reduced LIFO inventories, which are carried at lower costs than current inventory costs. The effect of the LIFO inventory liquidations was to decrease cost of products sold by approximately $51 million and $20 million in 2005 and 2004, respectively." *Source*: Amerada Hess 2005 10-K (p. 50)

Revenue Recognition:
"The Corporation recognizes revenues from the sale of crude oil, natural gas, petroleum products and other merchandise when title passes to the customer." (*idem*, p. 49)

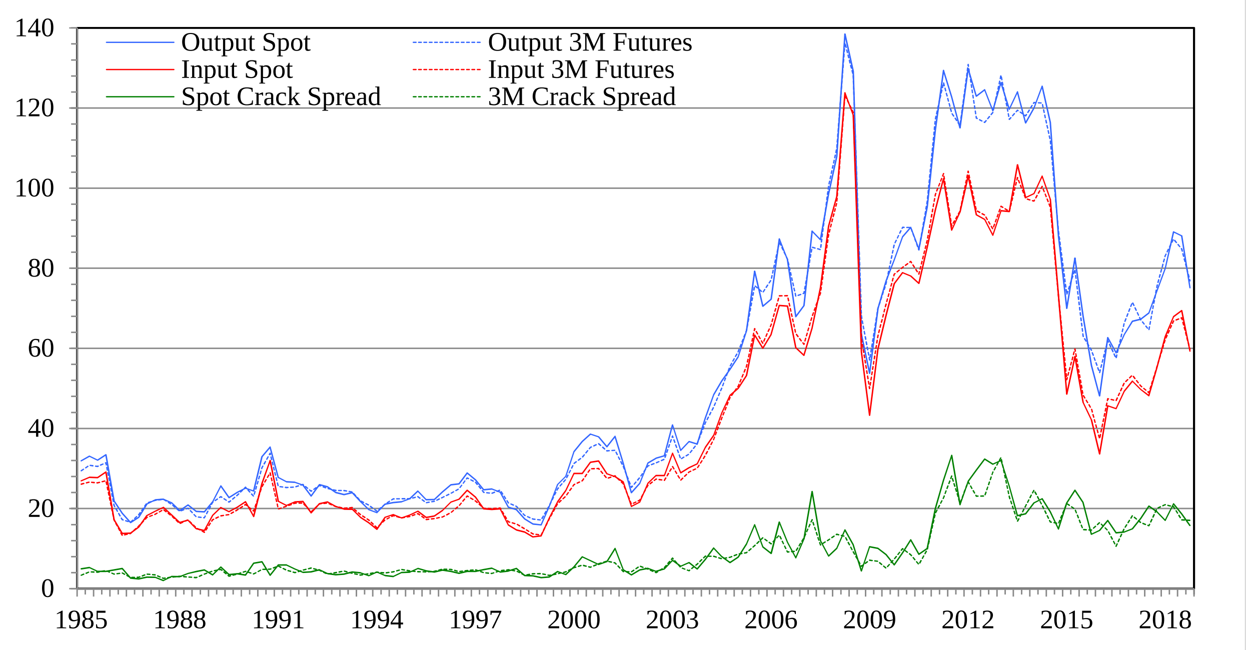


Figure 1. Quarterly energy prices from March 1985 to December 2018.

Quarterly energy spot (nearest-month) and 3-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 and input prices.

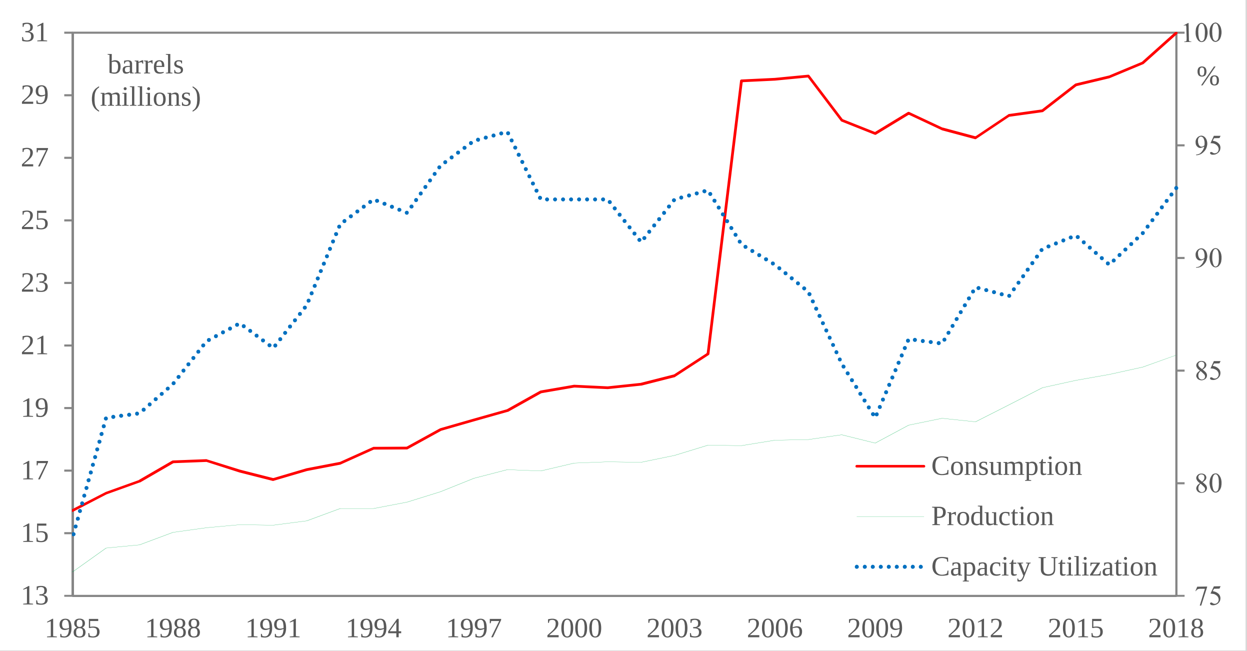
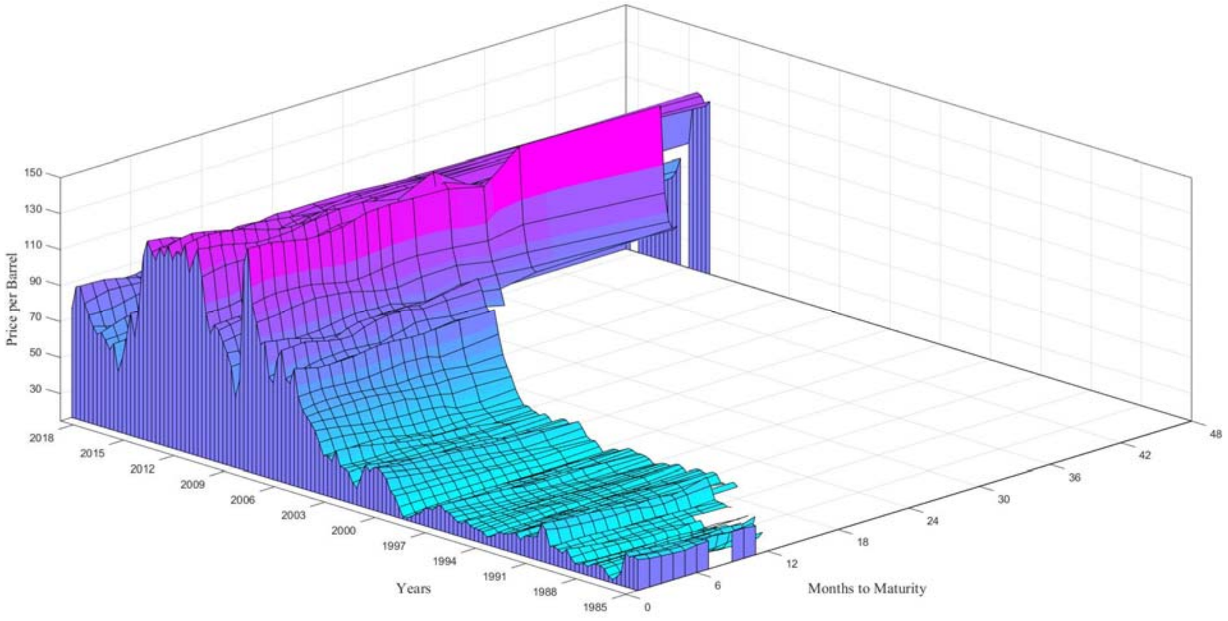


Figure 2. Annual oil refining statistics 1985 to 2018.

