# The Hedging Footprint

*Abstract*

Gains and losses on derivatives positions leave accounting footprints we can detect by regressing sales or costs on lagged output or input prices. Calibration for oil-refining and manufacturing firms yields estimated hedge intensities and maturities similar to those derived from financial-statement footnotes. We find that hedging patterns adjust rationally to exogenous variation in accounting standards, tax convexity, basis risk, and futures-market conditions, but also to historical prices. We further validate our method by replicating – and nuancing – past empirical associations between hedging activity and firm characteristics. The hedging footprint emerges an efficient alternative to noisy footnote measures and brings new insights on corporate risk management.

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 using 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 potentially be studied using this method. For instance, we also apply our method to track U.S. dollar index (USDX) hedging by sample firms across all manufacturing industries and corroborate its ability to emulate hedging activity reported in these firms' financial-statement footnotes.

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1 Smith and Stulz (1985) and Bessembinder (1991) show how hedging adds value when firms face imperfections that cause nonlinear payoffs (e.g., progressive taxation, bankruptcy costs, risk aversion, claimant conflicts). That 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 Carter *et al*. (2017) Bodnar *et al*. (2018, 2019), Geyer-Klingeberg *et al*. (2018), and Bessler *et al*. (2019) for recent literature reviews.

Before turning to our results, let us illustrate our proposed method with a simple example. Suppose a firm normally hedges half its sales-price exposure one quarter ahead of delivery. Then the sales it reports every quarter will track 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 the lagged futures prices we consider, i.e., 3, 6, 9, 12, 15, 18, 21, and 24 months. 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.[2] 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 hedge maturity structure (the time-weighted sum of the hedge rates normalized by hedge intensity).

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 40% of its sales exposure to refined-product prices and 24% of its costs exposure to the price of crude oil.[3] These estimates are robust to using a more parsimonious specification (the "decay model"), which avoids potential multi-collinearity by reducing the number of coefficients to two shape parameters and allows us to analyze hedging determinants through interaction terms.

Second, we find that the sample-median oil refiner hedges well beyond the nearest quarter, hedging out about 12 months for both sales and costs. Hedge intensity is nonlinear in maturity, as indicated by median sales and costs half-lives of about 10 months, and in that energy futures prices beyond 12 months tend to load weakly in the discrete model.[4]

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[2] 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.

[3] Structural analysis by Ghoddusi *et al*. (2020) may explain the gap between sales and costs hedge intensities, where uneven supply and demand shocks and changing industry conditions yield non-intuitive, dynamic hedge strategies.

[4] 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.

While our method rests on hedge-accounting principles and produces reasonable estimates, we validate it by relating our footprint estimates to the hedging activity reported in the footnotes to refiners' financial statements. The latter show a mean hedge intensity of 25% and hedge maturity of 5 months, slightly below our footprint estimates.[5] 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 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 (21) percentiles as footnote-hedge intensity varies over the sample interquartile range.

As a second approach to validating our method, we revisit past empirical relations between hedging activity and firm characteristics. We find that most of the determinants tested in previous studies (Purnanandam, 2008, Rampini *et al*., 2014, etc.) are only economically and statistically significant for <u>sales</u> hedging, with hedge intensity increasing in assets, cash holdings, inventories, collateral, CAPEX, Tobin's *q*, Altman's Z, financial leverage, and the dividend payout ratio. Most of these characteristics also coincide with longer hedge maturity. Other findings are more nuanced: Industrial diversification substitutes for hedging but geographic diversification is complementary. Credit rating increases with costs hedge intensity, but is not significantly related to sales hedging.

Although our reported associations are economically important and statistically significant, they hinge on partialed sorts, where each variable is first instrumented then regressed on the other firm characteristics, which may not fully dampen endogeneity bias. So, like the referenced studies, these tests of association do not robustly isolate root causes nor identify the direction of causation. The adoption of FAS 133 in 1998, which standardized hedge accounting, provides corroborating evidence in that estimated hedging intensity and maturity increase *post* FAS 133. At the firm level,

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[5] 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), closer to our footprint hedging estimates. As a cursory check of external validity, both our footprint estimates and the footnote measures fall in the range of percentage of assets hedged reported by Graham and Rogers (2002) and Campello *et al*. (2011) for broader sets of industries.

we follow Graham and Smith (1999) and Campello *et al*. (2011) by computing firm-year-quarter tax convexities, which we find to significantly increase estimated hedge intensities and maturities. Finally, our footprint hedge intensities and maturities track the basis risk (*aka* hedge effectiveness) and Sharpe ratios of quarterly-updated minimum-variance hedge portfolios.[6] Collectively, these rational adjustments to plausibly-exogenous factors lend further validating support to our method.

To illustrate other uses of our method, we test for evidence of retrospective and prospective decision-making in explaining the time-varying demand for corporate hedging. First, we find that hedging adjusts to price time-paths. For instance, sales (costs) hedging rises (falls) when prices are historically high (low), suggesting that refiners seek to fix (unfix) perceived high (low) prices, i.e., market timing. Sales and costs hedge intensities are inversely related to signed price momentum (last year's change), rational if mean-reversion is persistent. Second, hedging activity adjusts to prevailing futures-market conditions, consistent with prospective decision-making. For instance, we find that corporate hedging adjusts to 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 contingent hedging or market-timing/selective-hedging skills, and Bartram *et al*. (2011), who document down-side risk hedging. 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 used 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)[7].

This paper makes several contributions. First, we develop a method to backward-engineer corporate hedging activity based on accounting principles and standard data rather than footnotes,

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6 Ederington (1979) and Anderson and Danthine (1980, 1981) derive and calibrate univariate and multivariate basis risk (hedge effectiveness) for equity and commodity derivatives. Haushalter (2000) and Gilje and Taillard (2017) document the importance of basis risk to firms' financial hedging and real decisions, which we corroborate here.

7 Starting with fiscal year 2000, FAS 133 views purchase orders as derivatives, also eligible for hedge accounting.

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, which opens new avenues for empirical corporate risk-management research. Our calibration for oil refining, and external validation for a cross-section of manufacturing firms, yields reasonable results and shows promise in investigating other industries and price risks in future work.[8] Second, we corroborate past empirical associations, qualifying some of them, which further validates the proposed method and showcases its ability to identify new, more subtle relations. More robustly, we draw support from exogenous variation in accounting standards, tax convexity, and basis risk. Finally, we find that hedging activity adjusts to performance and conditions in the futures markets, indicative of both retrospective and prospective 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.

[8] Cornaggia (2011), Pérez-Gonzáles and Yun (2013), and Gilje and Taillard (2017) discuss why focusing on a single commodity industry mitigates econometric issues such as unobserved heterogeneity in production technology, risk sources, access to derivatives, competitive structure (Adam *et al*., 2006), and parallel trends. For these reasons, we emulate that practice by targeting the oil-refining industry before broadening our analysis to all of manufacturing.

## I. Motivation and Methodology

Obtaining reliable data on corporate hedging activity has long eluded financial economists. Researchers have generally resorted to one of three approaches (in roughly chronological order):

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 *residual* 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, 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 errors.

3) Sift through footnotes for large samples of firms, typically yielding a "hedge / 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). More recent work has often sought to construct 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), through labor-intensive or textual-analysis methods. But starting in 2000 (FAS 133), firms are not required to disclose their derivatives notional amounts, which certainly impairs this approach.

Footnote measures share other limitations: Firms may discuss derivatives usage qualitatively (*vs* quantitatively) and simply describe hedging policy (*vs* actual practice); reported numbers are typically notional amounts (*vs* position values or the schedule of exposures and hedges); positions are end-of-period (*vs* itemized transactions); hedging and speculative positions are not segregated.

*A. A Simple Alternative: The Hedging Footprint*

We propose an alternative method to measuring hedging activity based on hedge accounting. While not a panacea, our method addresses key limitations of the approaches outlined above and can therefore serve as an important complement to the empirical tools used so far by the profession. Besides conceptual simplicity and soundness, it is also straightforward to implement in practice.

Our method rests on two features of cash-flow hedge accounting.[9] First, gains and losses on derivatives designated as cash-flow hedges are reflected in sales and costs accounts rather than in "other comprehensive income", where non-designated derivatives gains and losses are reported.[10] Second, such designated gains and losses only migrate to the income statement in the period when the underlying transaction is recognized (until then, unrealized gains and losses are carried on the balance sheet under "other current assets" and "accumulated other comprehensive income").[11]

Because gains and losses on derivatives positions that do not qualify (or are not designated) as "cash-flow hedges" bypass sales and costs accounts, our method isolates *hedging* activity from other derivatives uses, such as speculation (e.g., Adam and Fernando, 2006, Brown *et al.*, 2006, Chernenko *et al.*, 2011). But FASB is conservative in defining qualified hedges, and firms might choose not to designate all qualified positions, which means our method tends to understate true corporate hedging activity. We see in this more of a strength than a shortcoming: By focusing on cash-flow hedges, our method offers a tighter link to theory because hedging models examine why firms would rationally seek to stabilize cash flow, not why they might speculate with derivatives.

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[9] 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). We contrast pre/post FAS 133, which took effect with fiscal year 2000 (superseding FAS 119, 1994, and FAS 80, 1984), and no longer required firms to disclose the notional amounts of their derivatives positions. Consequently, related footnote disclosures become *less* quantitatively informative – and our method *more* useful – beyond the year 1999.

[10] 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 10-K for Amerada-Hess, Appendix A).

[11] Reported income 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".

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) in the current 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, conceptually, we can decompose sales and costs as follows:

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

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

where $p_0$ and $w_0$ denote output and input spot prices, and $\dot{p}_{L\tau}$ and $\dot{w}_{L\tau}$ are $\tau$-lagged futures-price increment ("step") operators. For instance, $\dot{p}_{L1}$ is the current-quarter's spot (nearest-month) 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. I.e., $\dot{p}_{L\tau}$ and $\dot{w}_{L\tau}$ are historical ("time-stamped") mark-to-market operators.

Thus, $\dot{p}_{L1}$, $\dot{p}_{L2}$, …, $\dot{p}_{L8}$ form the set of adjacent hedging gains and losses a firm might carry over the eight trailing quarters we track. Aside from cleanly stratifying the hedging footprint, the adjacency of these price "steps" is important econometrically as it avoids the multicollinearity and variance-dampening germane to overlapping price series. These lagged futures-price *increments* should not be confused with price *changes*, say as the futures curve evolves across quarters. Put differently, these futures-price *increments* are changes both along the futures curve *and* over time, i.e., how the price 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 $\tau$-lagged futures-price differences (for $\tau$ = 1, 2, …, 8) *versus* spot (nearest-month) prices ($b_p$ and $b_w$).

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

$$\text{Sales Hedge Intensity:} \qquad HI_S = \textstyle\sum_\tau \hat{\beta}_\tau = \hat{\beta}_1 + \hat{\beta}_2 + \cdots + \hat{\beta}_8 \tag{3}$$

$$\text{Costs Hedge Intensity:} \qquad HI_C = \textstyle\sum_\tau \hat{\theta}_\tau = \hat{\theta}_1 + \hat{\theta}_2 + \cdots + \hat{\theta}_8 \tag{4}$$

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

Costs Hedge Maturity: $HM_C = \left[\sum_\tau \tau\hat{\theta}_\tau\right] \div HI_C$ (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: $HL_S = \hat{\phi} \ni \sum_\tau^\phi \hat{\beta}_t = \text{½} HI_S$ (7)

Costs Hedge Half-life: $HL_C = \hat{\varphi} \ni \sum_\tau^\varphi \hat{\theta}_t = \text{½} HI_C$ (8)

### *B. Empirical Specification: Discrete Model*

We map the conceptual model to the following simultaneous-equation specification, which contains equations for sales, costs, and the derived output-supply and input-demand equations:

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

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

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

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

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 $\tau$-lag futures-price increments 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).[12]

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

[12] 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.

