

Limits to Arbitrage and Hedging: Evidence from Commodity Markets

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We build an equilibrium model with commodity producers that are averse to future cash flow variability, and hedge using futures contracts. Their hedging demand is met by financial intermediaries who act as speculators, but are constrained in risk-taking. Increases (decreases) in producers' hedging demand (the risk-bearing capacity of speculators) increase the costs of hedging, which preclude producers from holding large inventories, and thus reduce spot prices. Using oil and gas market data from 1980-2006, we show that producers' hedging demand - proxied by their default risk - forecasts spot prices, futures prices and inventories, consistent with our model. Our analysis demonstrates that limits to financial arbitrage can generate limits to hedging by firms, affecting prices in both asset and goods markets.

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We build an equilibrium model with commodity producers that are averse to future cash flow variability, and hedge using futures contracts. Their hedging demand is met by financial intermediaries who act as speculators, but are constrained in risk-taking. Increases (decreases) in producers' hedging demand (the risk-bearing capacity of speculators) increase the costs of hedging, which preclude producers from holding large inventories, and thus reduce spot prices. Using oil and gas market data from 1980-2006, we show that producers' hedging demand - proxied by their default risk - forecasts spot prices, futures prices and inventories, consistent with our model. Our analysis demonstrates that limits to financial arbitrage can generate limits to hedging by firms, affecting prices in both asset and goods markets.

1 Introduction

The neoclassical theory of asset pricing (Debreu (1959)) has been confronted by theory and evidence that highlights the numerous frictions that are faced by financial intermediaries in undertaking arbitrage (Shleifer and Vishny (1997)), and the consequent price effects of such frictions. There is evidence that these price effects are amplified in situations in which financial intermediaries are substantially on one side of the market (say, for instance, when they bear the prepayment and default risk of households in mortgage markets, or when they provide catastrophe insurance to households (see Froot (1999))). In this paper, we apply this “limits to arbitrage” view to the analysis of commodity futures markets, in which capital constrained commodity investment funds (speculators) meet the demand for hedging by commodity producing firms (producers). We demonstrate, both theoretically and empirically, that these asset-market frictions translate themselves into “limits to hedging” experienced by producers, and consequently have impacts on real variables such as the spot commodity price.

Our first contribution is theoretical - we build a model in which speculators are subject to a constraint on their ability to deploy capital in the commodity futures market. This limit on the risk-taking capacity of speculators implies a price impact of the hedging demand of risk-averse producers, who are naturally short commodity futures. This price impact constitutes a cost of hedging, which has consequences for the optimal inventory holding of commodity producers, and in turn, the commodity spot price. Our model builds on the previous literature on hedging, and nests the two classical explanations for the behavior of commodity spot and futures prices: The *Theory of Storage* (Kaldor (1936), Working (1949), and Brennan (1958)), which has optimal inventory management as a main determinant of commodity prices, and the *Theory of Normal Backwardation* (Keynes (1930)), which posits that hedging pressure affects commodity futures prices.

We clear markets for futures and spot commodities (assuming exogenous spot demand functions) and derive implications of producer risk aversion and speculator capital constraints for the absolute and relative levels of futures and spot prices. To understand the comparative statics generated by the model, consider the following example: suppose that producers as a whole need to hedge more (perhaps on account of their default risk rising) by shorting futures contracts. Then, all else equal, their hedging pressure depresses futures prices and makes hedging more expensive. So producers scale back on holding inventory, releasing it into the market and depressing spot prices. Note that futures risk premia and expected spot returns have a common driver – the hedging demand of producers. Due to this common driver, the model predicts that the commodity convenience yield, or the basis between spot and futures prices, should not be strongly related to commodity futures risk premia. Increases in the capital constraints of speculators have similar effects.

Our second contribution is to provide empirical evidence for these effects using data on spot and

futures prices for heating oil, crude oil, gasoline and natural gas over the period 1980 to 2006.¹ As a key feature of our tests, we assume that producers' risk aversion and hedging demand increase in their default risk. This assumption is driven by extant theoretical and empirical work on hedging,² and we add to the evidence in this literature by examining the hedging disclosures of commodity producers between 1998 and 2006, exploiting the fact that the FAS 133 ruling of 1998 required firms to disclose their derivatives activities and to report the intended purpose of their derivatives trading (although not in a manner that is highly standardized). These disclosures allow us to confirm that oil and gas producers are in fact significant hedgers in the commodity futures markets, consistent with the evidence of Ederington and Lee (2002) that trading volume and open-interest positions in commodity futures are dominated by potential hedgers. While the lack of standardization in hedging disclosures makes it difficult to provide large-sample evidence linking the extent of hedging to default risk, we identify a small set of producers (Marathon Oil, Hess Corporation, Valero Energy Corporation, and Frontier Oil Corporation), which relatively unambiguously report their exact hedging positions. We find a strong time-series relationship between the extent of their hedging activity and the measures of their default risk that we subsequently employ in the aggregate.

Having established this link, we show that aggregate measures of oil and gas producers' fundamental hedging demand – proxied by their default risk – explain futures risk premia (identified through standard forecasting regressions (as in, e.g., Fama and French (1986)), and changes in spot prices and inventories, as implied by our model. Our main empirical findings are as follows: First, commodity producer default risk positively forecasts hedging demand as measured by the net short positions of market participants classified as 'hedgers' by the Commodity Futures Trading Commission (CFTC). Second, an increase in the default risk of producers forecasts an increase in excess returns on short-term futures of these commodities. The effect is robust to business-cycle conditions and economically significant: a one standard deviation increase in the aggregate commodity sector default risk is on average associated with a 4% increase in the respective commodity's quarterly futures' risk premium. Third, as producer default risk increases, our model implies that producers will hold less inventory, depressing current spot prices. This prediction is confirmed in the data – increases in the default risk of oil and gas producers in a quarter predict higher spot returns in the subsequent quarter.³ Fourth, the default risk of producers negatively forecasts inventory holdings.