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*; estimated price elasticity of demand (consumption) is -20%. *U. S. Department of Energy (Energy Information Administration).*

Output Futures Prices (Gasoline & Heating Oil)



Input Futures Prices (Light Crude Oil)

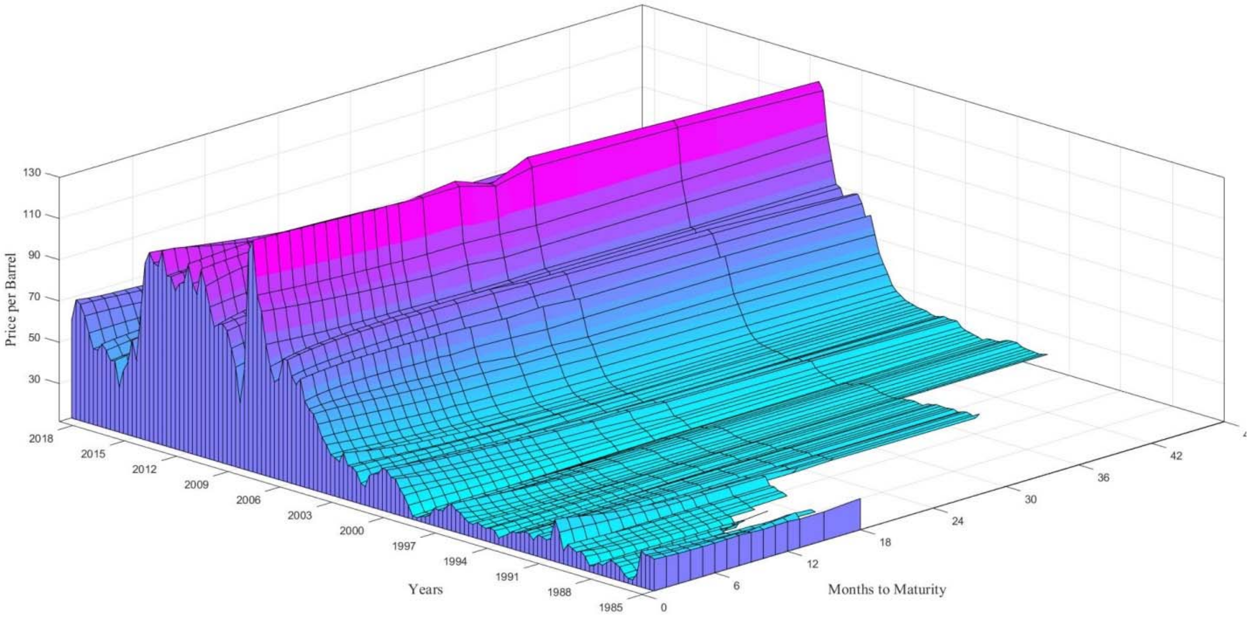
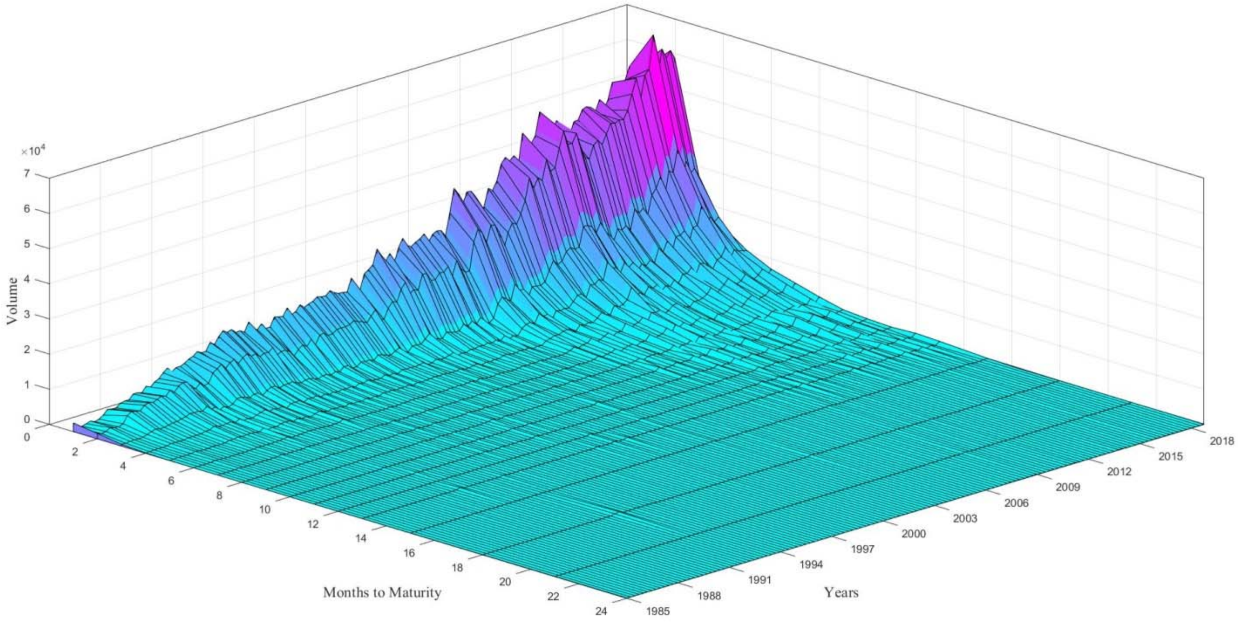
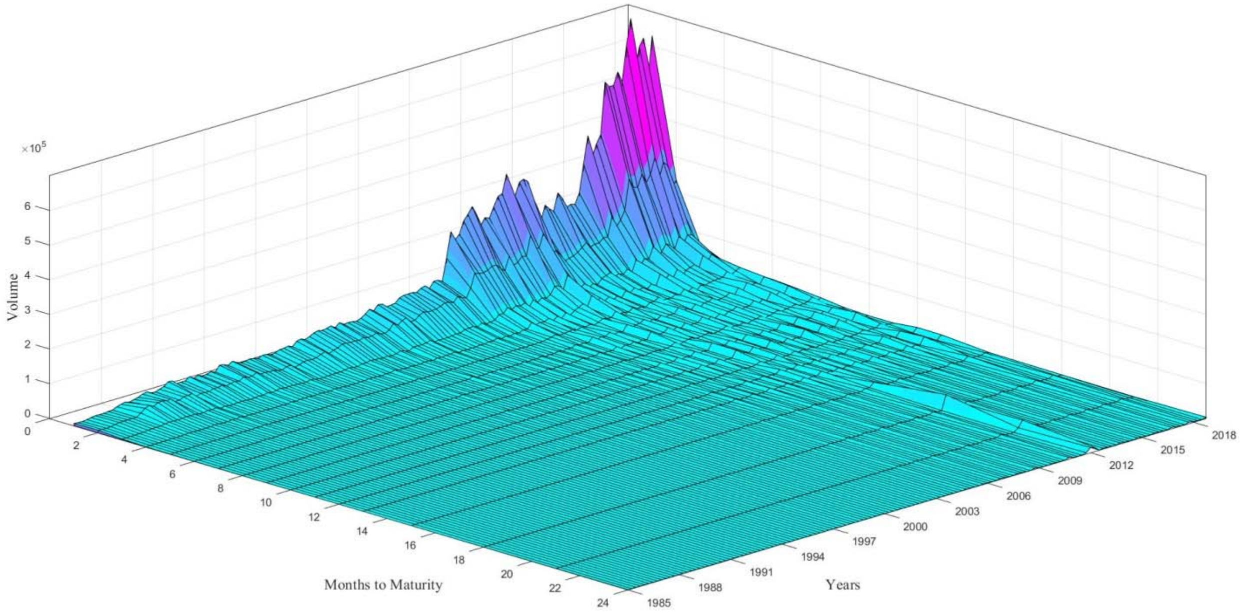


Figure 3a. Level of output and input futures by maturity Q1 1985 to Q4 2018.



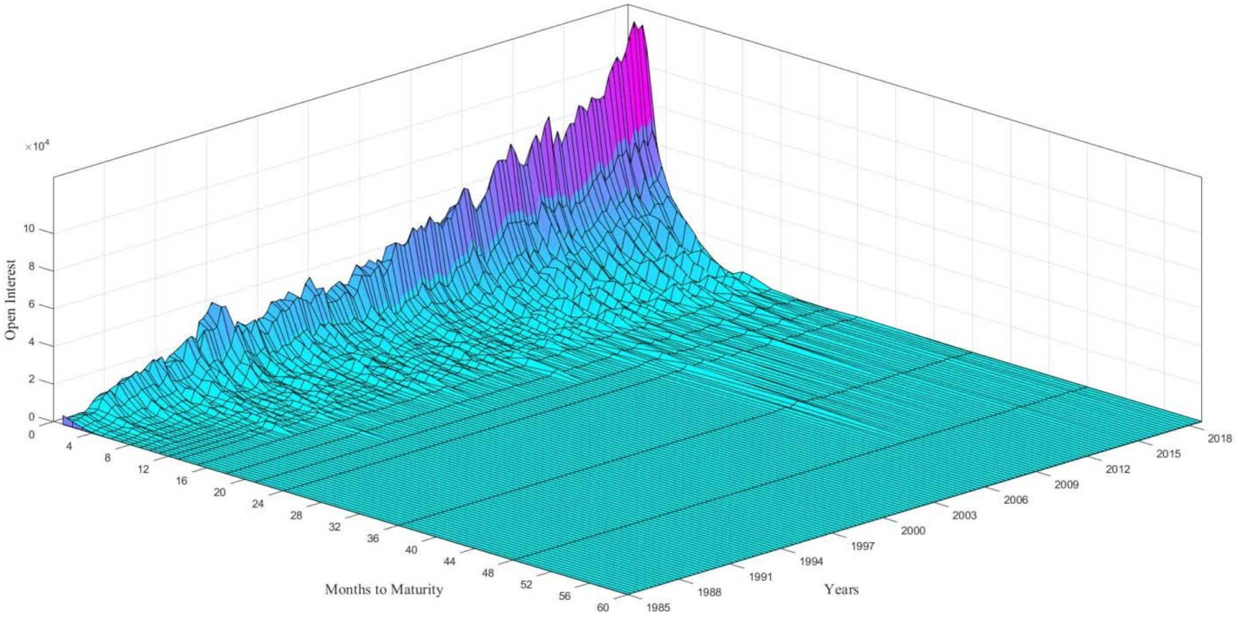
Trade Volume of Output Futures (Gasoline & Heating Oil)



Trade Volume of Input Futures (Light Crude Oil)

Figure 3b. Trade Volume for output and input futures by maturity Q1 1985 to Q4 2018.