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.[13] Firm-level control variables are change in inventories and net property, plant, and equipment (Net PPE), both in level and change in Net PPE. We use 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 presents some econometric issues. First, the lagged price increments, 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 keen to detect. Second, the set of maturities to keep or drop to mitigate collinearity is arbitrary, which is problematic in itself.

We therefore formulate a parsimonious time-decay specification, analogous to a distributed-lags model, where rather than jostle for econometric bandwidth, the time-series variation spanned by all eight lagged price increments is combined with sample time-series cross-sectional firm-level variation to estimate one or two shape parameters (*versus* eight separate hedge-rate parameters). Thus, the discrete-model specification is modified as follows:

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

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

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

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

[13] In order to retain the entire empirical sample period (1985 through 2018), we fit recursive cubic-spline algorithms using available nearby contracts to interpolate or extrapolate prices for maturities where contracts are unavailable. Given the high correlation of prices along the futures curve, an alternative approach consists in lagging spot prices, either to bridge gaps in the futures curve or to replace it entirely. We find this to yield qualitatively similar results.

where $p_{t0}$, $w_{t0}$, $\dot{p}_{tL\tau}$, $\dot{w}_{tL\tau}$ are the spot and $\tau$-lagged price differences defined earlier, and $\beta$, $\theta$, $\lambda$, $\gamma$ 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:
$$f[\beta,\lambda|\dot{p}_{tL\tau}] \equiv \beta\dot{p}_{tL1} + \cdots + \beta\dot{p}_{tL4} + \lambda\dot{p}_{tL5} + \cdots + \lambda\dot{p}_{tL8}\ , \quad (17)$$
$$g[\theta,\gamma|\dot{w}_{tL\tau}] \equiv \theta\dot{w}_{tL1} + \cdots + \theta\dot{w}_{tL4} + \gamma\dot{w}_{tL5} + \cdots + \gamma\dot{w}_{tL8} \quad (18)$$

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

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

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

where $x_1 \ldots x_8 \equiv \left\{\frac{1}{9},\ldots,\frac{8}{9}\right\}$ and $z_1 \ldots z_8 \equiv \left\{\frac{8}{9},\ldots,\frac{1}{9}\right\}$ subtend 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 first implement our method on a sample of 56 U.S.-listed oil refiners from 1985 to 2018. 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-side (crude oil) and the output-side (heating oil, gasoline) of the business, which allows for an integrated analysis of hedging activity. Finally, oil-related 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). We then broaden the scope to a range of manufacturing industries.

*A. Firm-level Data*

Our firm-level data 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* is the market-to-book value of assets, where the market value of equity is computed as 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 therefore set missing control-variable and interaction-variable observations to the industry-year mean to avoid problematic 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 past observations available.[14]

For oil refining firms, we use *COMPUSTAT* annual business-segment data to construct three additional variables: vertical integration, and industrial and geographic diversification. Vertical integration measures a firm's oil-refining related activities, both upstream (exploration and production) and downstream (chemicals, distribution, marketing, etc.).[15] Industrial diversification measures a firm's activities *unrelated* to oil refining or upstream and downstream industries. We

[14] 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.

[15] Specifically, we classify the following segments as upstream industries: 2-digit SIC 13 (exploration and production of crude and natural gas) and 4-digit SIC 4612 (crude oil pipelines) and 6792 (oil and gas royalties and leases). We classify the following segments as downstream industries: 2-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 4-digit SIC 3533 (oil and gas field machinery), 5541 (gasoline stations), 5984 (propane marketing), and 7549 (fast lube operations).

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.

In their seminal paper, Graham and Smith (1999) develop a measure of tax convexity to capture a central rationale for corporate hedging originally proposed by Smith and Stulz (1985). Following Graham and Rogers (2002), Campello *et al*. (2011), and others, we adopt their measure by applying the coefficient estimates published in Graham and Smith (1999) to our sample. Compared to firm characteristics, the Graham-Smith tax convexity measure is viewed as plausibly exogenous because it implements key aspects of the tax environment (see Campello *et al*., 2011).

Bonaimé *et al*. (2014) show that payout policy and risk management are empirically related, so we include dividends among our interaction variables. Theoretical arguments in Bessembinder (1991) and DeMarzo and Duffie (1991) link financial structure to corporate risk management. We therefore examine the association between financial leverage (total debt / total assets), debt maturity (short-term debt / total debt), profitability (operating income / PPN), liquidity (cash & equivalents / PPN), solvency (Altman's Z-score, S&P credit rating), and payout policy (dividends / PPN), both to corroborate past empirical findings and thereby further validate our method.

### *B*. *Futures-Market Data*

#### B.1 Energy Prices (Oil Refining)

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*.[16] From March 1985, delivery months for all three commodities have been available for every month

[16] 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.

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).[17]

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 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

[17] 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.

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.[18]

### B.2 USD Index (Manufacturing)

For manufacturing industries, we use the USD index (USDX) as the risk factor for both the output side (sales) and input side (costs).[19] The futures time-series starts November 20, 1985, and spans four quarterly deliveries trading on the Intercontinental Exchange (ICE). We construct one spot (nearest-quarter) price and futures prices for deliveries two, three, and four quarters out.

### B.3 Minimum-Variance Hedge Portfolios

Following Ederington (1979), Anderson and Danthine (1980), Gilje and Taillard (2017), and others, we construct multivariate minimum-variance futures-hedge portfolios to estimate basis risk ("hedge effectiveness"). We use the Sharpe ratios for these portfolios to gauge the cost of hedging. This multivariate approach is further motivated by Neuberger (1999), who shows that despite rollover risk, hedging effectiveness is improved when several maturities are used simultaneously. We use the following procedure for each year-quarter to allow for the dynamic hedging strategies.

Sales (costs) hedge portfolios use refined-product (crude oil) futures contracts. We estimate multivariate regressions of log-change in spot price on log-change in futures prices. Since contemporaneous price changes along the futures-curve are highly correlated, collinearity is severe. To avoid this issue, and recognize that adding contracts to the portfolio is costly, we use the Elastic Net model-selection method (Zou and Hastie, 2005, Kozak *et al*., 2020), that combines LASSO and ridge-regression methods to balance model parsimony and regressor correlation by constraining the sum of both the absolute and squared values of the coefficients ($L^1$ and $L^2$ norms).

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[18] As a practical matter, firms commonly roll over shorter contracts to hedge long-dated exposures because derivatives markets are either too thin, too illiquid, or consequently too pricey to operationalize a desired long-term hedge. Our method carries through because cash-flow hedge accounting treatment is allowed for qualified rollover strategies.

[19] In their meta-study of 47 papers, Bessler *et al*. (2019) report that the hedging of foreign exchange emerges as the largest contributor to firm value creation linked to risk management. Surveys by Bodnar *et al*. (1998, 2018) show that foreign-exchange is the most commonly-hedged risk in manufacturing. This motivates our use of the USDX.

In many periods, the resulting portfolio uses only the first and second maturities, with adjusted R-squares well over 80%, but as many as seven contracts occasionally enter the hedge-portfolio.[20]

As Neuberger (1999) cautions, rollover strategies must balance hedge-error reduction against hedge-portfolio rebalancing costs such as market depth, liquidity, price pressure, transaction costs, non-stationarity, etc. For this reason, we examine how these factors affect the demand for hedging by constructing dynamic proxies for many of these as the futures-curve evolves quarter to quarter.

*C. Sample Design*

C.1 Firm Selection: Oil Refiners

We retain all U.S.-listed oil refiners with non-missing key variables between 1985 and 2018. We discard observations where sales, costs, or asset are lower than 1,000,000 USD, which filters out a few hundred observations. These screens leave us with 4,239 firm-year observations. The panel is unbalanced, as firms are allowed to enter or leave the sample at any time, with some firms spanning the entire empirical period while others only appear for a few years. These dynamics are desirable since economic realities are captured and the resulting variability adds statistical power.

C.2 Firm Selection: Manufacturing

U.S. manufacturing (SIC 2000-3999) spans a broad range of activity and thousands of firms. Since our objective here is to externally validate the hedging footprint method beyond oil refining (SIC 2911) – including manual inspection of financial-statement footnotes for cross-validation – we employ a stratified block design to optimally structure this resource-intensive exercise.

Among twenty 2-digit SIC manufacturing industries, we omit three: 21 (Tobacco Products – too few firms, regulated), 29 (Petroleum Refining & Related Industries – mainly SIC 2911), and 39 (Miscellaneous Manufacturing Industries – too heterogeneous). For the remaining 17 industries, we regress firm-level operating cash flows on the sum of trailing USDX log returns (8 quarters)

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[20] Under FAS 133, a hedge is deemed "effective" if its correlation to the underlying is 80% or better.

by 3-digit SIC industry and retain the least and most USDX-sensitive 3-digit SIC industry within each 2-digit SIC industry. This contrast aims to maximize expected variation in hedging practices across firms in the same 2-digit SIC industry. Finally, within these select 3-digit SIC industries, we pick firms on the basis of size (one each in the lower and upper sales terciles of its 3-digit SIC) and longevity (firms spanning most of the sample period preferred over those with short histories).

Among the 68 firms thus identified, seven were later dropped due to missing data, whether on COMPUSTAT or on EDGAR, leaving 61 firms to cross-validate footprints against footnotes. A final stratification was used to optimize our footnote search over the 25-year period (1993-2018) where EDGAR filings were available: Rather than manually inspect footnotes for the 61 sample firms in each of these 26 years (potentially 1,586 10-Ks), we instead formed a staggered selection grid where firms' 10-Ks were inspected at (roughly) 5-year intervals. The inspection year sets were chosen such that the four firms retained in each 2-digit SIC industry (least/most USDX-sensitive, lower/upper sales terciles) where observed in the same years. Different year sets were used across industries, resulting in each year between 1993 and 2018 having 12 to 13 firms assigned to it. The final stratified sample resulted in 324 firm-years (10-Ks) being used to populate the panel with intermittent footnote-based measures of corporate hedging activity. We extrapolate these measures to populate the two or three years surrounding each year where a 10-K was directly inspected.[21]

C.3 Sample Selection: Bootstrapping

Several reasons cause us to use firm-cluster robust bootstrapping (see Cameron *et al*., 2008). First, since the panel nature of our samples involves repeated quarterly price data across firms and recurring firms over time, the usual problems of inconsistent standard errors and over rejection arise. Common parametric clustering correction methods make unverified restrictive assumptions on the correlation of residuals and are not valid for use with interactions or nonlinear estimation (Ai and Norton, 2003, Greene, 2010), all of which is applicable here.

[21] Based on the oil-refining sample, where we construct footnote-based measures for every available firm-year (annual reports pre-1992, 10-Ks from EDGAR post-1992), this extrapolation is most likely innocuous. Indeed, we find little or no variation in footnote-based hedging measures from year to year for oil refiners, a pattern we expect also holds true for manufacturing, given the lack of variation in footnote-based hedging measures even across 5-year intervals.

Second, our footprint-hedging measures are constructed by combining estimated hedge-rate coefficients (equations 3-8), which makes standard error computation intractable. In principle, the Wald statistic can be used, but being parametric in nature, it inherits the problems listed above.