¹Our choice of these commodities is partly driven by the data requirement that we have at least ten producers in each quarter to produce an average measure of default risk for a given commodity, and partly by the fact that these are the largest commodity markets in existence.

²A large body of theoretical work and empirical evidence on hedging has attributed managerial aversion to risk as a primary motive for hedging by firms (Amihud and Lev (1981), Tufano (1996, 1998), Acharya, Amihud and Litov (2007), and Gormley and Matsa (2008), among others); and has documented that top managers suffer significantly from firing and job relocation difficulties when firms default (Gilson (1989), Baird and Rasmussen (2006) and Ozelge (2007)). Research has also documented a link between high expected distress costs and firms' usage of derivatives (Graham and Rogers (2002)).

³We also verify that the default risk of producers does *not* explain the convenience yield or basis on the commodity very well, as implied by the model (these results are available upon request).

Fifth, we confirm that the basis does not contain significant forecasting power for the excess returns on short-term commodity futures, as noted by Fama and French (1986).

We confirm that our results are driven by changes in producer hedging demand in a number of ways. First, we employ a “matching” approach. In particular, we divide the sample of producers into firms that hedge commodity price exposure using derivatives (as disclosed by them during the period 1998-2006) and firms that do not hedge their commodity price exposures. We find that our results are driven *only* by measures of aggregate hedging demand derived from the hedging firms. This finding provides strong support for our model’s main prediction that hedging pressure affects commodity prices. It also provides a useful alternative to the classification schemes normally employed in the literature, namely, the CFTC reported classification of futures market participants into hedgers and speculators (see De Roon et. al., (2000)),⁴ and schemes based purely on the reported functions of commodity firms (such as producer, refiner, marketer or distributor) (see Ederington and Lee (2002) for evidence that such classifications are noisy measures of firms’ actual hedging activities). Second, we employ controls in our forecasting regressions, in the form of variables commonly employed to predict the equity premium, such as the aggregate dividend yield, and confirm that our results are unaffected by these additions. Third, though our classification of hedging producers is based on data from 1998 to 2006, we show that our results hold in the first half of our sample period as well as the second half, using the same classification. Finally, though not the primary focus of our empirical analysis, we confirm the role of speculative activity (measured as the growth in the balance-sheets of broker dealers, as in Etula (2009)): when broker-dealer balance-sheets are shrinking, the commodity futures risk premium is indeed higher. In the context of the broader asset-pricing literature, our model and empirical results imply that limits to arbitrage generate limits to hedging for firms in the real economy. Consequently, factors that capture time-variation in such limits have predictive power for asset prices, and can potentially also affect outcomes in underlying product markets.

Besides shedding light on limits to arbitrage and hedging in commodity markets, our model and results provide a useful lens through which to view an important debate about the causes of the recent gyrations in commodity prices. Between 2003 and June 2008, energy, base metals, and precious metals experienced price rises in excess of 100%. Over the same period, there was a huge increase in the amount of capital committed to long positions in commodity futures contracts – in July 2008, pension funds and other large institutions were reportedly holding over \$250 billion in commodity futures (mostly invested through indices such as the S&P GSCI) compared to their \$10 billion holding in 2000 (Financial Times, July 8 2008). While these trends occurred concurrently, some market practitioners and economists have vehemently argued that the speculative investments

⁴Questions about the usefulness of the CFTC classifications as an indicator of hedger versus speculator demand has led to a CFTC-initiated review of reporting (see, e.g., Wall Street Journal “CFTC to Review Hedge-Exemption Rules”, 12 March, 2009).

of financial players in the futures market have no direct relationship with commodity spot prices. Other commentators (most notably, Michael Masters, a hedge-fund manager, and George Soros, who both testified to the US Congress) have blamed speculative activity for recent commodity price rises. A third group (one that includes former Federal Reserve Chairman Alan Greenspan) has taken an intermediate view – that commodity spot prices are fundamentally driven by physical demand, but that financial speculation has played some role in recent price rises. This last set of commentators has also argued that financial speculation is in fact stabilizing, for some of the reasons we outline in the model: the long positions taken by financial investors have enabled producers to take short hedging positions and hold larger inventories, which increases current spot prices and should stabilize prices going forward.

In support of this last view, we agree with the chain of reasoning specified for the rise in spot prices. The fallout of the sub-prime crisis in 2008, however, increased speculator risk-aversion and simultaneously raised producer default risk. This increased producer hedging demand at the same time that it became costlier to hedge, causing inventories to fall and lowering spot prices. We acknowledge that our theory, which is based on risk-sharing between producers and speculators, is unlikely to explain the full *magnitude* of the rise and fall in oil prices. Rather than a complete explanation, we view the mechanism we have outlined as a likely contributing factor to recent price movements. Of course, other potential contributing factors to the observed price pattern could include shifts in global demand, and the possibility of a “bubble” in commodity prices that collapsed in the summer of 2008.

The organization of the paper is as follows. The remainder of the introduction relates our paper to the literature. Section 2 introduces our model. Section 3 presents the data we employ in our empirical tests. Section 4 establishes the link between the hedging demand of commodity producers, and measures of their default risk. Section 5 discusses our main empirical results, which come from our analysis of oil and gas producers at the aggregate level. Section 6 concludes. Proofs are contained in the Appendix.

1.1 Related Literature

Our paper is related to two main bodies of literature: The emerging work on limits to arbitrage, which highlights the impacts of these limits on asset prices; and the extensive body of work on the determinants of commodity spot and futures prices. Two related papers in the first group are Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2008), who assume the presence of financing frictions for intermediaries, and show the ultimate effects of these frictions on market liquidity. In addition, numerous papers show that contractual limits on the arbitrage activity of intermediaries arise endogenously due to agency problems. For example, Acharya and Viswanathan (2007) and Adrian and Shin (2008) consider the risk-shifting problem, a la Jensen and Meckling (1976), and show that this problem leads either to “hard” debt contracts or value-at-risk style

constraints on intermediaries. He and Xiong (2009) also consider the agency problem in delegation and derive investment-style restrictions as part of the efficient contracting outcome. Empirically, Mitchell, Pulvino and Stafford (2002) show that arbitrage is subject to risk arising from uncertainty about the distribution of returns as well as from the potential for forced liquidations if capital requirements bind. Wurgler and Zhuravskaya (2002) present similar evidence, which shows that the idiosyncratic risk of stock returns can be an impediment to arbitrage, as arbitrage trades are often not well-diversified. We contribute to this literature with a simple model and supporting evidence in an attempt to demonstrate that limits to financial arbitrage can also impact producers' decisions, and prices in goods markets through the channel of hedging.