Open Interest in Output Futures (Gasoline & Heating Oil)



Open Interest in Input Futures (Light Crude Oil)

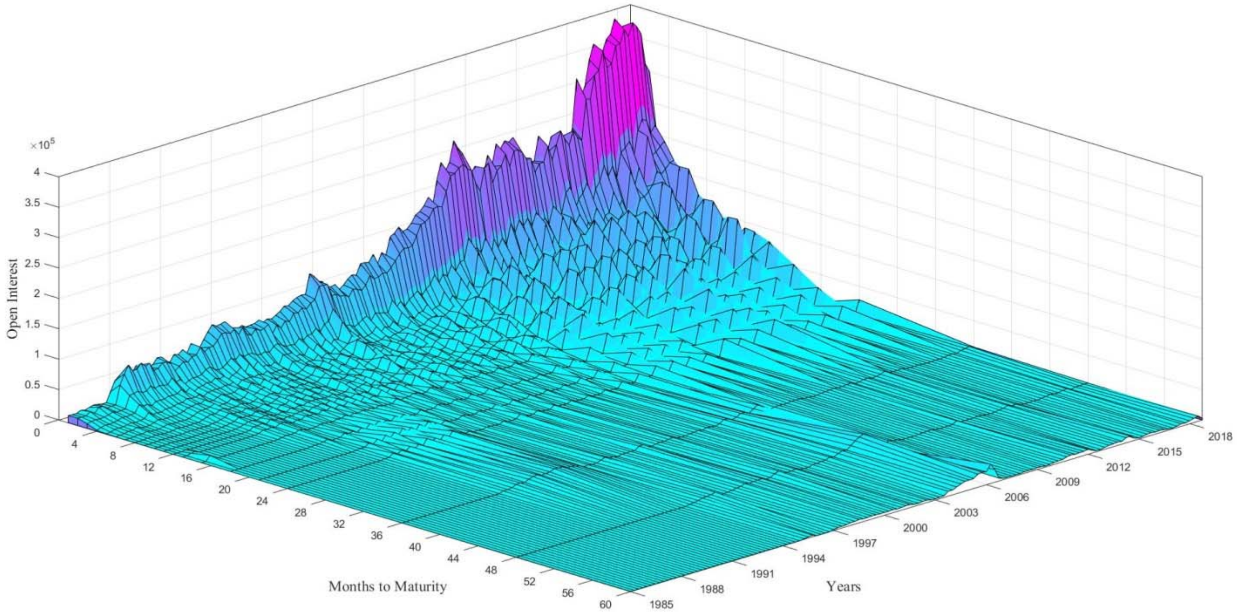


Figure 3c. Open interest for output and input futures by maturity Q1 1985 to Q4 2018.

Figure 4a. Hedge Accounting

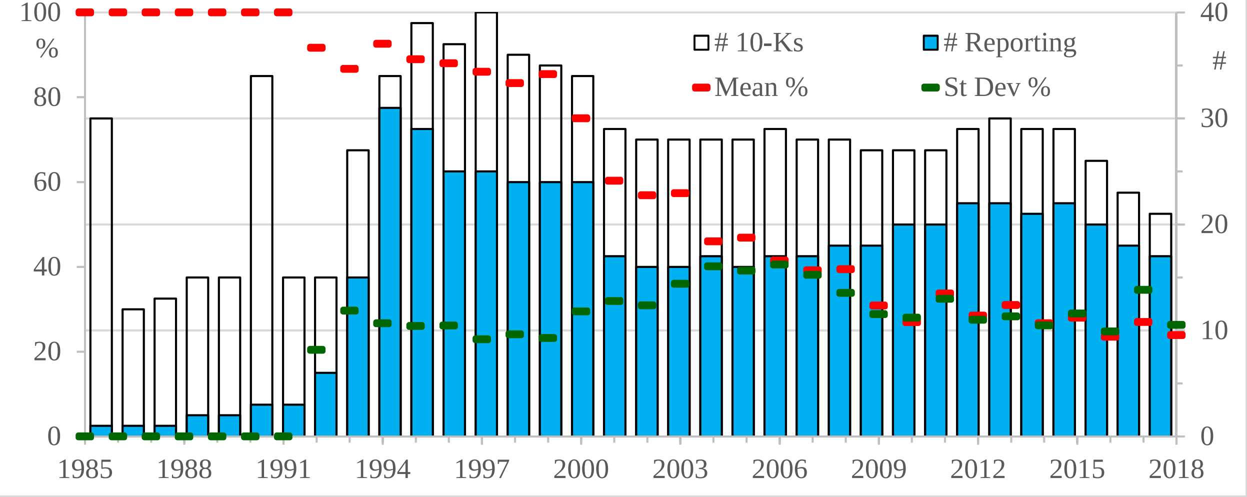


Figure 4b. Hedge Intensity

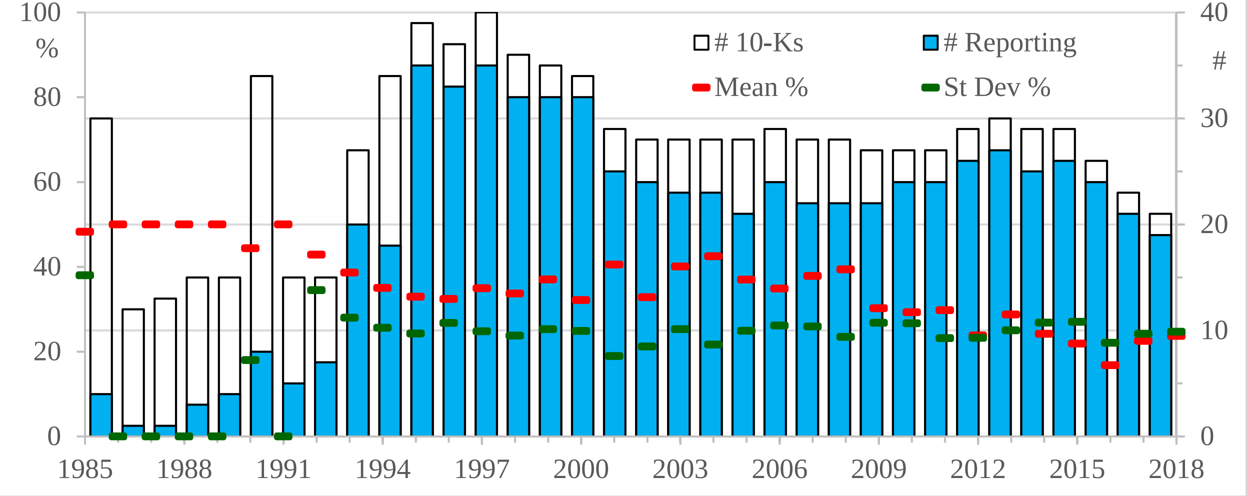


Figure 4c. Hedge Maturity

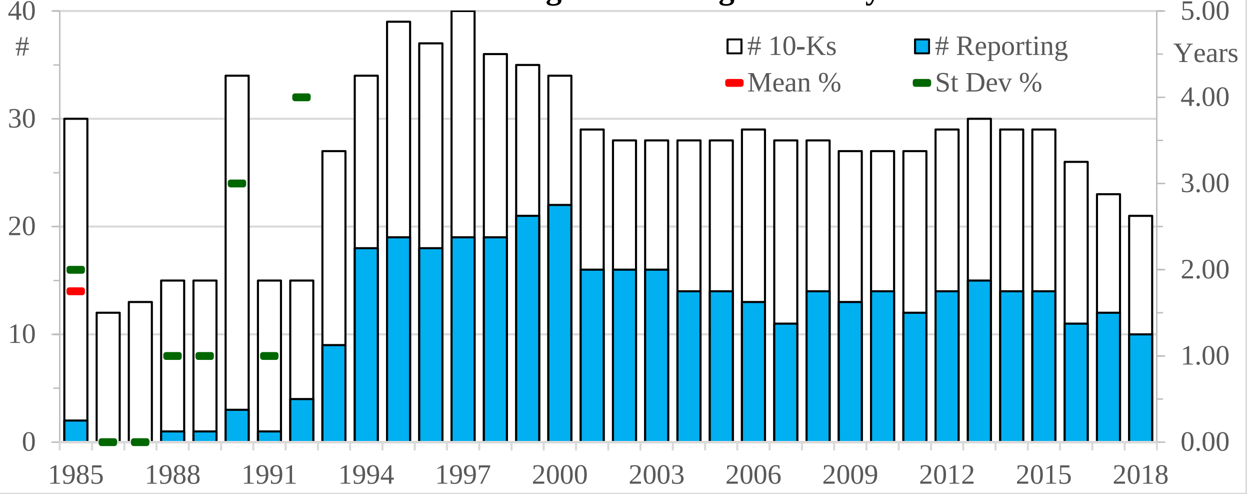


Table I
Summary Statistics: Quarterly Energy Prices

Quarterly energy spot (nearest-month) and 3-month futures prices constructed from daily NYMEX-traded futures contracts on light crude oil, heating oil, and unleaded gasoline from Datastream for March 1985 to December 2018. 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 prices, *p* – *w*.