Non-parametric structured bootstrapping is a simple, reliable way to avoid these problems. A large number of bootstrap samples is generated by randomly drawing observations from the original sample (with replacement) and the model is re-estimated for each bootstrap sample. The resulting set of coefficient estimates is then used to compute and analyze the statistics of interest. Clustering is handled by adjusting the probability that inter-dependent observations enter a given bootstrap sample. For instance, for panel data such as ours, firm clustering operates by having each firm either enter the sample for its entire available time-series or not all. Any dependence pattern, known or suspected, cross-sectional or longitudinal, can be accommodated in this manner. Non-parametric bootstrapping yields robust quantiles rather than parameter estimates. Aside from using non-parametric bootstrapping in our main regressions, we also use it to run paired-differences tests to investigate associations between our hedging footprint estimates, footnote hedging measures, firm characteristics, and exogenous futures-market conditions, tax convexity, basis risk, etc. Although we winsorize the data at percentiles 1 and 99, another advantage of bootstrapping is that it serves as a multivariate outlier shield and a form of cross-validation, adding further robustness.

## 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 measures 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, Faulkender, 2005, Bartram, 2019) illustrates another way in which the 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; the sales and costs equations contain all the model coefficients. We include the input and output equations in the system because the added structure mirrors firms' first-order conditions and the state of the product and factor markets, thus improving estimate efficiency.

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, since the panel nature of our sample involves repeated year-quarter price data across firms 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 nonparametric paired-differences tests, which we use to investigate associations between hedging, footnote hedging measures, firm characteristics, futures-market conditions, exogenous determinants, and other variables of interest.

### *B. Discussion of Results (forthcoming – sorry that some 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)

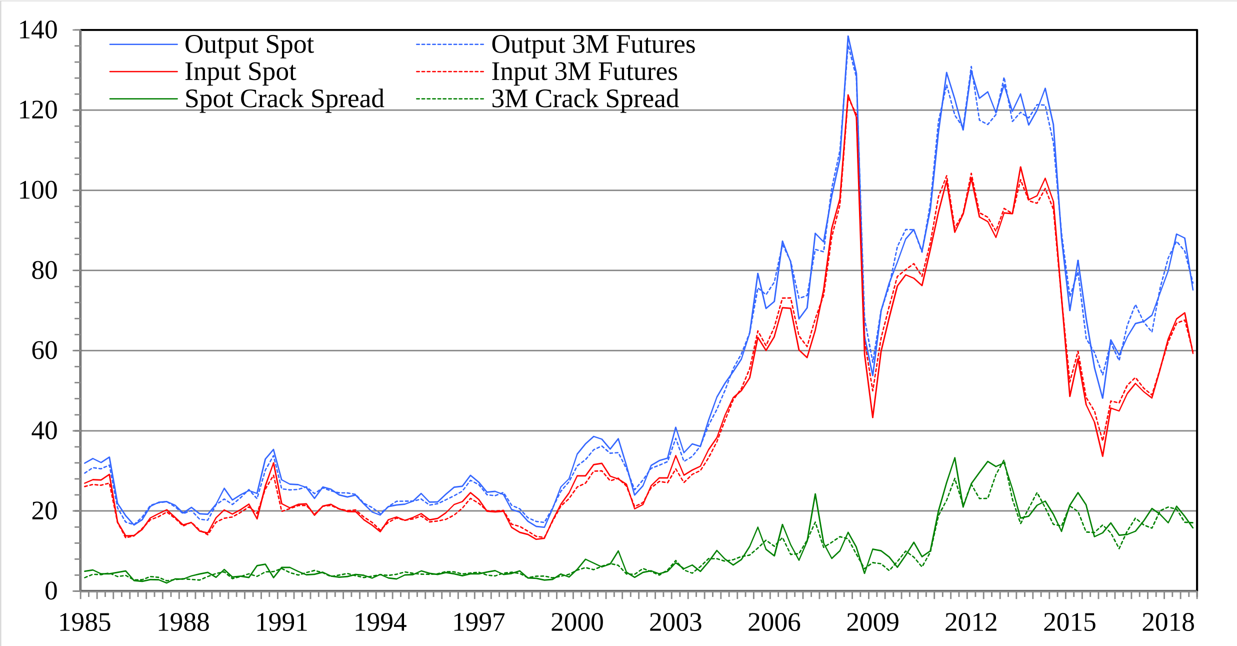



**Figure 1. Quarterly energy prices from March 1985 to December 2018.**

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.

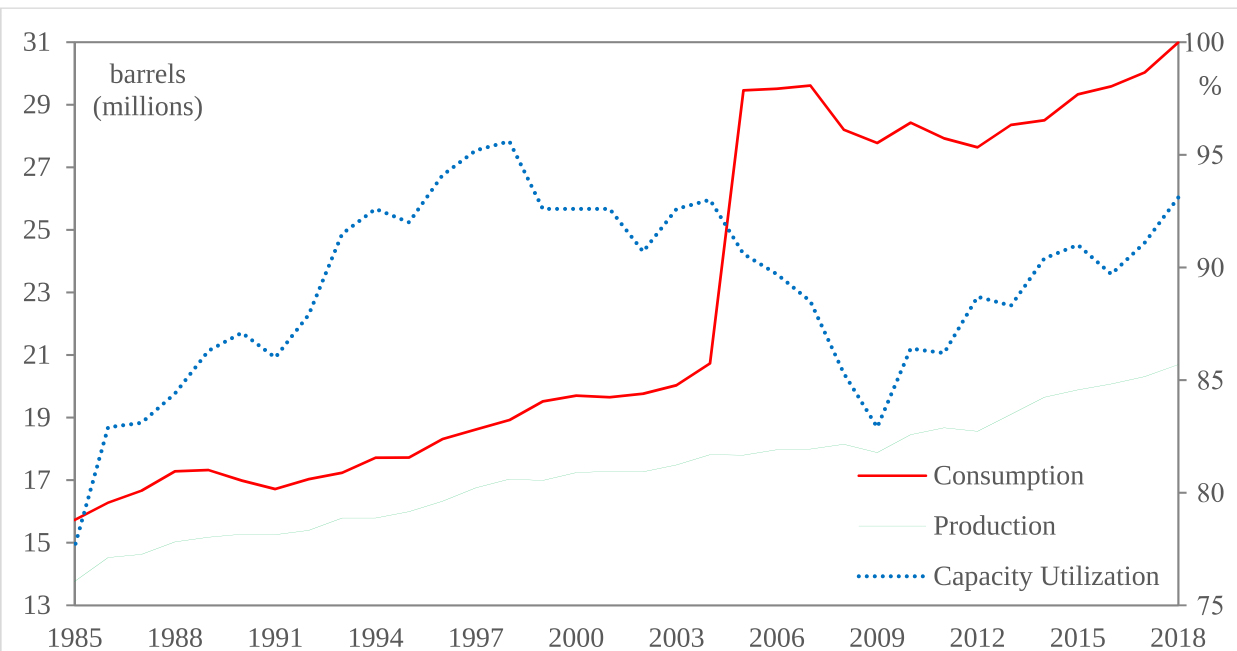
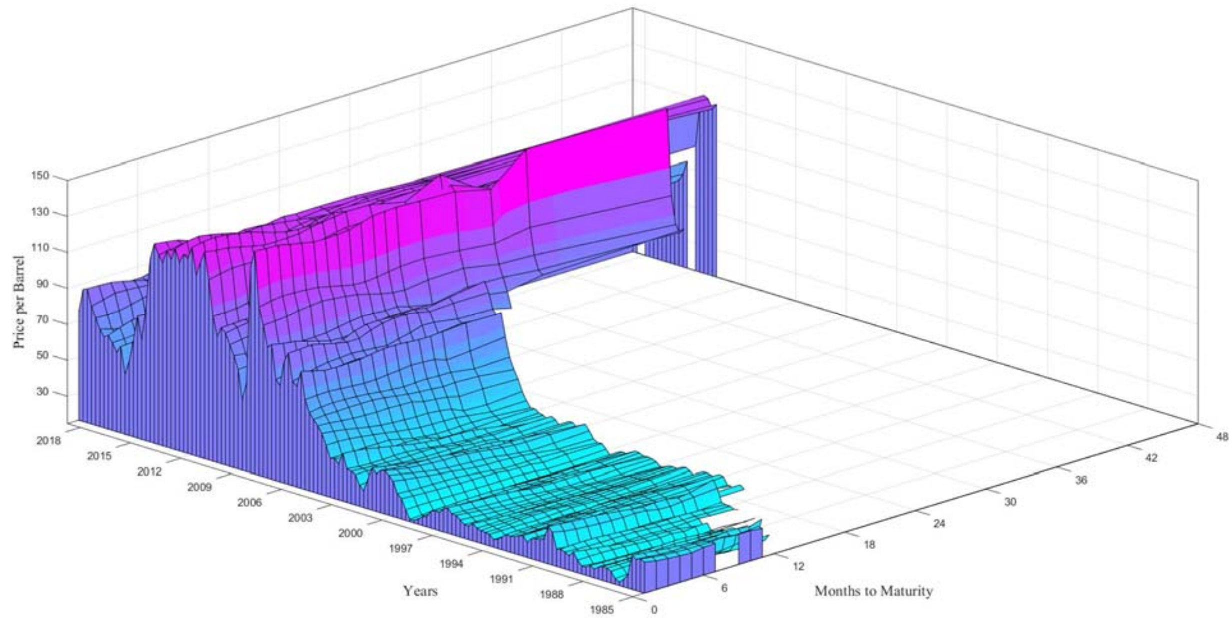