In the commodities literature, there are two classic views on the behavior of forward and futures prices. The *Theory of Normal Backwardation*, put forth by Keynes (1930), states that speculators, who take the long side of a commodity future position, require a risk premium for hedging the spot price exposure of producers (an early version of the “limits to arbitrage” argument). The risk premium on long forward positions is thus increasing in the amount of hedging pressure and should be related to observed hedger and speculator positions in the commodity forward markets. Bessembinder (1992) and De Roon, Nijman and Veld (2000) empirically link hedging pressure to futures excess returns, basis and the convenience yield, providing evidence in support of this theory.

On the other hand, the *Theory of Storage* (Kaldor (1936), Working (1949), and Brennan (1958)) postulates that forward prices are driven by optimal inventory management. In particular, this theory introduces the notion of a “convenience” yield to explain why anyone would hold inventory in periods in which spot prices are expected to decline. Tests of the theory include Fama and French (1988) and Ng and Pirrong (1994). In more recent work, Routledge, Seppi and Spatt (2000) introduce a forward market into the optimal inventory management model of Deaton and Laroque (1992) and show that time-varying convenience yields, consistent with those observed in the data, can arise even in the presence of risk-neutral agents.⁵ In this case, of course, the risk premium on commodity forwards is zero. The convenience yield arises because the holder of the spot also implicitly holds a timing option in terms of taking advantage of temporary spikes in the spot price. The time-variation in the value of this option is reflected in the time-variation in the observed convenience yield. Thus, time-variation in the observed convenience yield need not be due to a time-varying forward risk premium.

Note, however, that the two theories are not mutually exclusive. A time-varying risk premium on forwards is consistent with optimal inventory management if producers are not risk-neutral or face (say) bankruptcy costs; and speculator capital is not unlimited, as in our model. If producers

⁵There is a large literature on reduced form, no-arbitrage modeling of commodity futures prices (e.g., Brennan, (1991) Schwartz (1997)). Most recently, Cassasus and Collin-Dufresne (2004) show in a no-arbitrage latent factor affine model that the convenience yield is positively related to the spot price under the risk-neutral measure. In addition, these authors show that the level of convenience yield is increasing in the degree to which an asset serves for production purposes.

have hedging demands (absent from the Routledge, Seppi and Spatt model), speculators will take the opposite long positions if they are compensated with a fair risk premium on the position. In the data, we find that hedgers are on average net short forwards, while speculators are on average net long, which indicates that producers on average do have hedging demands. In support of this view, Haushalter (2000, 2001) surveys 100 oil and gas producers and finds that close to 50 percent of them hedge their production over the 1992 to 1994 period, and that they hedge, on average, approximately a quarter of their production each year.⁶

This unconditional risk premium on commodity futures, however, has proven difficult to explain with traditional asset pricing theory (see Jagannathan, (1985) for an earlier effort). Fama and French (1987) present early empirical evidence on the properties of commodity prices and their link to the Theory of Storage. In a recent paper, Gorton, Hayashi, and Rouwenhorst (2007) argue that time-varying futures risk premia are driven by inventory levels and not by net speculator or hedger positions. In particular, they show that a definition of hedging pressure based on classification of traders from the Commodity Futures and Trading Commission do not significantly forecast excess long forward returns, although the signs are consistent with Keynes' hypothesis. Inventory, on the other hand, forecasts future forward returns with a negative sign in their sample; i.e., when inventory levels are low, the forward risk premium is high. Our results are consistent with theirs in that our model also predicts that inventory should forecast commodity futures returns. However, the point of departure is that in our model this result is driven by the interaction between capital-constrained speculators and risk averse producers – whose fundamental hedging demands we proxy for using measures of default risk. Our most important and novel contribution is to identify and highlight the role of producers' default risk – the primitive risk that drives producers to hedge using futures contracts – in simultaneously explaining commodity inventories, spot prices, and futures hedging positions and risk premia.

Finally, in another closely related paper, Bessembinder and Lemmon (2002) show that hedging demand affects spot and futures prices in electricity markets when producers are risk averse, as we also assume in our model. They highlight that the absence of storage is what allows for predictable intertemporal variation in equilibrium prices. We show in this paper that the price impact can arise, and empirically does arise, also in the presence of storage in the oil and gas markets.

2 The Model

In this section, we present a two-period model of commodity spot and futures price determination that incorporates elements of two classes of models previously employed in the literature. First,

⁶Indirect evidence is available in Gorton and Rouwenhorst (2006), who show that long positions in commodity futures contracts on average have earned a risk premium. However, Erb and Harvey (2006) interpret this finding with caution, suggesting that much of the return to investing in futures contracts may be attributable to rebalancing or diversification.

the model resembles the optimal inventory management model of Deaton and Laroque (1992). Second, the model has similar features to the commodity speculation and hedging demand models of Anderson and Danthine (1981, 1983). The model illustrates how producer hedging demand affects commodity spot and futures prices in a simple and transparent setting and delivers a set of empirical predictions that we subsequently investigate using available U.S. data.