	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)	136	136	136	136	136	136
Mean	52.99	43.34	9.65	52.56	43.48	9.08
Median	35.40	28.85	5.95	33.20	27.46	5.32
Standard Deviation	35.45	29.11	7.66	35.35	29.54	6.93
Skewness	0.88	0.93	1.35	0.84	0.88	1.31
Kurtosis	-0.52	-0.36	0.99	-0.63	-0.51	0.80
Minimum	15.92	12.92	2.03	16.60	13.31	2.57
Maximum	138.48	123.80	33.27	136.26	123.18	32.73
Correlations (Spot & 3M)	0.99	0.99	0.96	0.99	0.99	0.96
Correlations (*p* & *w*)		0.99			0.99	

Table II
Summary Statistics: Quarterly Firm Operating Data and Characteristics

Panel A shows summary statistics for a sample of 56 US-listed oil refiners (SIC 2911) for fiscal years 1985 to 2018. Quarterly *COMPUSTAT* data definitions: sales (var #338), costs (cost of goods sold, var #119), total assets (var #98), operating income (sales minus costs), cash and equivalents (var #108), inventories (var #217), LIFO reserve (var #286), collateral (net property, plant, and equipment, var #293), capital expenditures (var #451), research and development (var #453), 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, var #120, times the quarter-end share price, var #679)), total debt (short-term debt, var #139, plus long-term debt, var #140), S&P long-term debt credit rating, and dividends (common dividends, var #677, plus preferred dividends, var #153). Vertical integration (industrial diversification) is one minus the Hirshman-Herfindahl Index (HHI) of firm-segment sales that are related (unrelated) to oil refining, and geographic diversification is one minus the HHI of firm geographic segment sales.

Quarterly Firm Operating Data							
	Mean	Median	St. Dev.	Min	Max	Within-firm Variation	1st Order Auto-correlation
Sales (in million $)	4,952	1,316	9,018	0.71	98,750	25%	90%
Costs (in million $)	4,091	1,028	7,722	0.83	89,326	25%	87%
Total Assets (in million $)	16,480	4,867	27,673	12.87	163,543	23%	96%
Operating Income / Net PPE	6%	6%	5%	-61%	41%	77%	38%
Cash & Equivalents / Assets	6%	4%	5%	-1%	43%	73%	78%
Inventories / Net PPE	16%	13%	12%	0%	115%	35%	88%
LIFO Reserve / Assets	6%	3%	8%	-10%	66%	56%	89%
Collateral (Net PPE / Assets)	46%	48%	9%	3%	67%	39%	90%
CAPEX / Net PPE	9%	7%	6%	0%	58%	90%	68%
R&D / Net PPE	1%	1%	1%	0%	89%	91%	2%
Tobin's *q*	1.34	1.24	0.41	0.54	3.55	71%	90%
Vertical Integration	20%	23%	17%	0%	57%	39%	92%
Industrial Diversification	5%	0%	10%	0%	50%	26%	92%
Geographic Diversification	6%	0%	14%	0%	61%	55%	93%
Altman's Z-score	1.03	1.04	0.45	-3.62	2.22	64%	87%
Short-term Debt / Total Debt	13%	8%	15%	0%	69%	47%	82%
Total Debt / Assets	22%	21%	11%	0%	82%	41%	90%
S&P LT-Debt Credit Rating	2.30	2.61	0.96	0.00	3.14	21%	72%
Dividends / Net PPE	1%	1%	3%	-3%	104%	86%	15%
Observations (firm-quarters)	4,239						

Table III
Corporate Risk Management: Footprint Hedging Estimates

Nonlinear Generalized Method-of-Moments bootstrap median estimates (1,000 replications) for quarterly sales and costs regressed on current-quarter output and input spot prices (p_{t0}, w_{t0}), τ-lagged futures price changes ($\dot{p}_{tL1}$, $\dot{p}_{tL2}$,…, $\dot{p}_{tL8}$ and $\dot{w}_{tL1}$, $\dot{w}_{tL2}$,…, $\dot{w}_{tL8}$), and control variables. Each model consists of four simultaneous equations corresponding to the revenue and cost functions (dependent variables: Sales and Costs) and the derived output-supply and input-demand equations (dependent variables: output quantity, y = Sales/p_0, and input quantity, x = Costs/w_0). The discrete parameters ($\hat{\beta}_1$, $\hat{\beta}_2$, …, $\hat{\beta}_8$ and $\hat{\theta}_1$, $\hat{\theta}_2$, …, $\hat{\theta}_8$) and the shape parameters ($\beta, \lambda, \theta, \gamma$) are assigned by the estimation to the τ-lagged futures-price differences (τ = 1, 2, …, 8). The discrete and decay specifications are:

Discrete Models (Tables III.A & III.B):

$$Sales_{ti} = a_p + b_p p_{t0} + c_p p_{t0}^2 + \beta_1 \dot{p}_{tL1} + \beta_2 \dot{p}_{tL2} + \ldots + \beta_8 \dot{p}_{tL8} + d_p q_{ti} + controls_{ti} + \tilde{\mu}_{sti}\,, \qquad y_{ti} = b_p + 2c_p p_{t0} + \tilde{\mu}_{yti} \qquad (9, 11)$$

$$Costs_{ti} = a_w + b_w w_{t0} + c_w w_{t0}^2 + \theta_1 \dot{w}_{tL1} + \theta_2 \dot{w}_{tL2} + \ldots + \theta_8 \dot{w}_{tL8} + d_w y_{ti} + controls_{ti} + \tilde{\mu}_{cti}\,, \qquad q_{ti} = b_w + 2c_w w_{t0} + \tilde{\mu}_{qti} \qquad (10, 12)$$

Decay Models (Table III.C, Models 1 to 8):

$$Sales_{ti} = a_p + b_p p_{t0} + c_p p_{t0}^2 + f[\beta, \lambda | \dot{p}_{tL1} \ldots \dot{p}_{tL8}] + d_p q_{ti} + controls_{ti} + \tilde{\mu}_{sti}, \qquad y_{ti} = b_p + 2c_p p_{t0} + \tilde{\mu}_{yti} \qquad (13, 15)$$

$$Costs_{ti} = a_w + b_w w_{t0} + c_w w_{t0}^2 + g[\theta, \gamma | \dot{w}_{tL1} \ldots \dot{w}_{tL8}] + d_w y_{ti} + controls_{ti} + \tilde{\mu}_{cti}\,, \qquad q_{ti} = b_w + 2c_w w_{t0} + \tilde{\mu}_{qti} \qquad (14, 16)$$

where $f[\beta, \lambda | \dot{p}_{tL\tau}]$ and $g[\theta, \gamma | \dot{w}_{tL\tau}]$ are time-decay functions for the following functional forms (1 or 2 shape parameters if $\beta = \lambda$ or $\beta \neq \lambda$ and $\theta = \gamma$ or $\theta \neq \lambda$):

$$\text{Uniform:} \quad f[\beta, \lambda | \dot{p}_{tL\tau}] \equiv \beta \dot{p}_{tL1} + \cdots + \beta \dot{p}_{tL4} + \lambda \dot{p}_{tL5} + \cdots + \lambda \dot{p}_{tL8}\,, \qquad g[\theta, \gamma | \dot{w}_{tL\tau}] \equiv \theta \dot{w}_{tL1} + \cdots + \theta \dot{w}_{tL4} + \gamma \dot{w}_{tL5} + \cdots + \gamma \dot{w}_{tL8} \qquad (17, 18)$$

$$\text{Exponential:} \quad f[\beta, \lambda | \dot{p}_{tL\tau}] \equiv \beta\left[e^{-0\lambda} \dot{p}_{tL1} + e^{-1\lambda} \dot{p}_{tL2} + \ldots + e^{-7\lambda} \dot{p}_{tL8}\right], \qquad g[\theta, \gamma | \dot{w}_{tL\tau}] \equiv \theta[e^{-0\gamma} \dot{w}_{tL1} + e^{-1\gamma} \dot{w}_{tL2} + \ldots + e^{-7\gamma} \dot{w}_{tL8}] \qquad (19, 20)$$

$$\text{Gamma:} \quad f[\beta, \lambda | \dot{p}_{tL\tau}] \equiv \beta^{\lambda}\left[x_1^{\lambda-1} e^{-\beta x_1} \dot{p}_{tL1} + \cdots + x_8^{\lambda-1} e^{-\beta x_8} \dot{p}_{tL8}\right], \qquad g[\theta, \gamma | \dot{w}_{tL\tau}] \equiv \theta^{\gamma}\left[x_1^{\gamma-1} e^{-\theta x_1} \dot{w}_{tL1} + \cdots + x_8^{\gamma-1} e^{-\theta x_8} \dot{w}_{tL8}\right] \qquad (21, 22)$$

$$\text{Beta:} \quad f[\beta, \lambda | \dot{p}_{tL\tau}] \equiv x_1^{\beta-1} z_1^{\lambda-1} \dot{p}_{tL1} + \ldots + x_8^{\beta-1} z_8^{\lambda-1} \dot{p}_{tL8}\,, \qquad g[\theta, \gamma | \dot{w}_{tL\tau}] \equiv x_1^{\theta-1} z_1^{\gamma-1} \dot{p}_{tL1} + \ldots + x_8^{\theta-1} z_8^{\gamma-1} \dot{p}_{tL8}\,, \qquad (23, 24)$$

where $x_1 \ldots x_8 \equiv \left\{\frac{1}{9}, \ldots, \frac{8}{9}\right\}$ and $z_1 \ldots z_8 \equiv \left\{\frac{8}{9}, \ldots, \frac{1}{9}\right\}$ span the unit interval.