**Figure 2. Annual oil refining statistics 1985 to 2018.**

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)**

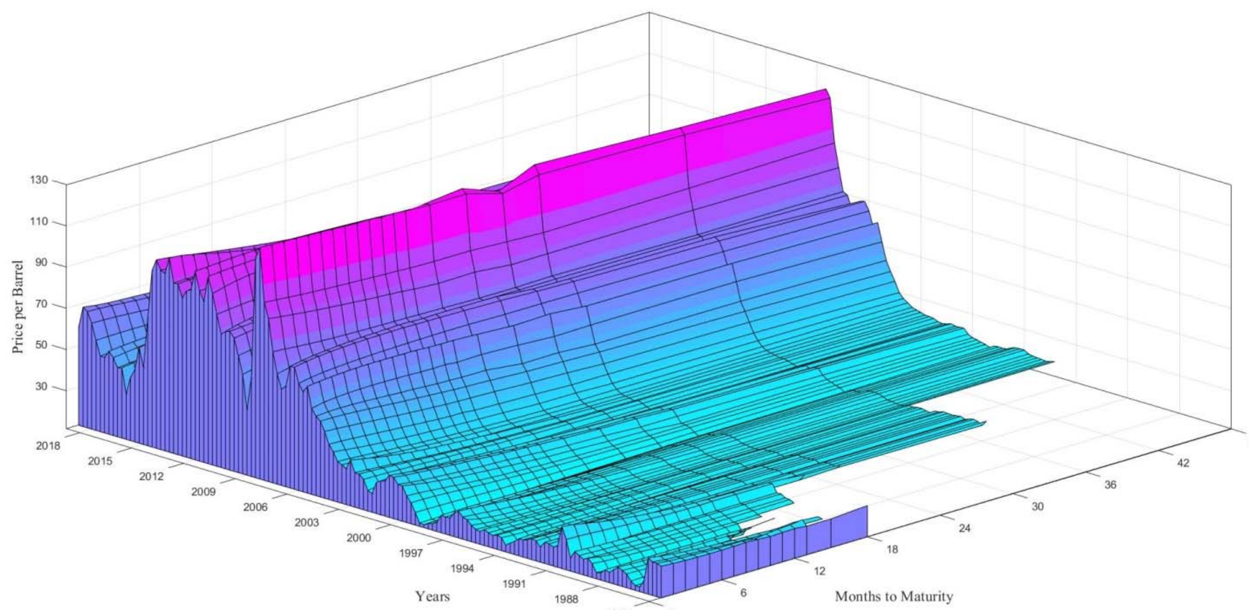
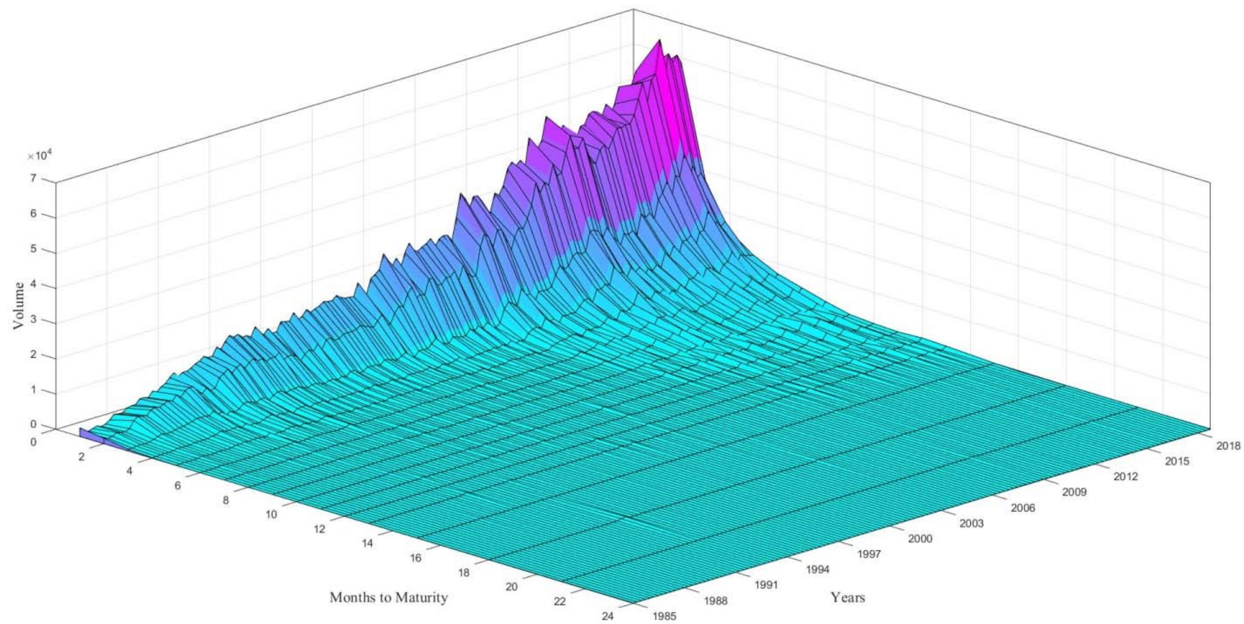



**Figure 3a. Level of output and input futures by maturity Q1 1985 to Q4 2018.**

**Trade Volume of Output Futures (Gasoline & Heating Oil)**




**Trade Volume of Input Futures (Light Crude Oil)**

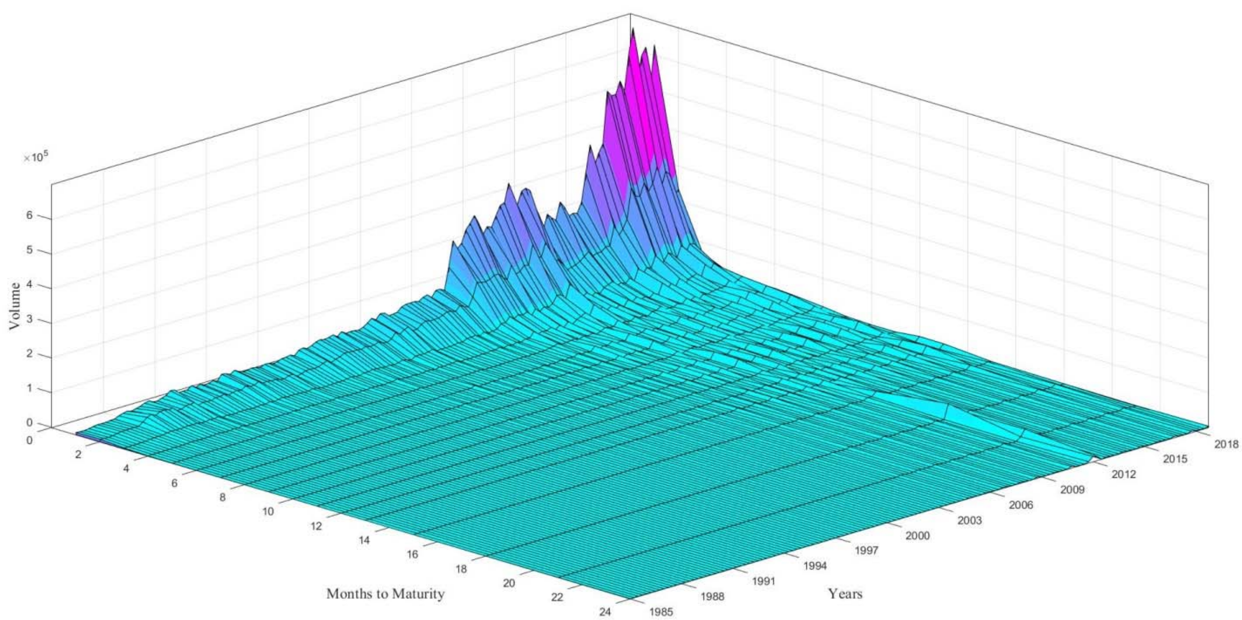
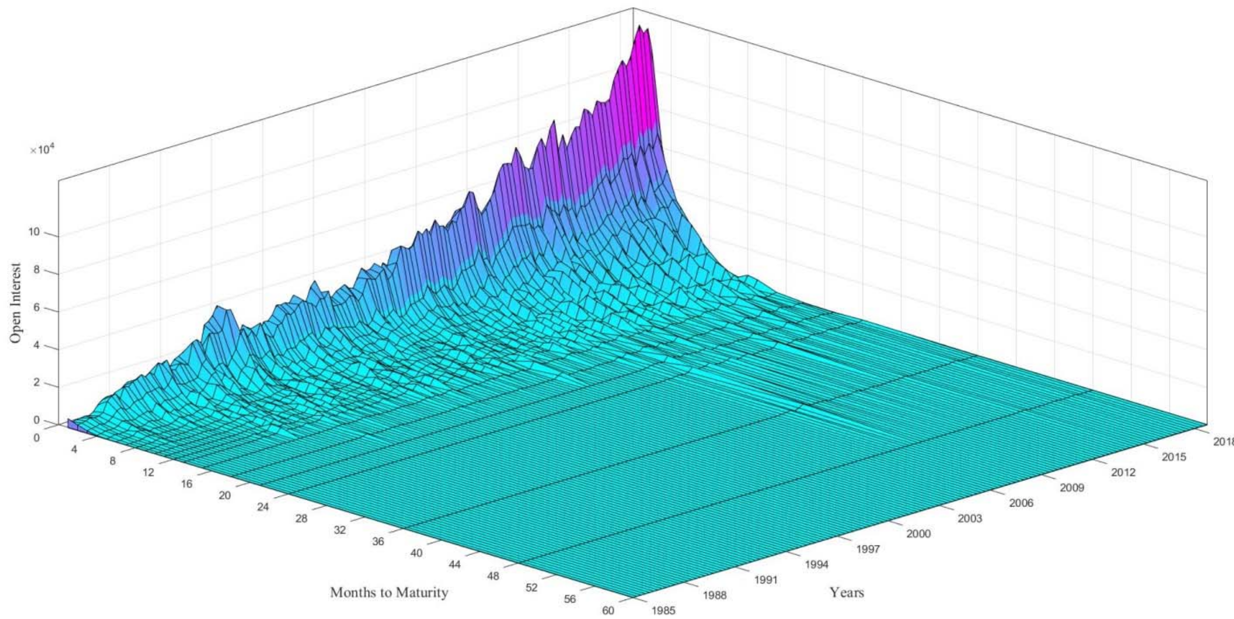



**Figure 3b. Trade Volume for output and input futures by maturity Q1 1985 to Q4 2018.**

**Open Interest in Output Futures (Gasoline & Heating Oil)**




**Open Interest in Input Futures (Light Crude Oil)**

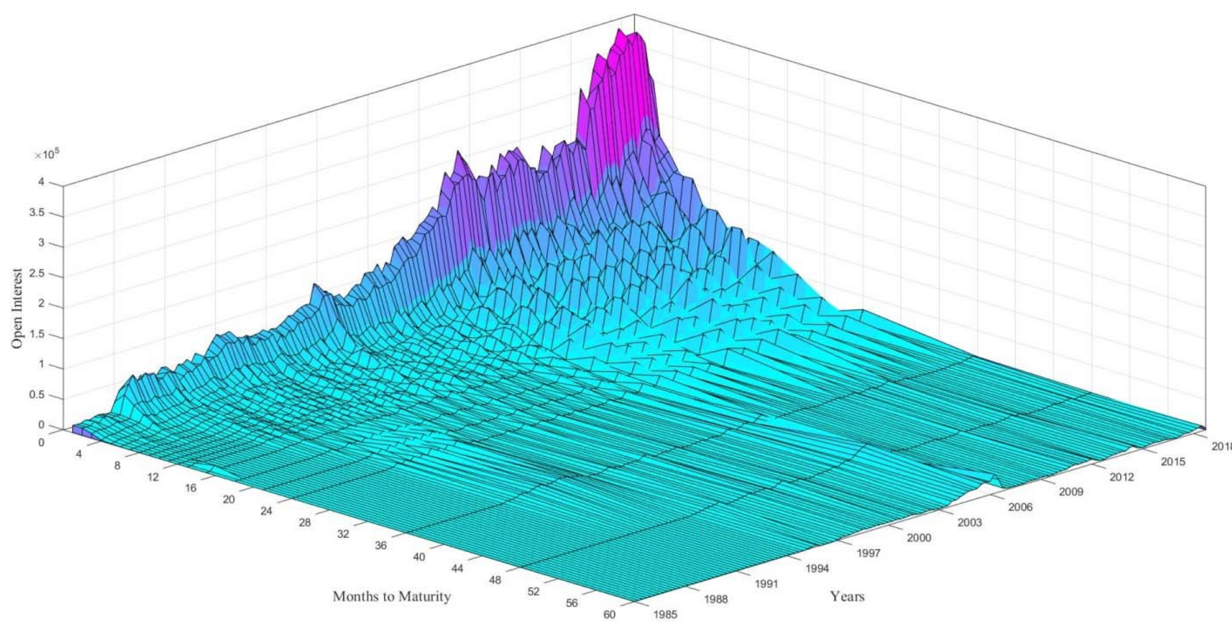



**Figure 3c. Open interest for output and input futures by maturity Q1 1985 to Q4 2018.**

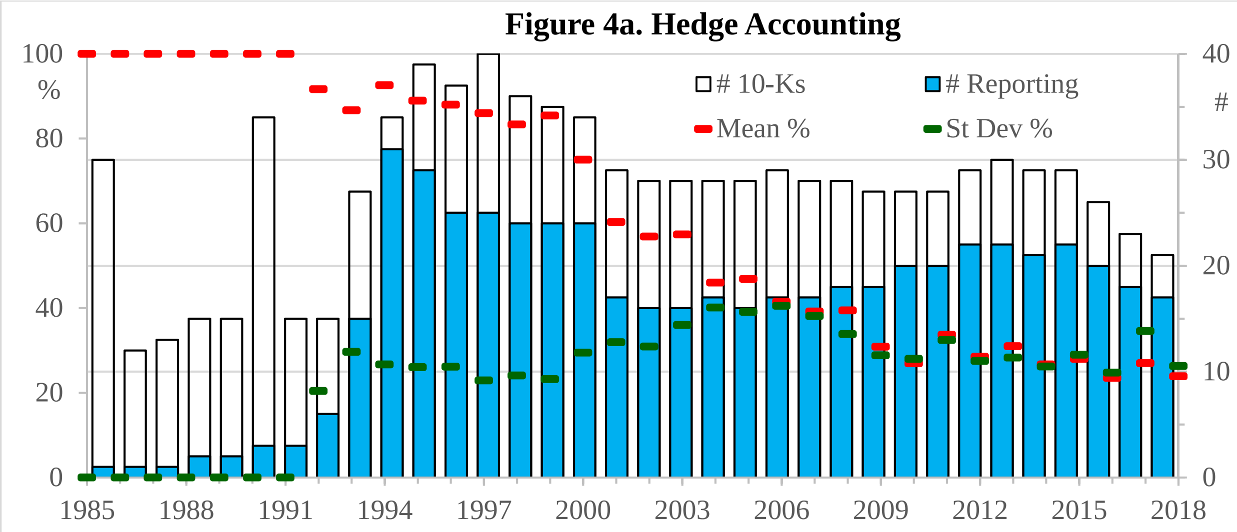


Figure 4a. Hedge Accounting
100
%
80
60
40
20
0
40
#
30
20
10
0
# 10-Ks
# Reporting
Mean %
St Dev %
1985
1988
1991
1994
1997
2000
2003
2006
2009
2012
2015
2018