There are three types of agents in the model: (1) consumers, whose demand for the spot commodity along with the equilibrium supply determine the commodity spot price; (2) commodity producers, who manage profits by optimally managing their inventory and by hedging with commodity futures; and (3) speculators, whose demand for the commodity futures along with the futures hedging demand of producers determine the commodity futures price.⁷

2.1 Consumption, Production and the Spot Price

Following Routledge, Seppi, and Spatt (2000), current commodity production $G_t(S_t)$ and “immediate use” consumption demand $C_t(S_t)$ are modeled as stochastic, reduced form functions of the spot price S_t . The spot price S_t is determined by market clearing, which demands that incoming aggregate inventory and current production, $G_t(S_t) + (1 - \delta) I_{t-1}$, equals current consumption and outgoing inventory, $C_t(S_t) + I_t$, where I_t is the aggregate inventory level. Here, δ is the cost of storage – individual producers can store i units of the commodity at $t - 1$ yielding $(1 - \delta) i$ units at t , where $\delta \in (0, 1)$.

The market clearing equality can be rearranged:

$$C_t(S_t) - G_t(S_t) = -\Delta I_t, \tag{1}$$

where $\Delta I_t \equiv I_t - (1 - \delta) I_{t-1}$. As in Routledge, Seppi, and Spatt (2000), the “immediate use” net demand $C_t(S_t) - G_t(S_t)$ is assumed to be monotone decreasing in the spot price S_t . This allows us to summarize the spot market with an inverse net demand function as follows:

$$S_t = a_t + f(\Delta I_t), \tag{2}$$

where the demand shock a_t is i.i.d. with variance σ^2 , and $f(\cdot)$ is decreasing in the net supply, $-\Delta I_t$.⁸ This net demand shock represents shifts in the demand and supply of the commodity that

⁷Note that we model consumers of the commodity as operating only in the spot market. This is an abstraction, which does not correspond exactly with the evidence - for instance airlines have been known periodically to hedge their exposure to the price of jet fuel (by taking long positions in the futures market). In the empirical section, we show that our results are not affected by controlling for a measure of consumers’ hedging demand. Furthermore the CFTC data on hedger positions indicates that speculative capital (e.g., in hedge funds) has historically been allocated to long positions in the commodity futures, indicating that the sign of net hedger demand for futures is consistent with our assumption.

⁸We assume throughout the analysis that a_t and $f(\cdot)$ are specified such that (a) prices are positive and (b) a market-clearing spot price exists.

are exogenous to our model. It captures changes in net demand which arise from sources such as technological changes in the production of substitutes and complements for the commodity, weather conditions, or supply shocks that are not explicitly accounted for in the model.

2.2 Producers

There are an infinite number of commodity producing firms in the model, with mass normalized to one, and each individual manager acts competitively as a price taker. The timing of managers' decisions in the model are as follows: In period 0, the firm stores an amount i as inventory from its current supply, g_0 , and so period 0 profits are simply $S_0(g_0 - i)$. In period 1, the firm also goes short a number h_p of futures contracts, to be delivered in period 1. In period 1, the firm sells its current inventory and production supply, honors its futures contracts and realizes a profit of $S_1((1 - \delta)i + g_1) + h_p(F - S_1)$, where F is the (period 1) price of the futures contracts and g_1 is supply in period 1.⁹

We assume that managers of commodity producing firms are risk averse – they maximize the value of the firm subject to a penalty for the variance of next period's earnings. (In the model the parameter $\tilde{\gamma}_p$ governs a manager's degree of aversion to variance in future earnings.) This variance penalty generates hedging demand, and is a frequent assumption when modeling commodity producer behavior (for one recent example see Bessembinder and Lemmon (2002)). The literature on corporate hedging provides several justifications for this modeling choice. Hedging demand could result from managers being underdiversified, as in Amihud and Lev (1981) and Stulz (1984), or better informed about the risks faced by the firm (Breedon and Viswanathan (1990), and DeMarzo and Duffie (1995)). Managers could also be averse due to private costs suffered upon distress, as documented by Gilson (1989) for example, or the firm may itself face deadweight costs of financial distress, as argued by Smith and Stulz (1985). Aversion to earnings volatility can also be generated from costs of external financing as in Froot, Scharfstein, and Stein (1993).¹⁰

Writing Λ for the pricing kernel of equity holders in the economy, and r for the risk-free rate, the firm's problem is¹¹:

$$\begin{aligned} \max_{\{i, h_p\}} \quad & S_0(g_0 - i) + E[\Lambda \{S_1((1 - \delta)i + g_1) + h_p(F - S_1)\}] \dots \\ & - \frac{\tilde{\gamma}_p}{2} Var[S_1((1 - \delta)i + g_1) + h_p(F - S_1)], \end{aligned} \quad (3)$$

⁹Note that the production schedule, g_0 and g_1 , is assumed to be pre-determined. The implicit assumption, which creates a role for inventory management, is that it is prohibitively costly to change production in the short-run.

¹⁰We have also developed a slightly more complicated version of our model which employs the Froot, Scharfstein, and Stein (1993) framework to model hedging demand as arising from costly external financing. This model delivers similar results to the one presented here, and is available upon request.

¹¹In our model, $E[\cdot]$ denotes the expectation conditional on the information set at time 0. The setup implicitly assumes that the equity-holders cannot write a complete contract with the managers, on account of (for instance) incentive reasons as in Holmstrom (1979).

subject to:

$$i \geq 0, \quad (4)$$

The first order condition with respect to inventory holding i is:

$$S_0 - (1 - \delta) E[\Lambda S_1] = -\tilde{\gamma}_p (1 - \delta) (i (1 - \delta) + g_1 - h_p) \sigma^2 + \lambda, \quad (5)$$

where λ is the Lagrange multiplier on the inventory constraint. If the current demand shock is sufficiently high, an inventory stock-out occurs (i.e., $\lambda > 0$), and current spot prices can rise above expected future spot prices. In such a circumstance, firms wish to have negative inventory, but cannot. Thus, a convenience yield for holding the spot arises, as those who hold the spot in the event of a stock-out get to sell at a temporarily high price. This is the *Theory of Storage* aspect of our model.¹²

Solving for optimal inventory, we have that:

$$i^* (1 - \delta) = \frac{(1 - \delta) E[\Lambda S_1] - S_0 + \lambda}{(1 - \delta) \tilde{\gamma}_p \sigma^2} - g_1 + h_p^*. \quad (6)$$

Thus, inventory is increasing in the expected future spot price, decreasing in the current spot price, and decreasing in the amount produced (g_1). Importantly, inventory is also increasing in the amount hedged in the futures market, h_p . That is, hedging allows the producer to hold more inventory as it reduces the amount of earnings variance that the producer would otherwise be exposed to. Thus, the futures market provides an important venue for risk sharing.