Quarterly energy spot (nearest-month) and futures prices are constructed from daily NYMEX-traded futures contracts on light crude oil, heating oil, and unleaded gasoline from Datastream. Missing data points for longer maturities are imputed by interpolating the prices surrounding delivery dates or extrapolating the two preceding maturity contracts. Bootstrap firm-cluster robust standard errors in parentheses. The value of risk management (normalized by predicted operating income) is given by Jensen's inequality (see MacKay and Moeller, 2007). Hedge intensity is the sum of the hedge rates ($HI_S \equiv \sum_\tau f(\hat{\beta}_\tau, \hat{\lambda}_\tau)$, $HI_C \equiv \sum_\tau g(\hat{\theta}_\tau, \hat{\gamma}_\tau)$), hedge maturity (years) is the time-weighted sum of the hedge rates divided by hedge intensity ($HM_S \equiv \sum_\tau \tau f(\hat{\beta}_\tau, \hat{\lambda}_\tau) \div HI_S$, $HM_C \equiv \left[\sum_\tau \tau g(\hat{\theta}_\tau, \hat{\gamma}_\tau)\right] \div HI_C$), and half-life is the time needed for the hedge rates to sum to half the hedge intensity $HL_S \equiv \hat{\phi} \ni \sum_\tau^{\phi} f(\hat{\beta}_\tau, \hat{\lambda}_\tau)_\tau = ½HI_S$, $HL_C \equiv \hat{\varphi} \ni \sum_\tau^{\varphi} g(\hat{\theta}_\tau, \hat{\gamma}_\tau) = ½HI_C$. Tests of differences compare paired bootstrap estimates. Superscripts a, b, c denote statistical significance at the 1%, 5%, and 10% confidence levels.

Table III.A Discrete Model with Individual Contract Maturities

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8	
	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs
Intercept	-0.56[a] 0.00	0.30[a] 0.00	-0.59[a] 0.00	0.27[a] 0.00	-0.61[a] 0.00	0.26[a] 0.00	-0.60[a] 0.00	0.27[a] 0.00	-0.60[a] 0.00	0.28[a] 0.00	-0.59[a] 0.00	0.27[a] 0.00	-0.59[a] 0.00	0.28[a] 0.00	-0.58[a] 0.00	0.28[a] 0.00
Prices Levels: p, w	0.78[a] 0.00	0.66[a] 0.00	0.79[a] 0.00	0.66[a] 0.00	0.79[a] 0.00	0.66[a] 0.00	0.79[a] 0.00	0.67[a] 0.00	0.78[a] 0.00	0.66[a] 0.00	0.78[a] 0.00	0.66[a] 0.00	0.78[a] 0.00	0.66[a] 0.00	0.78[a] 0.00	0.66[a] 0.00
Squared Prices: p^2, w^2	-0.15[a] 0.00	-0.11[a] 0.00	-0.15[a] 0.00	-0.12[a] 0.00	-0.15[a] 0.00	-0.12[a] 0.00	-0.16[a] 0.00	-0.12[a] 0.00	-0.15[a] 0.00	-0.12[a] 0.00	-0.15[a] 0.00	-0.12[a] 0.00	-0.15[a] 0.00	-0.12[a] 0.00	-0.15[a] 0.00	-0.12[a] 0.00
1 quarter: $\dot{p}_{L1}$, $\dot{w}_{L1}$	0.06[a] 0.00	0.04[a] 0.00														
2 quarters: $\dot{p}_{L2}$, $\dot{w}_{L2}$			0.06[a] 0.00	0.06[a] 0.00												
3 quarters: $\dot{p}_{L3}$, $\dot{w}_{L3}$					0.06[a] 0.00	0.04[a] 0.00										
4 quarters: $\dot{p}_{L4}$, $\dot{w}_{L4}$							0.08[a] 0.00	0.02[a] 0.00								
5 quarters: $\dot{p}_{L5}$, $\dot{w}_{L5}$									0.03[a] 0.00	-0.00[a] 0.00						
6 quarters: $\dot{p}_{L6}$, $\dot{w}_{L6}$											0.02[a] 0.00	0.01[a] 0.00				
7 quarters: $\dot{p}_{L7}$, $\dot{w}_{L7}$													0.01[a] 0.00	-0.01[a] 0.00		
8 quarters: $\dot{p}_{L8}$, $\dot{w}_{L8}$															0.02[a] 0.00	-0.01[a] 0.00
Degrees of Freedom	4,235	4,235	4,235	4,235	4,235	4,235	4,235	4,235	4,235	4,235	4,235	4,235	4,235	4,235	4,235	4,235
Hansen's J-Statistic (*p*-val)	806	0.00[a]	756	0.00[a]	737	0.00[a]	760	0.00[a]	782	0.00[a]	762	0.00[a]	782	0.00[a]	769	0.00[a]
Value of Risk Management	12%	9%[a]	12%	9%[a]	12%	9%[a]	12%	9%[a]	12%	9%[a]	12%	9%[a]	12%	9%[a]	12%	9%[a]
Hedge Intensity (S = C?)	6%	4%[a]	6%	6%[a]	6%	4%[a]	8%	2%[a]	3%	0%[a]	2%	1%[a]	1%	-1%[a]	2%	-1%[a]
Cumulative Hedge Intensity			12%	10%	18%	14%	25%	17%	29%	16%	31%	17%	32%	16%	32%	15%

Table III.B Discrete Model with Staggered Contract Maturities

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**		**Model 8**	
	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs
Intercept	-0.58^{a}	0.28^{a}	-0.59^{a}	0.28^{a}	-0.60^{a}	0.27^{a}	-0.61^{a}	0.27^{a}	-0.63	0.25^{a}	-0.63^{a}	0.25^{a}	-0.63^{a}	0.25^{a}	-0.63^{a}	0.26^{a}
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Prices Levels: p, w	0.78^{a}	0.66^{a}	0.79^{a}	0.66^{a}	0.79^{a}	0.67^{a}	0.79^{a}	0.67^{a}	0.79^{a}	0.67^{a}	0.79^{a}	0.67^{a}	0.79^{a}	0.67^{a}	0.79^{a}	0.67^{a}
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Squared Prices: p^2, w^2	-0.15^{a}	-0.11^{a}	-0.15^{a}	-0.11^{a}	-0.15^{a}	-0.12^{a}	-0.15^{a}	-0.12^{a}	-0.15^{a}	-0.12^{a}	-0.15^{a}	-0.12^{a}	-0.16^{a}	-0.12^{a}	-0.15^{a}	-0.12^{a}
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3 months: $\dot{p}_{L3}$, $\dot{w}_{L3}$	0.04^{a}	0.03^{a}	0.05^{a}	0.04^{a}	0.04^{a}	0.04^{a}	0.05^{a}	0.05^{a}	0.04^{a}	0.05^{a}	0.04^{a}	0.05^{a}	0.04^{a}	0.05^{a}	0.03^{a}	0.05^{a}
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6 months: $\dot{p}_{L6}$, $\dot{w}_{L6}$	0.06^{a}	0.05^{a}	0.04^{a}	0.04^{a}	0.05^{a}	0.04^{a}	0.04^{a}	0.04^{a}	0.06^{a}	0.05^{a}	0.05^{a}	0.05^{a}	0.05^{a}	0.05^{a}	0.06^{a}	0.05^{a}
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9 months: $\dot{p}_{L9}$, $\dot{w}_{L9}$			0.05^{a}	0.04^{a}	0.02^{a}	0.02^{a}	0.04^{a}	0.03^{a}	0.02^{a}	0.03^{a}	0.03^{a}	0.03^{a}	0.03^{a}	0.03^{a}	0.02^{a}	0.02^{a}
			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12 months: $\dot{p}_{L12}$, $\dot{w}_{L12}$					0.07^{a}	0.03^{a}	0.05^{a}	0.03^{a}	0.08^{a}	0.02^{a}	0.07^{a}	0.03^{a}	0.07^{a}	0.02^{a}	0.08^{a}	0.03^{a}
					0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15 months: $\dot{p}_{L15}$, $\dot{w}_{L15}$							0.03^{a}	0.02^{a}	0.00^{a}	0.01^{a}	0.02^{a}	0.01^{a}	0.01^{a}	0.02^{a}		
							0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
18 months: $\dot{p}_{L18}$, $\dot{w}_{L18}$									0.05^{a}	0.05^{a}	0.04^{a}	0.05^{a}	0.05^{a}	0.04^{a}	0.06^{a}	0.05^{a}
									0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
21 months: $\dot{p}_{L21}$, $\dot{w}_{L21}$											0.02^{a}	0.01^{a}	0.00^{-}	0.00^{-}		
											0.00	0.00	0.00	0.00		
24 months: $\dot{p}_{L24}$, $\dot{w}_{L24}$													0.05^{a}	0.01^{a}	0.05^{a}	0.00^{a}
													0.00	0.00	0.00	0.00
Degrees of Freedom	4,233	4,233	4,231	4,231	4,229	4,229	4,227	4,227	4,225	4,225	4,223	4,223	4,221	4,221	4,225	4,225
Hansen's J-Statistic (*p*-val)	767	0.00^{a}	732	0.00^{a}	711	0.00^{a}	704	0.00^{a}	664	0.00^{a}	670	0.00^{a}	671	0.00^{a}	668	0.00^{a}
Value of Risk Management	12%	9%^{a}	12%	9%^{a}	12%	10%^{a}	12%	10%^{a}	12%	10%^{a}	12%	10%^{a}	12%	10%^{a}	12%	10%^{a}
Hedge Intensity (S = C?)	10%	8%^{a}	13%	12%^{a}	18%	14%^{a}	21%	16%^{a}	26%	21%^{a}	30%	22%^{a}	30%	22%^{a}	30%	20%^{a}
Hedge Maturity (S = C?)	0.40	0.40^{-}	0.51	0.48^{a}	0.66	0.56^{a}	0.73	0.61^{a}	0.85	0.77^{a}	0.89	0.79^{a}	1.04	0.78^{a}	1.05	0.73^{a}
Hedge Half-life (S = C?)	0.36	0.41^{a}	0.43	0.43^{-}	0.58	0.46^{a}	0.65	0.49^{a}	0.84	0.60^{a}	0.87	0.63^{a}	1.01	0.65^{a}	1.04	0.59^{a}