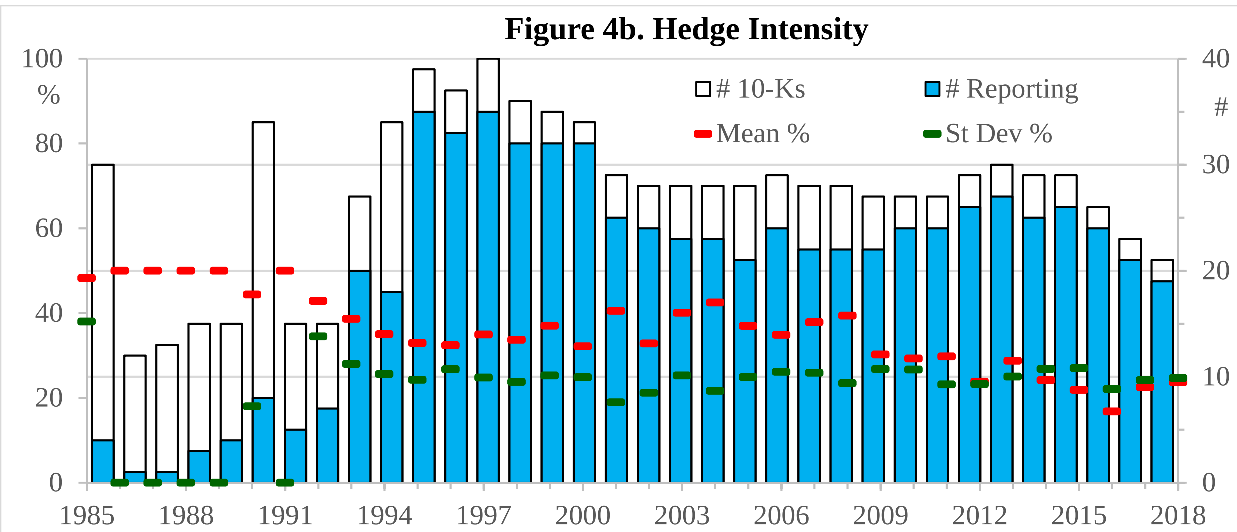


Figure 4b. Hedge Intensity
100
%
80
60
40
20
0
40
#
30
20
10
0
# 10-Ks
# Reporting
Mean %
St Dev %
1985
1988
1991
1994
1997
2000
2003
2006
2009
2012
2015
2018

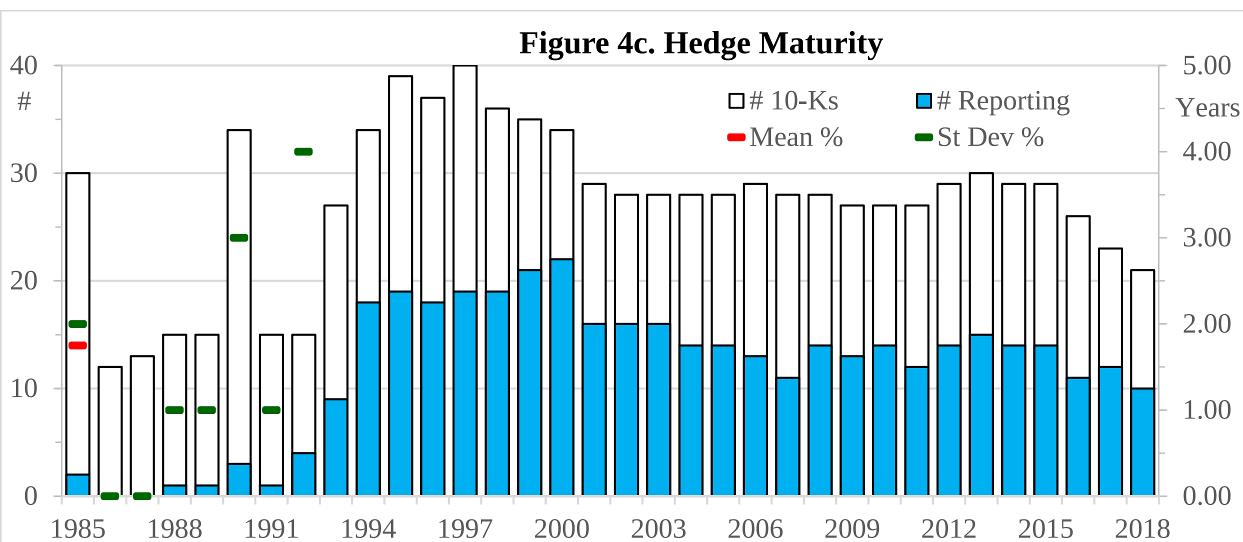


Figure 4c. Hedge Maturity
40
#
30
20
10
0
5.00
Years
4.00
3.00
2.00
1.00
0.00
# 10-Ks
# Reporting
Mean %
St Dev %
1985
1988
1991
1994
1997
2000
2003
2006
2009
2012
2015
2018

**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* is the market-to-book value of assets, where the market value of equity is computed as 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) | 4,257 | | | | | | |

## Table III
## Corporate Risk Management: Footprint Hedging Estimates

Nonlinear Generalized Method-of-Moments bootstrap medians (1,000 replications) for quarterly sales and costs regressed on current-quarter output and input spot (nearest-month) prices ($p_{t0}$, $w_{t0}$), $\tau$-lagged futures price steps ($\dot{p}_{tL1}$, $\dot{p}_{tL2}$,…, $\dot{p}_{tL8}$ and $\dot{w}_{tL1}$, $\dot{w}_{tL2}$,…, $\dot{w}_{tL8}$), 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/$w_0$). 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 $\tau$-lagged futures-price differences ($\tau$ = 1, 2, …, 8). The discrete and decay specifications are:

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

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

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

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

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

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

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 $\theta \neq \lambda$):

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

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

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

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

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. We fit recursive cubic-spline algorithms on available nearby contracts to interpolate or extrapolate prices for maturities where contracts are unavailable. 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 $HL_S \equiv \hat{\phi} \ni \sum_\tau^{\phi} f(\hat{\beta}_\tau, \hat{\lambda}_\tau)_\tau = ½ HI_S$, $HL_C \equiv \hat{\varphi} \ni \sum_\tau^{\varphi} g(\hat{\theta}_\tau, \hat{\gamma}_\tau) = ½ HI_C$. 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] | 0.30[a] | -0.59[a] | 0.27[a] | -0.61[a] | 0.26[a] | -0.60[a] | 0.27[a] | -0.60[a] | 0.28[a] | -0.59[a] | 0.27[a] | -0.59[a] | 0.28[a] | -0.58[a] | 0.28[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] | 0.66[a] | 0.79[a] | 0.67[a] | 0.78[a] | 0.66[a] | 0.78[a] | 0.66[a] | 0.78[a] | 0.66[a] | 0.78[a] | 0.66[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] | -0.12[a] | -0.15[a] | -0.12[a] | -0.16[a] | -0.12[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] |
| | 0.00 | 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 |
| 1 quarter: $\dot{p}_{L1}$, $\dot{w}_{L1}$ | 0.06[a] | 0.04[a] | | | | | | | | | | | | | | |
| | 0.00 | 0.00 | | | | | | | | | | | | | | |
| 2 quarters: $\dot{p}_{L2}$, $\dot{w}_{L2}$ | | | 0.06[a] | 0.06[a] | | | | | | | | | | | | |
| | | | 0.00 | 0.00 | | | | | | | | | | | | |
| 3 quarters: $\dot{p}_{L3}$, $\dot{w}_{L3}$ | | | | | 0.06[a] | 0.04[a] | | | | | | | | | | |
| | | | | | 0.00 | 0.00 | | | | | | | | | | |
| 4 quarters: $\dot{p}_{L4}$, $\dot{w}_{L4}$ | | | | | | | 0.08[a] | 0.02[a] | | | | | | | | |
| | | | | | | | 0.00 | 0.00 | | | | | | | | |
| 5 quarters: $\dot{p}_{L5}$, $\dot{w}_{L5}$ | | | | | | | | | 0.03[a] | -0.00[a] | | | | | | |
| | | | | | | | | | 0.00 | 0.00 | | | | | | |
| 6 quarters: $\dot{p}_{L6}$, $\dot{w}_{L6}$ | | | | | | | | | | | 0.02[a] | 0.01[a] | | | | |
| | | | | | | | | | | | 0.00 | 0.00 | | | | |
| 7 quarters: $\dot{p}_{L7}$, $\dot{w}_{L7}$ | | | | | | | | | | | | | 0.01[a] | -0.01[a] | | |
| | | | | | | | | | | | | | 0.00 | 0.00 | | |
| 8 quarters: $\dot{p}_{L8}$, $\dot{w}_{L8}$ | | | | | | | | | | | | | | | 0.02[a] | -0.01[a] |
| | | | | | | | | | | | | | | | 0.00 | 0.00 |
| Degrees of Freedom | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 | 4,249 |
| 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$^{a}$ | 0.26$^{a}$ | -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$^{a}$ | -0.15$^{a}$ | -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 |
| 1 quarter: $\dot{p}_{L1}$, $\dot{w}_{L1}$ | 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$^{a}$ | 0.03$^{a}$ | 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 |
| 2 quarters: $\dot{p}_{L2}$, $\dot{w}_{L2}$ | 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$^{a}$ | 0.06$^{a}$ | 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 |
| 3 quarters: $\dot{p}_{L3}$, $\dot{w}_{L3}$ | | | 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$^{a}$ | 0.02$^{a}$ | 0.02$^{a}$ | 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 |
| 4 quarters: $\dot{p}_{L4}$, $\dot{w}_{L4}$ | | | | | 0.07$^{a}$ | 0.03$^{a}$ | 0.05$^{a}$ | 0.03$^{a}$ | 0.08$^{a}$ | 0.02$^{a}$ | 0.07$^{a}$ | 0.03$^{a}$ | 0.08$^{a}$ | 0.03$^{a}$ | 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 |
| 5 quarters: $\dot{p}_{L5}$, $\dot{w}_{L5}$ | | | | | | | 0.03$^{a}$ | 0.02$^{a}$ | 0.00$^{a}$ | 0.01$^{a}$ | 0.02$^{a}$ | 0.01$^{a}$ | 0.02$^{a}$ | 0.01$^{a}$ | | |
| | | | | | | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | |
| 6 quarters: $\dot{p}_{L6}$, $\dot{w}_{L6}$ | | | | | | | | | 0.05$^{a}$ | 0.05$^{a}$ | 0.04$^{a}$ | 0.05$^{a}$ | 0.06$^{a}$ | 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 |
| 7 quarters: $\dot{p}_{L7}$, $\dot{w}_{L7}$ | | | | | | | | | | | 0.02$^{a}$ | 0.01$^{a}$ | 0.02$^{a}$ | 0.01$^{a}$ | | |
| | | | | | | | | | | | 0.00 | 0.00 | 0.00 | 0.00 | | |
| 8 quarters: $\dot{p}_{L8}$, $\dot{w}_{L8}$ | | | | | | | | | | | | | 0.05$^{a}$ | 0.00$^{a}$ | 0.05$^{a}$ | 0.00$^{a}$ |
| | | | | | | | | | | | | | 0.00 | 0.00 | 0.00 | 0.00 |
| Degrees of Freedom | 4,247 | 4,247 | 4,245 | 4,245 | 4,243 | 4,243 | 4,241 | 4,241 | 4,239 | 4,239 | 4,237 | 4,237 | 4,236 | 4,236 | 4,241 | 4,241 |
| 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 (nearest-month) prices ($p_{t0}$, $w_{t0}$), $\tau$-lagged futures price steps ($\dot{p}_{tL1}, \dot{p}_{tL2}, \ldots, \dot{p}_{tL8}$ 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 $\tau$-lagged futures-price differences ($\tau$ = 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 ($HL_S \equiv \hat{\varphi} \ni \sum_\tau^{\varphi} f(\hat{\beta}_\tau, \hat{\lambda}_\tau)_\tau = ½HI_S$, $HL_C \equiv \hat{\varphi} \ni \sum_\tau^{\varphi} g(\hat{\theta}_\tau, \hat{\gamma}_\tau) = ½HI_C$). Difference tests (S = C?) compare paired-bootstrap hedging-measure estimate percentiles across sales and costs.