The first order condition for the number h_p of futures contracts that the producer goes short is:

$$E[\Lambda (F - S_1)] = -\tilde{\gamma}_p (i (1 - \delta) + g_1 - h_p) \sigma_S^2 \quad (7)$$

\Updownarrow

$$h_p^* = i^* (1 - \delta) + g_1 - \frac{E[\Lambda (S_1 - F)]}{\tilde{\gamma}_p \sigma^2}. \quad (8)$$

Note that if the futures price F is such that $E[\Lambda (S_1 - F)] = 0$, there are no gains or costs to hedging activity in terms of expected, risk adjusted profits, and the producer will therefore simply minimize the variance of period 1 profits by hedging fully. In this case, the manager's optimal hedging strategy is independent of the degree of managerial risk aversion. This is a familiar result that arises by no-arbitrage in frictionless markets.

If, however, the futures price is lower than what is considered fair from the equity-holders perspective (i.e., $E[\Lambda (S_1 - F)] > 0$), it is optimal for the producer to increase the expected profits by entering a long *speculative* futures position after having fully hedged the period 1 supply. In

¹²In a multi-period setting, a convenience yield of holding the spot arises in these models even if there is no actual stock-out, but as long as there is a positive *probability* of a stock-out (see Routledge, Seppi, and Spatt (2000)).

other words, in this situation, the hedge is costly due to perceived mispricing in the commodity market. Thus, it is no longer optimal to hedge the period 1 price exposure fully. Since the inventory manager is naturally short, this entails shorting fewer futures contracts. Note that increases in the manager's risk aversion $\tilde{\gamma}_p$ decrease this implicit speculative futures position.

2.2.1 The Basis

The futures price can be written using the usual no-arbitrage relation (e.g., Hull (2008)) as:

$$F = S_0 \frac{1+r}{1-\delta} - S_0 y, \quad (9)$$

where the first term (the cost of carry) accounts for interest and storage costs, while the second term implicitly defines a convenience yield, y . The futures basis is then:

$$basis \equiv \frac{S_0 - F}{S_0} = y - \frac{r + \delta}{1 - \delta}. \quad (10)$$

The second equality shows that the basis can only be positive when there is a positive convenience yield, as the risk-free rate and cost of storage are both positive.

Combining the first order conditions of the firm, the futures basis in our model is given by:

$$\frac{S_0 - F}{S_0} = \frac{\lambda}{S_0} \left(1 + \frac{\delta + r}{1 - \delta} \right) - \frac{\delta + r}{1 - \delta}, \quad (11)$$

which implies that the convenience yield in the model is:

$$y = \frac{\lambda}{S_0} \frac{1+r}{1-\delta}. \quad (12)$$

The convenience yield only differs from zero if the shadow price of the inventory constraint (λ) is positive (this is the same as in Routledge, Seppi, and Spatt (2000)). In this case, the expected future spot price is low relative to the current spot price, and this results in the futures price also being low relative to the current spot price.

Our model shows that the basis is not a good measure of the futures risk premium. Producers in the model can obtain exposure to future commodity prices in one of two ways – either by going long a futures contract, or by holding inventory. In equilibrium, the marginal payoff from these strategies must coincide. Thus, producers managing inventory enforce a common component in the payoff to holding the spot and holding the futures, with offsetting impacts on the basis.¹³

¹³This prediction of the model is borne out in our empirical results, and is consistent with the findings of Fama and French (1986).

2.3 Speculators

Speculators are the other participants in the futures market. They take the long positions that offset producers' naturally short positions, and allow the market to clear. We assume that these speculators are specialized investment management companies, with superior investment ability in the commodity futures market (e.g., commodity hedge funds and investment bank commodity market trading desks). As a consequence of this superior investment technology, investors in other financial assets (the equity-holders) only invest in commodity markets by delegating their investments to these specialized funds. As in Berk and Green (2004), the managers of these funds extract all the surplus of this activity and the outside investors only get their fair risk compensation. The net present value of a commodity fund's payoff is given by:

$$h_s E[\Lambda[S_1 - F]] - h_s Y, \quad (13)$$

where Y is the time 0 compensation awarded to the fund managers per futures contract and h_s is the number of futures contracts that the fund goes long. Since the managers extract all the surplus, we have that $Y = E[\Lambda(S_1 - F)]$. Thus, the net present value for equity-holders of investing in a commodity fund is zero, as dictated by no-arbitrage.

The commodity fund managers are assumed to be risk-neutral, but they are subject to capital constraints. These constraints could arise from costs of leverage such as margin requirements, as well as from value-at-risk (VaR) limits. We model these capital constraints as proportional to the variance of the fund's position, in the spirit of a VaR constraint, as in Danielsson, Shin, and Zigrand (2008).¹⁴ Commodity funds are assumed to behave competitively, and we assume the existence of a representative fund. The aggregate objective function for commodity funds can be written as follows:

$$\max_{h_s} h_s Y - \frac{\tilde{\gamma}_s}{2} \text{Var}[h_s(S_1 - F)] \quad (14)$$

↓

$$h_s = \frac{Y}{\tilde{\gamma}_s \sigma^2} = \frac{E[\Lambda(S_1 - F)]}{\tilde{\gamma}_s \sigma^2}, \quad (15)$$

where $\tilde{\gamma}_s$ is the severity of the capital constraint. If commodity funds were not subject to any constraints (i.e., $\tilde{\gamma}_s = 0$), the market clearing futures price would be the same as that which would prevail if markets were frictionless: i.e., such that $E[\Lambda[S_1 - F]] = 0$. In this case, the producers would simply hedge fully, as discussed previously, and the futures risk premium would be independent of the level of managerial risk aversion. With $\tilde{\gamma}_s, \tilde{\gamma}_p > 0$, however, the equilibrium futures price will in general not satisfy the usual relation, $E[\Lambda(S_1 - F)] = 0$, as the risk-adjustment implicit in the

¹⁴Such a constraint is also assumed by Etula (2009) who finds empirical evidence to support the role of speculator capital constraints in commodity futures pricing.

speculators' objective function is different from that of the equity-holders.