Table III.C Time Decay Models

Nonlinear Generalized Method-of-Moments bootstrap median estimates (1,000 replications) for quarterly sales and costs regressed on current-quarter output and input spot prices (p_{t0}, w_{t0}), τ-lagged futures price changes ($\dot{p}_{tL1}, \dot{p}_{tL2}, \ldots, \dot{p}_{tL8}$ and $\dot{w}_{tL1}, \dot{w}_{tL2}, \ldots, \dot{w}_{tL8}$), and the control variables. Each model consists of four simultaneous equations corresponding to the revenue and cost functions (dependent variables: Sales and Costs) and the derived output-supply and input-demand equations (dependent variables: output quantity, y = Sales/p_0, and input quantity, x = Costs/w_0):

$$Sales_{ti} = a_p + b_p p_{t0} + c_p p_{t0}^2 + f[\beta, \lambda | \dot{p}_{tL1} \ldots \dot{p}_{tL8}] + d_p x_{ti} + controls_{ti} + \tilde{\mu}_{sti}, \qquad y_{ti} = b_p + 2c_p p_{t0} + \tilde{\mu}_{yti} \qquad (13, 15)$$

$$Costs_{ti} = a_w + b_w w_{t0} + c_w w_{t0}^2 + g[\theta, \gamma | \dot{w}_{tL1} \ldots \dot{w}_{tL8}] + d_w y_{ti} + controls_{ti} + \tilde{\mu}_{cti}, \qquad x_{ti} = b_w + 2c_w w_{t0} + \tilde{\mu}_{xti}, \qquad (14, 16)$$

where $\beta, \lambda, \theta, \gamma$ are the shape parameters the estimation assigns to τ-lagged futures-price differences (τ = 1, 2, …, 8). The value of risk management (normalized by predicted operating income) is given by Jensen's inequality (see MacKay and Moeller, 2007). Hedge intensity is the sum of the hedge rates ($HI_S \equiv \sum_\tau f(\hat{\beta}_\tau, \hat{\lambda}_\tau)$, $HI_C \equiv \sum_\tau g(\hat{\theta}_\tau, \hat{\gamma}_\tau)$), hedge maturity (in years) is the time-weighted sum of the hedge rates divided by hedge intensity ($HM_S \equiv \sum_\tau \tau f(\hat{\beta}_\tau, \hat{\lambda}_\tau) \div HI_S$, $HM_C \equiv \left[\sum_\tau \tau g(\hat{\theta}_\tau, \hat{\gamma}_\tau)\right] \div HI_C$), and half-life is the time needed for the hedge rates to sum to half the hedge intensity ($HL_S \equiv \hat{\phi} \ni \sum_\tau^{\phi} f(\hat{\beta}_\tau, \hat{\lambda}_\tau)_\tau = ½HI_S$, $HL_C \equiv \hat{\varphi} \ni \sum_\tau^{\varphi} g(\hat{\theta}_\tau, \hat{\gamma}_\tau) = ½HI_C$). Difference tests (S = C?) compare paired-bootstrap hedging-measure estimate percentiles across sales and costs.

Contract Maturities:	**Model 1** Uniform $(\beta = \lambda)$ $(\theta = \gamma)$		**Model 2** Uniform $(\beta \neq \lambda)$ $(\theta \neq \gamma)$		**Model 3** Exponential $(\beta = \lambda)$ $(\theta = \gamma)$		**Model 4** Exponential $(\beta \neq \lambda)$ $(\theta \neq \gamma)$		**Model 5** Gamma $(\beta = \lambda)$ $(\theta = \gamma)$		**Model 6** Gamma $(\beta \neq \lambda)$ $(\theta \neq \gamma)$		**Model 7** Beta $(\beta = \lambda)$ $(\theta = \gamma)$		**Model 8** Beta $(\beta \neq \lambda)$ $(\theta \neq \gamma)$	
	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs	Sales	Costs
Intercept			-0.13^{a}	-0.05^{a}			-0.13^{a}	-0.05^{a}	-0.13^{a}	-0.05^{a}	-0.13^{a}	-0.05^{a}	-0.13^{a}	-0.04^{a}	-0.13^{a}	-0.05^{a}
			0.01	0.01			0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Prices Levels: p, w			0.81^{a}	0.69^{a}			0.82^{a}	0.69^{a}	0.82^{a}	0.69^{a}	0.82^{a}	0.69^{a}	0.81^{a}	0.69^{a}	0.83^{a}	0.70^{a}
			0.01	0.01			0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Squared Prices: p^2, w^2			-0.18^{a}	-0.14^{a}			-0.18^{a}	-0.14^{a}	-0.18^{a}	-0.14^{a}	-0.17^{a}	-0.14^{a}	-0.17^{a}	-0.13^{a}	-0.18^{a}	-0.14^{a}
			0.00	0.00			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hedge rates: β, θ			1.05^{a}	1.03^{a}			1.05^{a}	1.03^{a}	0.07^{a}	0.04^{a}	0.03^{c}	0.09^{b}	0.98^{a}	0.99^{a}	0.97^{a}	0.99^{a}
			0.01	0.01			0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
Decay rates: λ, γ			0.00^{a}	-0.00^{-}			0.03^{a}	-0.00^{-}	0.15^{a}	0.27^{a}	0.90^{a}	1.34^{a}	0.98^{a}	0.99^{a}	0.99^{a}	0.99^{a}
			0.00	0.00			0.01	0.01	0.00	0.00	0.11	0.16	0.00	0.00	0.00	0.00
Degrees of Freedom			4,226	4,226			4,226	4,226	4,226	4,226	4,226	4,226	4,226	4,226	4,226	4,226
Hansen's J-Statistic (p-val)			1,018	0.00^{a}			1,018	0.00^{a}			1,011	0.00^{a}	1,078	0.00^{a}	959	0.00^{a}
Value of Risk Management			13%	10%^{a}			13%	10%^{a}	12%	10%^{a}	13%	10%^{a}	12%	10%^{a}	13%	15%^{a}
Hedge Intensity (S = C?)			29%	23%^{a}			29%	22%^{a}	32%	19%^{a}	32%	24%^{a}	32%	19%^{a}	31%	24%^{b}
Hedge Maturity (S = C?)			0.98	1.15^{b}			0.98	1.15^{b}	1.13	1.13^{-}	1.09	1.23^{b}	1.13	1.13^{-}	1.02	1.22^{b}
Hedge Half-life (S = C?)			0.78	1.05^{a}			0.78	1.05^{a}	0.94	0.94^{-}	0.93	1.18^{b}	0.94	0.94^{-}	0.80	1.16^{b}

Table IV
Footnote Hedging Measures

Reported hedging activity for 56 oil refiners from 1985 to 2018 collected from annual reports and 10-K filings (updated yearly from 1993 to 2018 using EDGAR and from hardcopy sources for 1985 to 1992). Hedge accounting is a mixed categorical-interval variable coded as 0%, 50%, or 100% if a firm explicitly reports recording none, some, or most of its derivatives positions using cash-flow hedge accounting; if a firm specifies a percentage or discloses data that allow us to compute a percentage then we use that percentage instead; if there is no explicit mention of hedge accounting then we code it as zero. A similar tiered approach is used to code the maturity-specific hedge rates. Hedge intensity is the equally-weighted average of maturity-specific hedge rates for maturities up to 7 years. Hedge maturity (in years) is the time-weighted sum of a firm's maturity-specific hedge rates divided by hedge intensity, and half-life is the time needed for the sum of hedge rates to reach half the hedge intensity.