| Functional Form (1 or 2 parameters) | **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$^{a}$ | -0.12$^{a}$ | -0.04$^{a}$ | -0.12$^{a}$ | -0.04$^{a}$ | -0.14$^{a}$ | -0.06$^{a}$ | -0.14$^{a}$ | -0.06$^{a}$ | -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 | 0.01 | 0.01 | 0.01 | 0.01 |
| Prices Levels: $p$, $w$ | 0.81$^{a}$ | 0.69$^{a}$ | 0.81$^{a}$ | 0.69$^{a}$ | 0.81$^{a}$ | 0.71$^{a}$ | 0.81$^{a}$ | 0.71$^{a}$ | 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 | 0.01 | 0.01 | 0.01 | 0.01 |
| Squared Prices: $p^2$, $w^2$ | -0.21$^{a}$ | -0.19$^{a}$ | -0.21$^{a}$ | -0.19$^{a}$ | -0.15$^{a}$ | -0.13$^{a}$ | -0.15$^{a}$ | -0.13$^{a}$ | -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 | 0.00 | 0.00 | 0.00 | 0.00 |
| Scale Parameters: $\beta$, $\theta$ | 0.56$^{a}$ | 0.45$^{a}$ | 0.67$^{a}$ | 0.53$^{a}$ | 0.75$^{a}$ | 0.53$^{a}$ | 1.05$^{a}$ | 1.03$^{a}$ | 0.27$^{a}$ | 0.34$^{a}$ | 0.03$^{c}$ | 0.09$^{b}$ | 0.98$^{a}$ | 0.99$^{a}$ | 0.97$^{a}$ | 0.99$^{a}$ |
| | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Shape Parameters: $\lambda$, $\gamma$ | 0.56$^{a}$ | 0.45$^{a}$ | 0.43$^{a}$ | 0.37$^{a}$ | 0.75$^{a}$ | 0.50$^{b}$ | 0.03$^{a}$ | -0.00$^{-}$ | 0.27$^{a}$ | 0.37$^{a}$ | 0.90$^{a}$ | 1.34$^{a}$ | 0.98$^{a}$ | 0.99$^{a}$ | 0.99$^{a}$ | 0.99$^{a}$ |
| | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 | 0.11 | 0.16 | 0.00 | 0.00 | 0.00 | 0.00 |
| Degrees of Freedom | 4,249 | 4,249 | 4,247 | 4,247 | 4,249 | 4,249 | 4,247 | 4,247 | 4,249 | 4,249 | 4,247 | 4,247 | 4,249 | 4,249 | 4,247 | 4,247 |
| Hansen's J-Statistic ($p$-val) | 1,468 | 0.00$^{a}$ | 1,277 | 0.00$^{a}$ | 1,218 | 0.00$^{a}$ | 1,018 | 0.00$^{a}$ | 1,232 | 0.00$^{a}$ | 1,011 | 0.00$^{a}$ | 1,078 | 0.00$^{a}$ | 874 | 0.00$^{a}$ |
| Value of Risk Management | 18% | 15%$^{a}$ | 16% | 14%$^{a}$ | 14% | 13%$^{a}$ | 15% | 13%$^{a}$ | 14% | 12%$^{a}$ | 14% | 13%$^{a}$ | 15% | 12%$^{a}$ | 16% | 13%$^{a}$ |
| Hedge Intensity (S = C?) | 36% | 24%$^{a}$ | 35% | 23%$^{a}$ | 35% | 23%$^{a}$ | 34% | 23%$^{a}$ | 36% | 22%$^{a}$ | 37% | 24%$^{a}$ | 39% | 22%$^{a}$ | 40% | 23%$^{a}$ |
| Hedge Maturity (S = C?) | 0.95 | 1.09$^{-}$ | 0.94 | 1.08$^{-}$ | 0.95 | 1.02$^{-}$ | 0.94 | 1.01$^{-}$ | 0.97 | 1.01$^{-}$ | 0.99 | 1.03$^{-}$ | 0.95 | 1.03$^{-}$ | 0.99 | 1.06$^{-}$ |
| Hedge Half-life (S = C?) | 0.87 | 0.98$^{-}$ | 0.83 | 0.95$^{-}$ | 0.80 | 0.90$^{-}$ | 0.79 | 0.89$^{-}$ | 0.81 | 0.87$^{-}$ | 0.83 | 0.88$^{-}$ | 0.84 | 0.87$^{-}$ | 0.83 | 0.91$^{-}$ |

## 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
## Hedging Footprint Estimates *versus* Hedging Footnote Measures – Oil Refining

Bootstrap medians (1,000 replications) for the 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 2 years. Hedge maturity and half-life as above. Pre/post FAS 133 contrasts 1985-1999 and 2000-2018. Tax convexity is as per Graham and Harvey (1999). Adjusted $R^2$s and Sharpe ratios for quarterly-updated minimum-variance portfolio measure hedging effectiveness (Anderson and Danthine, 1980) and hedging opportunity cost. Contrasts use partialed sort-variable interactions to shift the 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* | 0.16 | | 0.13[a] | | 0.40 | | 0.23[a] | |
| *Footnote Measures* | *Low* | *High* | *Low* | *High* | *Low* | *High* | *Low* | *High* |
| Hedge Accounting | 0.25 | 0.09[a] | 0.20 | 0.07[b] | 0.26 | 0.55[a] | 0.15 | 0.31[a] |
| Hedge Intensity | 0.25 | 0.09[c] | 0.21 | 0.07[c] | 0.31 | 0.51[c] | 0.13 | 0.34[b] |
| Hedge Maturity | 0.22 | 0.10[-] | 0.19 | 0.08[-] | 0.31 | 0.51[a] | 0.16 | 0.32[c] |
| Hedge Half-life | 0.08 | 0.19[-] | 0.06 | 0.17[-] | 0.49 | 0.27[-] | 0.12 | 0.32[-] |
| *Exogenous Factors* | *Low* | *High* | *Low* | *High* | *Low* | *High* | *Low* | *High* |
| Pre/post FAS 133 | 0.21 | 0.18[-] | 0.20 | 0.16[-] | 0.36 | 0.49[a] | 0.21 | 0.33[-] |
| Tax Convexity | 0.19 | 0.11[-] | 0.16 | 0.09[-] | 0.25 | 0.56[a] | 0.12 | 0.35[c] |
| Basis: Effectiveness | 0.07 | 0.24[-] | 0.18 | 0.08[-] | 0.23 | 0.58[a] | 0.11 | 0.36[-] |
| Basis: Sharpe Ratio | 0.23 | 0.10[a] | 0.19 | 0.08[a] | 0.31 | 0.38[-] | 0.09 | 0.38[b] |

| **Footprint Estimates** | **Hedge Maturity** | | | | **Hedge Half-life** | | | |
|---|---|---|---|---|---|---|---|---|
| | Sales | | Costs | | Sales | | Costs | |
| *Pooled Sample* | 0.99 | | 1.06[-] | | 0.83 | | 0.91[-] | |
| *Footnote Measures* | *Low* | *High* | *Low* | *High* | *Low* | *High* | *Low* | *High* |
| Hedge Accounting | 0.73 | 1.22[c] | 1.83 | 0.24[-] | 0.60 | 0.96[c] | 0.60 | 0.96[-] |
| Hedge Intensity | 0.86 | 1.10[b] | 1.04 | 1.08[-] | 0.68 | 0.92[b] | 0.68 | 0.92[-] |
| Hedge Maturity | 0.93 | 1.04[c] | 1.17 | 0.98[-] | 0.76 | 0.87[b] | 0.76 | 0.87[-] |
| Hedge Half-life | 1.16 | 0.76[-] | 0.94 | 1.11[-] | 0.89 | 0.65[-] | 0.88 | 0.65[-] |
| *Exogenous Factors* | *Low* | *High* | *Low* | *High* | *Low* | *High* | *Low* | *High* |
| Pre/post FAS 133 | 0.96 | 1.03[a] | 1.11 | 1.12[-] | 0.80 | 0.88[a] | 0.80 | 0.88[-] |
| Tax Convexity | 0.75 | 1.20[b] | 0.93 | 1.10[-] | 0.58 | 0.98[b] | 0.58 | 0.98[-] |
| Basis: Effectiveness | 0.68 | 1.28[a] | 0.79 | 1.27[-] | 0.54 | 1.09[a] | 0.54 | 1.09[-] |
| Basis: Sharpe Ratio | 0.73 | 1.24[-] | 0.80 | 1.21[c] | 0.75 | 0.94[-] | 0.75 | 0.94[c] |

## Table VI
## Corporate Risk Management and Firm Characteristics

Bootstrap medians (1,000 replications) for the 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 instrumented partialed sort-variable interactions to shift the curvature and shape parameters. Contrasts use instrumented partialed sort-variable interactions to shift the curvature and shape parameters $(c_p, c_w, \beta, \lambda, \theta, \gamma)$.