This assumption of a capital constraint and its consequential impact on commodity futures prices places our model in the growing literature on limits-to-arbitrage (Shleifer and Vishny, 1997), which argues that sustained deviations from the law of one price can arise due to capital constraints and specialization in the delegated asset management industry. Gromb and Vayanos (2002) show in an equilibrium setting that arbitrageurs, facing constraints akin to the one we assume in this paper, will exploit but not fully correct relative mispricing between the same asset traded in otherwise segmented markets. Motivating such constraints on speculators, He and Xiong (2008) show that narrow investment mandates and capital immobility are natural outcomes of an optimal contract in the presence of unobservable effort on the part of the investment manager. In our model, these limits to speculative arbitrage allow producers' hedging activity to have a direct impact on the futures risk premium.

2.4 Equilibrium

The futures contracts are in zero net supply and therefore $h_s = h_p$, in equilibrium. From equations (8) and (15) we thus have that

$$(\gamma_s + \gamma_p) E[\Lambda(S_1 - F)] = I^*(1 - \delta) + g_1, \quad (16)$$

where $\gamma_p \equiv 1/(\tilde{\gamma}_p\sigma^2)$ and $\gamma_s \equiv 1/(\tilde{\gamma}_s\sigma^2)$. Using the expression for the basis, we have that $(S_0 - \lambda)\frac{1+r}{1-\delta} = F$, and we get:

$$(\gamma_s + \gamma_p) (E[\Lambda S_1(I^*)] - (S_0(I^*) - \lambda(I^*)) / (1 - \delta)) = I^*(1 - \delta) + g_1. \quad (17)$$

Since $I^*(1 - \delta) + g_1 > 0$, we have that $E[\Lambda(1 - \delta)S_1(I^*)] - S_0(I^*) + \lambda > 0$, which is a necessary condition for market clearing. In the case of no stock-out, this implies that $E[\Lambda(1 - \delta)S_1] > S_0$, and so future expected risk-adjusted spot prices are higher than the current spot price. When there is a stock-out, however, current spot prices can be higher than expected future spot prices as λ in this case is greater than zero. Equation (17) gives the solution for I^* . Given I^* and the inverse demand function in equation (2), we can calculate $E[S_1(I^*)]$. Since $F = (S_0(I^*) - \lambda(I^*))\frac{1+r}{1-\delta}$, the equilibrium supply of short futures contracts can be found using equation (8).

2.5 Model Predictions

We now present the main predictions of the model for commodity spot and futures prices as we vary the model parameters. In particular, we are interested in comparative statics around producers' propensity to hedge, $\tilde{\gamma}_p$ (which we refer to henceforth as producers' *fundamental hedging demand*), and the degree of the capital constraint on speculators, $\tilde{\gamma}_s$.

Proofs of the following Propositions are relegated to the Appendix, and we only give the economic intuition for the results in this section.

Proposition 1 *The futures risk premium and the expected spot price return are increasing in producers fundamental hedging demand, $\tilde{\gamma}_p$:*

$$\frac{d \frac{E[S_1 - F]}{F}}{d \tilde{\gamma}_p} > 0 \quad \text{and} \quad \frac{d \frac{E[S_1 - S_0]}{S_0}}{d \tilde{\gamma}_p} > 0, \quad (18)$$

where the latter result only holds if there is not a stock-out. In the case of a stock-out, $\frac{d \frac{E[S_1 - S_0]}{S_0}}{d \tilde{\gamma}_p} = 0$.

The model's predictions with respect to changes in fundamental hedging demand are summarized in Figure 1a and 1b. Figure 1a illustrates the comparative statics in the case of no inventory stock-out. Recall that inventory is risky for the firm since future spot prices are uncertain. It is never optimal for the firm to fully hedge its inventory, however, as the abnormal futures risk premium, $E[\Lambda(S_1 - F)]$, is positive.¹⁵ When fundamental hedging demand increases, this causes the firm to have increased sensitivity to the risk of holding unhedged inventory, and the inventory holding therefore decreases in equilibrium. This means that more of the commodity is sold on the spot market, which depresses current spot prices and raises future spot prices. Since two equivalent hedging strategies are to 1.) sell the commodity in the spot market and invest the cash and 2.) hold an extra unit of inventory and hedge it with a short futures contract, the return to both of these strategies must be equal in equilibrium. This is the reason why, as Figure 1a illustrates, a high expected spot price is accompanied by a high futures risk premium. Figure 1b shows the case of an inventory stock-out. In this situation, current and future expected spot prices are constant. The increased benefit of hedging with the futures contract leads to a higher demand for short futures contracts, which can only be accommodated by increasing the futures risk premium.

In sum, the model predicts that the futures risk premium is increasing in producers' fundamental hedging demand. Furthermore, in the case of no stock-out, increased hedging demand *ceteris paribus* also leads to lower current spot prices and higher expected future spot prices. Optimal inventory risk management thus induces a common component in expected futures and spot returns, and the cost of hedging in futures markets (the abnormal futures risk premium) affects the spot markets.

Corollary 2 *The basis, $\frac{S_0 - F}{F}$, is not informative of the futures risk premium in times of no stock-out.*

¹⁵This makes it costly for the firm to hedge, since futures are priced less than fairly - relative to a frictionless no-arbitrage setting - from the perspective of the equity-holders.

When the expected future spot price is high relative to the current spot price, it encourages the producer to hold more inventory. This increased inventory holding generates increased hedging demand for short futures contracts, which increases the futures risk premium needed to induce speculators to take the opposite side of these contracts. Thus, the futures risk premium and expected change in the spot price move together in a manner that leaves the basis unaffected.