Summary Statistics

	Mean	Median	St. Dev.	Within-firm Variation	Min	Max	N
Hedge Accounting	33%	0%	41%	73%	0%	100%	924
Hedge Intensity	25%	13%	26%	56%	0%	100%	924
Hedge Maturity (years)	0.92	0.63	0.70	55%	0.25	4.27	924
Hedge Half-life (years)				59%			924
3-month hedge rate	16%	0%	24%		0%	100%	924
6-month hedge rate	15%	0%	23%		0%	100%	924
9-month hedge rate	14%	0%	23%		0%	100%	924
12-month hedge rate	12%	0%	22%		0%	100%	924
18-month hedge rate	6%	0%	17%		0%	100%	924
2-year hedge rate	5%	0%	16%		0%	100%	924
3-year hedge rate	4%	0%	14%		0%	94%	924
4-year hedge rate	3%	0%	13%		0%	94%	924
5-year hedge rate	3%	0%	12%		0%	94%	924
6-year hedge rate	2%	0%	12%		0%	94%	924
7-year hedge rate	1%	0%	9%		0%	94%	924

Table V
Footprint Hedging Estimates *versus* Footnote Hedging Measures – Oil Refining

Bootstrap medians (1,000 replications) for value of risk management, hedge intensity, hedge maturity, and hedge half-life computed from regressions corresponding to Model 8 in Table III.C (the 2-shape-parameter *beta* function). *Footprint Estimates*: The value of risk management (normalized by predicted operating income) is given by Jensen's inequality (see MacKay and Moeller, 2007). Hedge intensity is the sum of the hedge rates, hedge maturity (in years) is the time-weighted sum of the hedge rates divided by hedge intensity, and half-life is the time needed for the hedge rates to sum to half the hedge intensity. *Footnote Measures*: Collected from 10-K filings and annual reports. Hedge accounting is the percentage of its derivatives positions a firm records using hedge accounting. Hedge intensity is the equally-weighted average of maturity-specific hedge rates for maturities up to 7 years. Hedge maturity (in years) is the time-weighted sum of a firm's maturity-specific hedge rates divided by hedge intensity, and half-life is the time needed for the sum of hedge rates to reach half the hedge intensity. Hedge asymmetry captures option-like hedges by contrasting lagged futures-prices losses and gains. Pre/post FAS 133 compares periods before and after FAS 133 (1998). Pre/post 2001 contrasts 1985-2001 and 2002-2018. Contrasts use sort-variable interactions to shift curvature and shape parameters $(c_p, c_w, \beta, \lambda, \theta, \gamma)$. Difference tests compare paired-bootstrap estimate percentiles.

Footprint Estimates	**Value of Risk Management**				**Hedge Intensity**			
	Sales		Costs		Sales		Costs	
Pooled Sample	0.13		0.15^{a}		0.31		0.24^{b}	
	Loss	*Gain*	*Loss*	*Gain*	*Loss*	*Gain*	*Loss*	*Gain*
Hedge Asymmetry	0.15	0.15	0.12	0.12	0.21	0.51^{a}	0.18	0.13
	Sales		Costs		Sales		Costs	
Footnote Measures	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Hedge Accounting	0.17	0.03^{b}	0.14	0.02^{b}	0.11	0.92^{b}	0.05	0.81^{b}
Hedge Intensity	0.21	0.06^{b}	0.18	0.04^{b}	0.17	1.09^{c}	0.12	0.96^{b}
Hedge Maturity	0.19	0.12^{c}	0.16	0.09^{c}	0.10	0.74^{c}	0.09	0.59^{-}
Hedge Half-life	0.19	0.13^{c}	0.16	0.10^{b}	0.10	0.65^{c}	0.09	0.52^{-}
Sub-period	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Pre/post FAS 133	0.16	0.15^{-}	0.15	0.13^{-}	0.09	0.58^{a}	0.14	0.41^{c}
Pre/post year 2001	0.09	0.12^{c}	0.09	0.11^{-}	0.28	0.53^{a}	0.28	0.35^{-}

Footprint Estimates	**Hedge Maturity**				**Hedge Half-life**			
	Sales		Costs		Sales		Costs	
Pooled Sample	1.02		1.22^{b}		0.80		1.16^{b}	
	Loss	*Gain*	*Loss*	*Gain*	*Loss*	*Gain*	*Loss*	*Gain*
Hedge Asymmetry	0.55	1.06^{a}	0.86	0.56	0.36	1.01^{a}	0.79	0.34
	Sales		Costs		Sales		Costs	
Footnote Measures	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Hedge Accounting	0.37	1.32^{-}	1.22	1.28^{-}	0.26	1.35^{c}	1.06	1.27^{-}
Hedge Intensity	0.31	1.43^{b}	1.05	1.32^{-}	0.26	1.55^{b}	0.81	1.34^{-}
Hedge Maturity	0.55	1.23^{-}	1.07	1.28^{-}	0.30	1.18^{-}	0.82	1.27^{-}
Hedge Half-life	0.54	1.21^{-}	1.08	1.28^{-}	0.30	1.14^{-}	0.84	1.27^{-}
Sub-period	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Pre/post FAS 133	0.36	1.24^{c}	0.79	1.34^{b}	0.16	1.21^{b}	0.51	1.38^{-}
Pre/post year 2001	0.72	1.20^{a}	0.97	1.38^{a}	0.40	1.13^{a}	0.65	1.47^{-}

Table VI
Corporate Risk Management and Firm Characteristics

Bootstrap medians (1,000 replications) for value of risk management, hedge intensity, hedge maturity, and hedge half-life computed from regressions corresponding to Model 8 in Table III.C (the 2 shape-parameter *beta* function). Contrasts use sort-variable interactions to shift the curvature and shape parameters. Each sort variable is the residual of a regression on the other firm characteristics. Difference tests compare paired-bootstrap estimate percentiles.

Footprint Hedging Estimates:	**Value of Risk Management**				**Hedge Intensity**			
	Sales		Costs		Sales		Costs	
Firm Characteristics	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Total Assets ($ millions)	0.07	0.26	0.05	0.21	0.35	0.12	0.08	0.00
Operating Income / Net PPE	0.21	0.13	0.18	0.11	0.33	0.08	0.05	0.06
Cash & Equivalents / Assets	0.09	0.19	0.08	0.15	0.12	0.28	0.09	0.01
Inventories / Net PPE	0.21	0.09	0.18	0.06	0.17	0.15	0.09	0.14
LIFO Reserve / Assets	0.21	0.10	0.17	0.08	0.33	0.06	0.06	0.11
Collateral (Net PPE / Assets)	0.17	0.14	0.14	0.12	0.18	0.01	0.09	0.09
CAPEX / Net PPE	0.17	0.13	0.13	0.11	0.09	0.27	0.07	0.14
R&D / Net PPE	0.15	0.18	0.12	0.17	0.35	0.17	0.04	0.03
Tobin's *q*	0.18	0.08	0.14	0.06	0.19	0.13	0.04	0.09
Vertical Integration	0.16	0.15	0.13	0.13	0.20	0.23	0.03	0.15
Industrial Diversification	0.17	0.13	0.13	0.11	0.29	0.10	0.08	0.01
Geographic Diversification	0.29	0.12	0.25	0.09	0.17	0.31	0.02	0.01
Altman's Z-score	0.13	0.15	0.12	0.12	0.11	0.33	0.04	0.09
Short-term Debt / Total Debt	0.21	0.10	0.17	0.07	0.19	0.04	0.05	0.01
Total Debt / Assets	0.10	0.21	0.09	0.16	0.36	0.29	0.02	0.08
S&P LT-Debt Credit Rating	0.18	0.07	0.14	0.06	0.26	0.28	0.03	0.06
Dividends / Net PPE	0.12	0.26	0.09	0.21	0.24	0.20	0.07	0.14

Footprint Hedging Estimates:	**Hedge Maturity**				**Hedge Half-life**			
	Sales		Costs		Sales		Costs	
Firm Characteristics	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Total Assets ($ millions)	1.03	1.50	0.70	1.07	0.96	1.47	0.57	1.05
Operating Income / Net PPE	0.71	0.58	0.35	0.52	0.53	0.42	0.18	0.35
Cash & Equivalents / Assets	0.41	0.66	0.56	0.75	0.23	0.48	0.38	0.70
Inventories / Net PPE	0.87	0.66	0.47	0.68	0.78	0.47	0.28	0.53
LIFO Reserve / Assets	0.71	0.43	0.40	0.64	0.54	0.26	0.20	0.52
Collateral (Net PPE / Assets)	1.23	1.55	0.59	0.79	1.27	0.45	0.41	0.58
CAPEX / Net PPE	0.34	0.62	0.39	0.62	0.17	0.44	0.21	0.48
R&D / Net PPE	1.06	0.54	0.98	0.81	1.01	0.32	0.65	0.80
Tobin's *q*	0.64	0.39	0.82	0.44	0.49	0.21	0.76	0.23
Vertical Integration	1.05	0.64	0.44	0.60	1.01	0.48	0.27	0.44
Industrial Diversification	0.82	1.11	0.85	1.00	0.69	1.11	0.79	0.42
Geographic Diversification	0.49	0.97	1.17	1.10	0.29	0.84	1.21	1.03
Altman's Z-score	0.37	0.75	0.45	0.66	0.20	0.58	0.26	0.52
Short-term Debt / Total Debt	0.87	1.41	0.66	0.95	0.78	1.30	0.52	0.87
Total Debt / Assets	0.68	1.20	0.63	0.69	0.52	1.20	0.52	0.52
S&P LT-Debt Credit Rating	1.00	0.78	0.71	0.58	0.93	0.63	0.59	0.45
Dividends / Net PPE	0.81	0.45	0.39	0.62	0.67	0.26	0.22	0.48