| **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) | 0.00 | 0.24[a] | 0.00 | 0.19[a] | 0.19 | 0.49[a] | 0.04 | 0.11[-] |
| Operating Income / Net PPE | 0.28 | 0.17[a] | 0.14 | 0.24[a] | 0.25 | 0.25[-] | 0.06 | 0.03[a] |
| Cash & Equivalents / Net PPE | 0.12 | 0.16[-] | 0.11 | 0.13[-] | 0.12 | 0.50[a] | 0.13 | 0.25[-] |
| Inventories / Net PPE | 0.38 | 0.18[a] | 0.32 | 0.14[a] | 0.19 | 0.47[a] | 0.30 | 0.17[-] |
| LIFO Reserve / Net PPE | 0.25 | 0.16[a] | 0.20 | 0.13[a] | 0.32 | 0.28[-] | 0.18 | 0.14[-] |
| Collateral (Net PPE / Assets) | 0.18 | 0.40[a] | 0.14 | 0.33[a] | 0.32 | 0.38[c] | 0.09 | 0.17[c] |
| CAPEX / Net PPE | 0.19 | 0.16[a] | 0.15 | 0.13[a] | 0.15 | 0.52[a] | 0.24 | 0.25[-] |
| R&D / Net PPE | 0.16 | 0.12[-] | 0.14 | 0.11[-] | 0.41 | 0.22[a] | 0.13 | 0.15[-] |
| Tobin's *q* | 0.23 | 0.15[a] | 0.19 | 0.12[a] | 0.28 | 0.41[a] | 0.16 | 0.23[-] |
| Vertical Integration | 0.16 | 0.20[-] | 0.13 | 0.18[-] | 0.37 | 0.33[-] | 0.22 | 0.38[-] |
| Industrial Diversification | 0.17 | 0.25[-] | 0.15 | 0.23[-] | 0.35 | 0.00[a] | 0.25 | 0.00[a] |
| Geographic Diversification | 0.13 | 0.08[-] | 0.10 | 0.05[-] | 0.59 | 0.65[a] | 0.49 | 0.55[b] |
| Altman's Z-score | 0.30 | 0.21[a] | 0.25 | 0.17[a] | 0.30 | 0.35[a] | 0.24 | 0.28[-] |
| Short-term Debt / Total Debt | 0.23 | 0.04[a] | 0.18 | 0.04[a] | 0.53 | 0.20[-] | 0.02 | 0.14[-] |
| Total Debt / Assets | 0.16 | 0.28[a] | 0.12 | 0.22[a] | 0.33 | 0.67[a] | 0.16 | 0.60[b] |
| S&P LT-Debt Credit Rating | 0.09 | 0.04[a] | 0.07 | 0.03[a] | 0.42 | 0.44[-] | 0.42 | 0.48[a] |
| Dividends / Net PPE | 0.16 | 0.17[c] | 0.13 | 0.14[-] | 0.21 | 0.47[a] | 0.17 | 0.25[-] |

| **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) | 0.86 | 0.99[a] | 0.56 | 0.65[-] | 0.62 | 0.88[-] | 0.40 | 0.47[-] |
| Operating Income / Net PPE | 0.78 | 0.82[-] | 0.32 | 0.25[b] | 0.54 | 0.56[-] | 0.17 | 0.13[c] |
| Cash & Equivalents / Net PPE | 0.58 | 0.97[a] | 0.57 | 0.79[-] | 0.36 | 0.92[a] | 0.40 | 0.56[-] |
| Inventories / Net PPE | 0.83 | 1.05[b] | 1.00 | 0.97[-] | 0.64 | 0.85[-] | 0.80 | 0.68[-] |
| LIFO Reserve / Net PPE | 0.80 | 0.78[-] | 0.54 | 0.48[-] | 0.60 | 0.51[-] | 0.38 | 0.29[-] |
| Collateral (Net PPE / Assets) | 0.98 | 0.99[-] | 1.13 | 1.13[-] | 0.83 | 0.85[-] | 1.01 | 1.00[-] |
| CAPEX / Net PPE | 0.69 | 1.01[a] | 0.73 | 0.77[-] | 0.57 | 0.89[a] | 0.46 | 0.52[-] |
| R&D / Net PPE | 0.95 | 0.75[a] | 0.61 | 0.69[-] | 0.62 | 0.36[-] | 0.42 | 0.46[-] |
| Tobin's *q* | 0.87 | 1.00[a] | 0.67 | 0.81[-] | 0.62 | 0.88[-] | 0.45 | 0.58[-] |
| Vertical Integration | 0.95 | 0.90[-] | 0.86 | 0.96[-] | 0.64 | 0.54[-] | 0.63 | 0.79[-] |
| Industrial Diversification | 0.93 | 0.00[a] | 0.92 | 0.00[b] | 0.58 | 0.00[a] | 0.58 | 0.00[b] |
| Geographic Diversification | 1.09 | 1.10[a] | 1.09 | 1.10[-] | 0.80 | 0.79[a] | 0.80 | 0.79[-] |
| Altman's Z-score | 0.94 | 0.99[a] | 0.92 | 0.97[c] | 0.89 | 0.89[-] | 0.70 | 0.80[-] |
| Short-term Debt / Total Debt | 0.87 | 0.69[-] | 0.30 | 0.72[-] | 0.57 | 0.40[-] | 0.16 | 0.52[-] |
| Total Debt / Assets | 0.86 | 0.93[-] | 0.74 | 0.92[c] | 0.62 | 0.64[-] | 0.59 | 0.74[-] |
| S&P LT-Debt Credit Rating | 1.02 | 1.04[b] | 1.03 | 1.05[a] | 0.86 | 0.84[a] | 0.85 | 0.83[a] |
| Dividends / Net PPE | 0.76 | 0.99[a] | 0.65 | 0.76[-] | 0.63 | 0.89[c] | 0.42 | 0.53[-] |

## 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 instrumented partialed 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 (pending revisions)
## Hedging Footprint Estimates *versus* Hedging Footnote Measures – Manufacturing

Bootstrap medians (1,000 replications) for the 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 2 years. Hedge maturity and half-life as above. Pre/post FAS 133 contrasts 1985-1999 and 2000-2018. Tax convexity is as per Graham and Harvey (1999). Adjusted $R^2$s and Sharpe ratios for quarterly-updated minimum-variance portfolio measure hedging effectiveness (Anderson and Danthine, 1980) and hedging opportunity cost. Contrasts use partialed sort-variable interactions to shift the 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* | 0.04 | | 0.02[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 | 0.07 | 0.02[b] | 0.04 | 0.01[c] | 0.09 | 0.16[b] | 0.03 | 0.09[c] |
| Hedge Intensity | 0.08 | 0.01[b] | 0.05 | 0.01[b] | 0.02 | 0.27[a] | 0.01 | 0.12[a] |
| Hedge Maturity | 0.06 | 0.03[c] | 0.03 | 0.01[c] | 0.07 | 0.12[b] | 0.02 | 0.07[-] |
| Hedge Half-life | 0.03 | 0.05[-] | 0.01 | 0.03[-] | 0.07 | 0.10[-] | 0.04 | 0.06[-] |
| *Sub-period* | *Low* | *High* | *Low* | *High* | *Low* | *High* | *Low* | *High* |
| Pre/post FAS 133 | 0.07 | 0.02[b] | 0.05 | 0.01[c] | 0.05 | 0.14[b] | 0.09 | 0.03 |
| Pre/post year 2001 | 0.07 | 0.02[b] | 0.05 | 0.01[c] | 0.04 | 0.16[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] |

## References


Ai, Chunrong, and Edward C. Norton, 2003, Interaction terms in logit and probit models, Economics Letters 80, 123-129.

Acharya, Viral, Yakov Amihud, and Lubomir Litov, 2011, Creditor rights and corporate risk-taking, *Journal of Financial Economics* 102,150-166.

Acharya, Viral, Lars A. Lochstoer, and Tarun Ramadorai, 2013, Limits to arbitrage and hedging: Evidence from commodity markets, *Journal of Financial Economics* 109, 441-465.

Adam, Tim R., Sudipto Dasgupta, and Sheridan Titman, 2007, Financial constraints, competition, and hedging in industry equilibrium, *Journal of Finance* 62, 2445-2473.

Adam, Tim R., and Chitru S. Fernando, 2006, Hedging, speculation, and shareholder value, *Journal of Financial Economics* 81, 283-309.

Adam, Tim R., Chitru S. Fernando, and Salas 2017, Why do firms engage in selective hedging? Evidence from the gold mining industry, *Journal of Banking and Finance* 77, 269-282.

Alexander, Carol, Marcel Prokopczuk, and Anannit Sumawong, 2013, The (de)merits of minimum-variance hedging: Application to the crack spread, *Energy Economics* 36, 698-707.

Allayannis, George, and Jane Ihrig, 2001, Exposure and markups, *Review of Financial Studies* 14, 805-835.

Allayannis, George, and James P. Weston, 2001, The use of foreign currency derivatives and firm market value, *Review of Financial Studies* 14, 243-276.

Almansur, Abdullah M., William L. Megginson, and Leonid Pugachev, 2016, Hedging gone wild: Was Delta Air Lines' purchase of Trainer Refinery a sound risk management strategy?

Almeida, Heitor, Kristine Watson Hankins, and Ryan Williams, 2017, Risk management with supply contracts, *The Review of Financial Studies* 30, 4179-4215.

Anderson, Ronald W., and Jean-Pierre Danthine, 1980, Hedging and Joint Production: Theory and Illustrations, *Journal of Finance* 35, 487-498.

Anderson, Ronald W., and Jean-Pierre Danthine, 1981, Cross Hedging, *Journal of Political Economy* 89, 1182-1196.

Atanasov, Vladimir A. and Bernard S. Black, 2017, The trouble with instruments: Re-examining shock-based IV designs, ECGI - Finance Working Paper; Northwestern Law & Econ Research Paper 16-01; Northwestern Public Law Research Paper No. 15-26.

Bakke, Tor Erik, Hamed Mahmudi, Chitru S. Fernando, and J. Salas, 2016, The causal effect of option pay on corporate risk management, *Journal of Financial Economics* 120, 623-643.

Bartram, Sohnke, 2019, Corporate hedging and speculation with derivatives, *Journal of Corporate Finance* 57, 9-34.

Bartram, Sohnke, Gregory W. Brown, and Frank F. Fehle, 2009, International evidence on financial derivatives usage, *Financial Management* 38, 185-206.

Bartram, Sohnke, Gregory W. Brown, and Jennifer Conrad, 2011, The effects of derivatives on firm risk and value, *Journal of Financial and Quantitative Analysis* 46, 967-999.

Bessembinder, Hendrik, 1991, Forward contracts and firm value: Investment incentive and contracting effects, *Journal of Financial and Quantitative Analysis* 26, 519-532.

Bessler, Wolfgang, Thomas Conlon, and Xing Huan, 2019, Does corporate hedging enhance shareholder value? A meta-analysis, *International Review of Financial Analysis* 61, 222-232.

Blanco, Iván, and David Wehrheim, 2017, The bright side of financial derivatives: Options trading and financial innovation, *Journal of Financial Economics* 125, 99-119.

Bodnar, Gordon M., Gregory S. Hayt, and Richard C. Marston, 1998 Wharton survey of financial risk management by US non-financial firms, *Financial management*, 70-91.

Bodnar, Gordon M., Erasmo Giambona, John R. Graham, and Campbell R. Harvey, 2018, The theory and practice of corporate risk management: Evidence from the field, *Financial Management* 47, 783-832.

Bodnar, Gordon M., Erasmo Giambona, John R. Graham, and Campbell R. Harvey, 2019, A view inside corporate risk management, *Management Science* 65, 5001-26.

Bonaimé, Alice Adams, Kristine Watson Hankins, and Jarrad Harford, 2014, Financial flexibility, risk management, and payout choice, *The Review of Financial Studies* 27, 1074-1101.

Borenstein, Severin, and Andrea Shepard, 2002, Sticky prices, inventories, and market power in wholesale gasoline markets, *RAND Journal of Economics* 33, 116-139.