Proposition 3 *The futures risk premium and the expected spot price return are increasing in the severity of speculators' capital constraints, $\tilde{\gamma}_s$:*

$$\frac{d\frac{E[S_1-F]}{F}}{d\tilde{\gamma}_s} > 0 \quad \text{and} \quad \frac{d\frac{E[S_1-S_0]}{S_0}}{d\tilde{\gamma}_s} > 0, \quad (19)$$

where the latter result only holds if there is not a stock-out. In the case of a stock-out, $\frac{d\frac{E[S_1-S_0]}{S_0}}{d\tilde{\gamma}_s} = 0$.

Relaxing the severity of capital constraints on speculators (alternatively increasing speculator risk appetite) increases speculative demand for long futures positions. This decreases the futures risk premium in equilibrium, making it cheaper for the producers to hedge their inventory, thus raising producers' inventory holding. Holding more inventory means that less of the commodity is sold in the spot market, so the spot price increases. Thus, the model predicts a direct link between the capital constraints of speculators and the level of the spot price. In a standard model with no frictions, such a link would not be present. Neither would the impact of producer hedging demand on the futures risk premium.

We now turn to describing the data employed in the study and, subsequently, to empirically testing the predictions of the model.

3 Data

3.1 Sample

To construct proxies for fundamental producer hedging demand, we employ data on commodity producing firms' accounting and stock returns from the CRSP-Compustat database. The use of Compustat data limits the study to the oil and gas markets as these are the only commodity markets where there are enough producer firms to create a reliable time-series of aggregate commodity sector producer hedging demand. Our empirical analysis thus focuses on four commodities: crude oil, heating oil, gasoline, and natural gas.

In particular, the full sample of producers includes all firms with SIC codes 1310 and 1311 (Petroleum Refiners) and 2910 and 2911 (Crude Petroleum and Gas Extraction).¹⁶ The total

¹⁶These SIC classifications, however, are rather coarse: firms designated as "Petroleum Refiners" (e.g., Exxon) often also engage in extraction, and vice versa.

sample of producers consists of 525 firms with quarterly data going back to 1974 for some firms. We also use data on firms' explicitly disclosed hedging activities from accounting statements available in the EDGAR database from 1998 to 2006.

3.2 Proxies for Fundamental Hedging Demand

“The amount of production we hedge is driven by the amount of debt on our consolidated balance sheet and the level of capital commitments we have in place.”

- St. Mary Land & Exploration Co. in their 10-K filing for 2006.

In the model, we refer to the variance aversion of the producers, $\tilde{\gamma}_p$, as producers' fundamental hedging demand. In the empirical analysis, we propose that variation in the aggregate level of $\tilde{\gamma}_p$ can be proxied by using measures of aggregate default risk for the producers of the commodity. There are both empirical and theoretical motivations for this choice, which we discuss below. In addition, we show in the following section that the available micro-evidence of individual producer hedging behavior in our sample supports this assumption.

The driver of hedging demand we appeal to in this paper is managerial aversion to distress and default. In particular, we postulate that managers act in an increasingly risk averse manner as the likelihood of distress and default increases. Amihud and Lev (1981) and Stulz (1984) proposes general aversion of managers to variance of cash flows as a driver of hedging demand, the rationale being that while shareholders can diversify across firms in capital markets, managers are significantly exposed to their firms' cash-flow risk due to incentive compensation as well as investments in firm-specific human capital. Empirical evidence has demonstrated that managerial turnover is indeed higher in firms with higher leverage and deteriorating performance. For example, Coughlan and Schmidt (1985), Warner et al. (1988) and Weisbach (1988) provide evidence that top management turnover is predicted by declining stock market performance. In an important study, Gilson (1989) refines this evidence, and examines the role of defaults and leverage. He first finds that management turnover is more likely following poor stock-market performance. He then investigates the sample of firms (each year) that are in the bottom five percent of stock-market performance over a preceding three-year period, and finds that within this group, the firms that are highly leveraged or in default on their debt experience higher top management turnover than their counterparts.¹⁷ However, management turnover by itself would not lead to variance aversion (and hence hedging demand) if the personal costs that managers face from such turnover are small. Gilson documents that following their resignation from firms in default, managers are not subsequently employed by another exchange-listed firm for at least three years, a result that is consistent with managers experiencing large personal costs when their firms default. Finally, Haushalter (2000, 2001) in an

¹⁷Gilson's sample constitutes firms that are listed on the NYSE and AMEX over the period 1979 to 1984.

important survey of one hundred oil and gas firms over the 1992 to 1994 period, uncovers that their propensity to hedge is highly correlated with their financing policies as well as their level of assets in place. In particular, he finds that the oil and gas producers in his sample that used more debt financing also hedged a greater fraction of their production, and interprets his result as evidence that companies hedge to reduce the likelihood of financial distress.

Given this theoretical and empirical motivation, we employ both balance-sheet and market-based measures of default risk as our empirical proxies for the cost of external finance. The balance-sheet based measure we employ is the Zmijewski (1984) score. This measure is positively related to default risk and is a variant of the Z-score of Altman (1968). The methodology for calculating the Zmijewski-score was developed by identifying the firm-level balance-sheet variables that help “discriminate” whether a firm is likely to default or not. The market-based measures we employ are first, (following Gilson (1989), who relates low cumulative unadjusted three-year stock returns to default and managerial turnover) the rolling three-year average stock return of commodity producers, and second, the naive expected default frequency (or naive EDF) computed by Bharath and Shumway (2008).