Table VII
Corporate Risk Management and Futures Markets Performance and Conditions

Bootstrap medians (1,000 replications) for value of risk management, hedge intensity, hedge maturity, and hedge half-life across one-year lagged futures-market performance or conditions subsamples. Footprint hedging estimates are computed from regressions corresponding to Model 8 in Table III.C (the 2 shape-parameter *beta* function). The value of risk management (divided by predicted operating income) is given by Jensen's inequality (see MacKay and Moeller, 2007). Hedge intensity is the sum of the hedge rates, hedge maturity (in years) is the time-weighted sum of the hedge rates divided by hedge intensity, and half-life is the time needed for the hedge rates to sum to half the hedge intensity. Crack spread is the difference between the refined-product price (output), p, and the price of crude oil (input), w. Price volatility (co-movement) is the variance (correlation) of daily prices over a trailing 3-month moving window. Price momentum is the change in spot price in the past year. Futures-curve slope is the nearest-month price (p for Sales, w for Costs) divided by the 12-month futures price. Futures-curve risk is the coefficient of variation (standard deviation divided by the mean) of prices along the futures curve. Futures-curve depth (liquidity) is the sum of open interest (trade volume) for the 6, 9, 12, 18, and 24-month contracts divided by open interest (trade volume) for the 3-month contract. Contrasts use sort-variable interactions to shift the curvature and shape parameters $(c_p, c_w, \beta, \lambda, \theta, \gamma)$. Each sort variable is the residual of a regression on the other futures-market measures. Difference tests compare paired-bootstrap estimate percentiles.

Footprint Hedging Estimates:	**Value of Risk Management**				**Hedge Intensity**			
	Sales		Costs		Sales		Costs	
Futures-Markets Performance	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Crack Spread (output – input price, $p - w$)	0.12	0.07^{a}	0.10	0.06^{a}	0.36	0.22^{a}	0.13	0.11^{a}
Price Levels (output p, input w)	0.09	0.04^{a}	0.07	0.03^{a}	0.33	0.59^{a}	0.34	0.19^{a}
Price Volatility (variance of p, w)	0.15	0.06^{a}	0.12	0.05^{a}	0.25	0.55^{a}	0.13	0.08^{a}
Price Co-movement (correlation of p & w)	0.12	0.15^{a}	0.08	0.13^{a}	0.25	0.40^{a}	0.21	0.13^{a}
Momentum (past year's price change)	0.14	0.13^{a}	0.09	0.10^{a}	0.49	0.22^{a}	0.08	0.02^{a}
Futures-Markets Conditions	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Futures-curve Slope (far/near price)	0.12	0.15^{a}	0.08	0.13^{a}	0.34	0.33^{-}	0.14	0.11^{a}
Futures-curve Risk (coef. of variation)	0.12	0.14^{a}	0.09	0.10^{a}	0.37	0.42^{a}	0.09	0.11^{a}
Futures-curve Depth (far/near open int.)	0.12	0.13^{a}	0.07	0.14^{a}	0.31	0.34^{a}	0.08	0.09^{a}
Futures-curve Liquidity (far/near volume)	0.14	0.11^{a}	0.08	0.12^{a}	0.35	0.32^{a}	0.11	0.07^{a}

Footprint Hedging Estimates:	**Hedge Maturity**				**Hedge Half-life**			
	Sales		Costs		Sales		Costs	
Futures-Markets Performance	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Crack Spread (output – input price, $p - w$)	0.92	0.71^{a}	0.73	0.49^{a}	0.69	0.44^{a}	0.50	0.30^{a}
Price Levels (output p, input w)	0.76	0.97^{a}	0.98	0.74^{a}	0.47	0.76^{a}	0.78	0.49^{a}
Price Volatility (variance of p, w)	0.68	0.91^{a}	0.75	0.75^{-}	0.40	0.67^{a}	0.52	0.66^{a}
Price Co-movement (correlation of p & w)	0.62	0.92^{a}	0.80	0.81^{-}	0.36	0.67^{a}	0.59	0.70^{a}
Momentum (past year's price change)	0.99	0.69^{a}	0.74	0.73^{-}	0.78	0.40^{a}	0.56	0.60^{b}
Futures-Markets Conditions	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Futures-curve Slope (far/near price)	0.73	0.95^{a}	0.73	0.88^{a}	0.44	0.72^{a}	0.53	0.83^{a}
Futures-curve Risk (coef. of variation)	0.96	0.84^{a}	0.64	0.57^{a}	0.74	0.58^{a}	0.44	0.37^{a}
Futures-curve Depth (far/near open int.)	0.81	0.97^{a}	0.75	0.45^{a}	0.54	0.75^{a}	0.60	0.27^{a}
Futures-curve Liquidity (far/near volume)	0.88	0.90^{a}	0.76	0.47^{a}	0.62	0.65^{a}	0.58	0.32^{a}

Table VIII
Footprint Hedging Estimates *versus* Footnote Hedging Measures – Manufacturing

Bootstrap medians (1,000 replications) for value of risk management, hedge intensity, hedge maturity, and hedge half-life computed from regressions corresponding to Model 8 in Table III.C (the 2 shape-parameter *beta* function). The value of risk management (normalized by predicted operating income) is given by Jensen's inequality (see MacKay and Moeller, 2007). Hedge intensity is the sum of the hedge rates, hedge maturity (in years) is the time-weighted sum of the hedge rates divided by hedge intensity, and half-life is the time needed for the hedge rates to sum to half the hedge intensity. *Footnote Measures*: Collected from annual reports and 10-K filings. Hedge accounting is the percentage of its derivatives positions a firm records using hedge accounting. Hedge intensity is the equally-weighted average of maturity-specific hedge rates for maturities up to 7 years. Hedge maturity (in years) is the time-weighted sum of a firm's maturity-specific hedge rates divided by hedge intensity, and half-life is the time needed for the sum of hedge rates to reach half the hedge intensity. Hedge asymmetry captures option-like hedges by contrasting lagged futures-price losses and gains. Pre/post FAS 133 compares periods before and after FAS 133 (1998). Pre/post 2001 contrasts 1985-2001 and 2002-2018. Contrasts use sort-variable interactions to shift curvature and shape parameters ($c_p, c_w, \beta, \lambda, \theta, \gamma$). Difference tests compare paired-bootstrap estimate percentiles.

Footprint Estimates	**Value of Risk Management**				**Hedge Intensity**			
	Sales		Costs		Sales		Costs	
Pooled Sample	0.01		0.01^{a}		0.08		0.05	
	Loss	*Gain*	*Loss*	*Gain*	*Loss*	*Gain*	*Loss*	*Gain*
Hedge Asymmetry								
	Sales		Costs		Sales		Costs	
Footnote Measures	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Hedge Accounting	0.01	0.01	0.01	0.01	0.10	0.06	0.00	0.03
Hedge Intensity	0.01	0.01	0.01	0.01^{c}	0.08	0.27	0.00	0.04
Hedge Maturity	0.01	0.01	0.01	0.01^{c}	0.07	0.12	0.01	0.01
Hedge Half-life	0.01	0.01	0.01	0.01^{c}	0.07	0.10	0.01	0.01
Sub-period	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Pre/post FAS 133	0.01	0.01	0.01	0.01^{b}	0.15	0.10	0.09	0.03
Pre/post year 2001	0.01	0.01^{b}	0.01	0.01^{a}	0.22	0.44^{b}	0.01	0.10^{a}

Footprint Estimates	**Hedge Maturity**				**Hedge Half-life**			
	Sales		Costs		Sales		Costs	
Pooled Sample	1.01		0.65^{b}		0.78		0.54	
	Loss	*Gain*	*Loss*	*Gain*	*Loss*	*Gain*	*Loss*	*Gain*
Hedge Asymmetry								
	Sales		Costs		Sales		Costs	
Footnote Measures	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Hedge Accounting	1.19	1.35	0.67	0.75^{c}	0.95	0.92	0.52	0.48
Hedge Intensity	1.45	1.66	0.67	1.18	1.19	1.32	0.53	0.52
Hedge Maturity	1.41	1.51	0.69	0.77	1.22	1.21	0.56	0.53
Hedge Half-life	1.40	1.49	0.69	0.76	1.22	1.23	0.56	0.54
Sub-period	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Pre/post FAS 133	1.50	1.46	0.79	0.67	1.34	0.93	0.64	0.51
Pre/post year 2001	1.56	1.18	0.46	0.67	1.54	1.10	0.23	0.53^{c}

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