Brown, Gregory W., and Klaus Bjerre Toft, 2002, How firms should hedge, *Review of Financial Studies* 15, 1283-1324.

Brown, Gregory W., Peter R. Crabb and David Haushalter, 2006, Are firms successful at selective hedging?, *Journal of Business* 79, 2925-49.

Cameron, A. C., Jonah E. Gelbach, and Douglas L. Miller, 2008, Bootstrap-based improvements for inference with clustered errors, *Review of Economics and Statistics* 90, 414-427.

Campello, Murillo, Chen Lin, Yue Ma, and Hong Zou, 2011, The real and financial implications of corporate hedging, *Journal of Finance* 66, 1615-1647.

Carter, David A., Daniel A. Rogers, and Betty J. Simkins, 2006, Does fuel hedging affect firm value? Evidence from the U.S. airline industry, *Financial Management* 35, 53-86.

Carter, David A., Daniel A. Rogers, Betty J. Simkins, and Stephen D. Treanor, 2017, A review of the literature on commodity risk management, *Journal of Commodity Markets* 8, 1-17.

Charnes, J. M., P. Koch, and H. Berkman, 2003, Measuring hedge effectiveness for FAS 133 compliance, *Journal of Applied Corporate Finance* 15, 95-103.

Cheng, Ing-Haw, and Wei Xiong, 2014, Why do hedgers trade so much?, *Journal of Legal Studies*, 2014, 43, 183-207.

Casassus, Jaime, Peng Liu, and Ke Tang, 2013, Economic linkages, relative scarcity, and commodity futures returns, *The Review of Financial Studies* 26, 1324-1362.

Chernenko, Sergey, and Michael, Faulkender, 2011, The two sides of derivative usage: Hedging and speculating with interest rates, *Journal of Financial and Quantitative Analysis* 46, 1727-54.

Cornaggia, Jess, 2013, Does risk management matter? Evidence from the U.S. agricultural industry, *Journal of Financial Economics* 109, 419-440.

De Angelis, David and S. Abraham Ravid, 2017, Input hedging, output hedging, and market power, *Journal of Economics & Management Strategy* 26, 123-151.

DeMarzo, Peter, and Darrell Duffie, 1991, Corporate financial hedging with propriety information, *Journal of Economic Theory* 53(2), 261-286.

DeMarzo, Peter, and Darrell Duffie, 1995, Corporate incentives for hedging and hedge accounting, *Review of Financial Studies* 8, 743-771.

Ederington, Louis H., 1979, The hedging performance of the new futures markets, *Journal of Finance* 34, 157-170.

Faulkender, Michael, 2005, Hedging or market timing? Selecting the interest rate exposure of corporate debt, *Journal of Finance* 60, 931-962.

Fehle, F. and S. Tsyplakov, 2005, Dynamic risk management: Theory and evidence, *Journal of Financial Economics* 78 (1), 3-47.

Flannery, Mark J., and Christopher M. James, 1984, The effect of interest rate changes on the common stock returns of financial institutions, *Journal of Finance* 39, 1141-1153.

Froot, Kenneth A., David S. Scharfstein, and Jeremy C. Stein, 1993, Risk management: Coordinating corporate investment and financing policies, *Journal of Finance* 48, 1629-1658.

Gamba, Andrea, and Triantis, Alexander J., 2014. Corporate risk management: Integrating liquidity, hedging, and operating policies, *Management Science* 60, 246-264.

Geczy, Christopher, Bernadette A. Minton, and Catherine Schrand, 1997, Why firms use currency derivatives, *Journal of Finance* 52, 1323-1354.

Geyer-Klingeberg, J., M. Hang, A. Rathgeber, S. Stökl, and M. Walter, 2018, What do we really know about corporate hedging? A meta-analytical study, *Business Research* 11, 1-31.

Giambona, Erasmo, and Ye Wang, 2017, Derivatives supply and corporate hedging: Evidence from the safe harbor reform of 2005, Working paper.

Gibson, Rajna, and Eduardo S. Schwartz, 1990, Stochastic convenience yield and the pricing of oil contingent claims, *Journal of Finance* 45, 959-976.

Gilje, Erik P., and Jérôme P. Taillard, 2017, Does hedging affect firm value? Evidence from a natural experiment, *The Review of Financial Studies* 30, 4083-4132.

Ghoddusi, Hamed, Sheridan Titman, and Stathis Tompaidis, 2019, Hedging input commodity price risk: An equilibrium view, Working paper.

Graham, John R., and Daniel A. Rogers, 2002, Do firms hedge in response to tax incentives? *Journal of Finance* 57, 815-839.

Graham, John R., and Clifford W. Smith, Jr., 1999, Tax incentives to hedge, *Journal of Finance* 54, 2241-2262.

Greene, William, 2010, Testing hypotheses about interaction terms in nonlinear models, *Economics Letters* 107, 291-296.

Guay, Wayne, and S.P. Kothari, 2003, How much do firms hedge with derivatives? *Journal of Financial Economics* 70, 423-461.

Hansen, Lars P., 1982, Large sample properties of generalized method of moments estimators, *Econometrica* 34, 646-660.

Haushalter, David G., 2000, Financing policy, basis risk, and corporate hedging: Evidence from oil and gas producers, *Journal of Finance* 55, 107-152.

Haushalter, David G., Randall A. Heron, and Erik Lie, 2002, Price uncertainty and corporate value, *Journal of Corporate Finance: Contracting, Governance and Organization* 8, 271-286.

Haushalter, David G., Sandy A. Klasa, and William F. Maxwell, 2007, The influence of product market dynamics on a firm's cash holdings and hedging behavior, *Journal of Financial Economic* 84, 797-825.

Hentschel, L., Kothari, S. P., 2001. Are corporations reducing or taking risks with derivatives? *Journal of Financial and Quantitative Analysis* 36, 93-118.

Hirshleifer, David, 1991, Seasonal patterns of futures hedging and the resolution of output uncertainty, *Journal of Economic Theory* 53, 304-327.

Hoberg, Gerald, and S. K. Moon, 2017, Offshore activities and financial *vs* operational hedging, *Journal of Financial Economics* 125, 217-244.

Jin, Yanbo, and Philippe Jorion, 2006, Firm value and hedging: Evidence from U.S. oil and gas producers, *Journal of Finance* 61, 893-919.

Jorion, Philippe, 1990, The exchange-rate exposure of U.S. multinationals, *The Journal of Business* 63, 331-345.

Kamara, Avraham, 1993, Production flexibility, stochastic separation, hedging, and futures prices, *Review of Financial Studies*, 6, 935-957.

Kang, Wenjin, K. Geert Rouwenhorst, and Ke Tang, 2020, A Tale of Two Premiums: The Role of Hedgers and Speculators in Commodity Futures Markets, *Journal of Finance* 75, 377-417.

Kieso, Donald E., Jerry J. Weygandt, and Terry D. Warfield, 2019, Intermediate Accounting, 17th edition, Wiley.

Kilian, Lutz, 2009, Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market, *American Economic Review* 99, 1053-1069.

Kozak, Serhiy, Stefan Nagel, and Shrihari Santosh, 2020, Shrinking the cross-section, *Journal of Financial Economics* 135, 271-292.

Kumar, Praveen and R. Rabinovitch, 2013, CEO Entrenchment and corporate hedging: Evidence from the oil and gas industry, *Journal of Financial and Quantitative Analysis* 48, 887-917.

Kuzmina, Olga, and Olga Kuznetsovab, 2018, Operational and financial hedging: Evidence from export and import behavior, *Journal of Corporate Finance* 48, 109-121.

Lins, Karl, V. Henri Servaes, and Ane Tamayo, 2011, Does fair-value reporting affect risk management? International survey evidence, *Financial Management*, 525-551.

Litzenberger, Robert L., and Nir Robonowitz, 1995, Backwardation in oil futures markets: Theory and empirical evidence, *Journal of Finance* 50, 1517-1545.

MacKay, Peter, 2003, Real flexibility and financial structure: An empirical analysis, *Review of Financial Studies* 16, 1131-1165.

MacKay, Peter and Sara Moeller, 2007, The value of corporate risk management, *Journal of Finance* 62, 1379-1419.

Mello, Antonio and John Parsons, 1995, Maturity structure of a hedge matters: Lessons from the Metallgesellschaft debacle, *Journal of Applied Corporate Finance* 8, 106-120.

Minton, Bernadette A., and Catherine Schrand, 1999, The impact of cash flow volatility on discretionary investment and the costs of debt and equity financing, *Journal of Financial Economics* 54, 423-460.

Moschini, G. and Harvey Lapan, 1992, Hedging price risk with options and futures for the competitive firm with production flexibility, *International Economic Review* 33, 607-618.

Nance, Deana, Clifford W. Smith, and Charles Smithson, 1993, On the determinants of corporate hedging, *Journal of Finance* 48, 267-284.

New York Mercantile Exchange (NYMEX), 2000, *Crack Spread Handbook*.

Neuberger, Anthony, 1999, Hedging long-term exposures with multiple short-term futures contracts, *Review of Financial Studies* 12, 429-459.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, hetero-skedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Pérez-Gonzáles, F. and H. Yun, 2013, Risk management and firm value: Evidence from weather derivatives, *Journal of Finance* 68, 2143-2176.

Pincus, Morton, and Shivaram Rajgopal, 2002, The interaction between accrual management and hedging: Evidence from oil and gas Firms, *Accounting Review* 77, 127-160.

Purnanandam, Amiyatosh, 2008, Financial distress and corporate risk management: Theory and evidence, *Journal of Financial Economics* 87, 706-739.

Rampini, Adriano A., and S. Viswanathan, 2010, Distribution of debt capacity, *Journal of Finance* 65, 2293–2322.

Rampini, Adriano A., and S. Viswanathan, 2013, Collateral and capital structure, *Journal of Financial Economics* 109, 466-492.

Rampini, Adriano A., Amir Sufi, and S. Viswanathan, 2014, Dynamic risk management, *Journal of Financial Economics* 111, 271-296.

Reinartz, Sebastian J., and Thomas Schmid, 2016, Production flexibility, product markets, and capital structure decisions, *Review of Financial Studies* 29, 1501-1548.

Rigobon, Roberto, 2003, Identification through heteroscedasticity, *Review of Economics and Statistics* 85, 777-792.

Roberts, Michael, R., and Toni M., Whited, 2013, Endogeneity in Empirical Corporate Finance, *Handbook of the Economics of Finance* 2, 493-572.

Rolfo, Jacques, 1980, Optimal hedging under price and quantity uncertainty: The Case of a cocoa producer, *Journal of Political Economy* 88, 100-116.

Schwartz, Eduardo S., 1997, The stochastic behavior of commodity prices: Implications for valuation and hedging, *Journal of Finance* 52, 923-973.

Sharpe, William F., 1988, Determining a fund's effective asset mix, *Investment Management Review*, 59-69.

Smith, Clifford W., and Rene Stulz, 1985, The determinants of firms' hedging policies, *Journal of Financial and Quantitative Analysis* 20, 391-405.

Strong, John S., 1991, Using oil share portfolios to hedge oil price risk, *Quarterly Journal of Economics* 31, 48-63.

Tufano, Peter, 1996, Who manages risk? An empirical examination of risk management practices in the gold mining industry, *Journal of Finance* 51, 1097-1137.

Tufano, Peter, 1998, The determinants of stock price exposure: Financial engineering and the gold mining industry, *Journal of Finance* 53, 1015-1052.

Zou, Hui and Hastie, Trevor, 2005, Regularization and variable selection via the Elastic Net, *Journal of the Royal Statistical Society* 67, 301-320.