Each firm’s Zmijewski-score is calculated as:

$$\begin{aligned} Zmijewski\text{-score} = & -4.3 - 4.5 * NetIncome/TotalAssets + 5.7 * TotalDebt/TotalAssets \\ & -0.004 * CurrentAssets/CurrentLiabilities. \end{aligned} \quad (20)$$

Each firm’s rolling three-year average stock return, writing R_{it} for the cum-dividend stock return for a firm i calculated at the end of month t , is calculated as:

$$ThreeYearAvg_{i,t} = \frac{1}{36} \sum_{k=0}^{35} \ln(1 + R_{i,t-k}) \quad (21)$$

Finally, we obtain each firm’s naive EDF. The EDF from the KMV-Merton model is computed using the formula:

$$EDF = \Phi \left(- \left(\frac{\ln(V/F) + (\mu - 0.5\sigma_v^2)T}{\sigma_v\sqrt{T}} \right) \right) \quad (22)$$

where V is the total market value of the firm, F is the face value of the firm’s debt, σ_v is the volatility of the firm’s value, μ is an estimate of the expected annual return of the firm’s assets, and T is the time period, in this case, one year. Bharath and Shumway (2008) compute a ‘naive’ estimate of the EDF, employing certain assumptions about the variable used as inputs into the formula above. We use their estimates in our empirical analysis.¹⁸ Of the set of 525 firms, we have naive EDF estimates for 435 firms.

In the next section, we first confirm Haushalter’s (2000, 2001) results in our sample of firms –

¹⁸We thank Sreedhar Bharath and Tyler Shumway for providing us with these estimates.

i.e., that our default risk measures are indeed related to individual producer firms' hedging activity. We then aggregate these firm-specific measures within each commodity sector to obtain aggregate measures of fundamental producer hedging demand, which are used to test the pricing implications of the model. To arrive at these aggregate measures of producer's hedging demand, we construct an equal-weighted Zmijewski-score, 3-year lagged stock returns, and Naive EDF from the producers in each commodity sector. While our sample of firms goes back until 1974, the number of firms in any given quarter varies with data availability at each point in time. There are, however, always more than 10 firms underlying the aggregate hedging measure in any given quarter. Figures 2a and 2b show the resulting time-series of aggregate Zmijewski-score, 3-year lagged return, and Naive EDF for the Crude Oil, Heating Oil, and Gasoline sectors, as well as for the Natural Gas sector. For ease of comparison, the series have been normalized to have zero mean and unit variance. All the measures are persistent and stationary. The latter is confirmed in that unit root tests are rejected for all the measures, but this is not reported. As expected, the aggregate Zmijewski-scores and Naive EDF's are positively correlated, while the aggregate 3-year producer lagged stock return measure is negatively correlated with these measures. Table I reports the mean, standard deviation and quarterly autocorrelation of the aggregate hedging measures. The reason these summary statistics are different for Crude Oil, Heating Oil, and Gasoline is that the futures returns data are of different sample sizes across the commodities.

3.3 Commodity Futures and Spot Prices

Our commodity futures price data is for NYMEX contracts and is obtained from Datastream. The longest futures return sample period available in Datastream goes from the first quarter of 1980 until the fourth quarter of 2006 (108 quarters; crude oil).

To create the basis and returns measures, we follow the methodology of Gorton, Hayashi and Rouwenhorst (2007). We construct rolling commodity futures excess returns at the end of each month as the one-period price difference in the nearest to maturity contract that would not expire during the next month. That is, the excess return from the end of month t to the next is calculated as:

$$\frac{F_{t+1,T} - F_{t,T}}{F_{t,T}}, \quad (23)$$

where $F_{t,T}$ is the futures price at the end of month t on the nearest contract whose expiration date T is after the end of month $t + 1$, and $F_{t+1,T}$ is the price of the same contract at the end of month $t + 1$. The quarterly return is constructed as the product of the three monthly gross returns in the quarter.

The futures basis is calculated for each commodity as $(F1/F2 - 1)$, where $F1$ is the nearest futures contract and $F2$ is the next nearest futures contract. The statistical properties of our data match up very closely to those employed by Gorton, Hayashi and Rouwenhorst (2007), summary

statistics about these quarterly measures are presented in Table I. Note that the means and medians of the basis in the table are computed using the raw data, while the standard deviation and first-order autocorrelation coefficient are computed using the deseasonalized basis, where the deseasonalized basis is simply the residual from a regression of the actual basis on four quarterly dummies. The basis is persistent across all commodities once seasonality has been accounted for.

Table I further shows that the excess returns are on average positive for all three commodities, ranging from 2.5% to 6.7%, with relatively large standard deviations (overall in excess of 20%). As expected, the sample autocorrelations of excess returns on the futures are close to zero. The spot returns are defined using the nearest-to-expiration futures contract, again consistent with Gorton, Hayashi and Rouwenhorst (2007):

$$\frac{F_{t+1,t+2} - F_{t,t+1}}{F_{t,t+1}}. \quad (24)$$

Again, the quarterly return is constructed by aggregating monthly returns as defined above. Note that the spot returns display negative autocorrelation, consistent with mean-reversion in the level of the spot price.

3.4 Inventory

Aggregate inventories are created as per the specifications in Gorton, Hayashi and Rouwenhorst (2007). For all four energy commodities, these are obtained from the Department of Energy’s Monthly Energy Review. For Crude Oil, we use the item: “U.S. crude oil ending stocks non-SPR, thousands of barrels.” For Heating Oil, we use the item: “U.S. total distillate stocks”. For Gasoline, we use: “U.S. total motor gasoline ending stocks, thousands of barrels.” Finally, for Natural Gas, we use: “U.S. total natural gas in underground storage (working gas), millions of cubic feet.” Following Gorton, Hayashi and Rouwenhorst (2007), we compute a measure of the discretionary level of aggregate inventory by subtracting fitted trend inventory from the quarterly realized inventory. Quarterly trend inventory is created using a Hodrick-Prescott filter with the recommended smoothing parameter (1600). In all specifications employing inventories, we employ quarterly dummy variables. We do so in order to control for the strong seasonality present in inventories. Table I shows summary statistics of the resulting aggregate inventory measure, i.e., the cyclical component of inventory stocks, for the commodities. Once the seasonality in inventories is accounted for, the trend deviations in inventory are persistent.

3.5 Hedger Positions Data.

The Commodity Futures Trading Commission (CFTC) reports aggregate data on net “hedger” positions in a variety of commodity futures contracts. These data have been used in several papers that arrive at differing conclusions about their usefulness. Gorton, Hayashi and Rouwenhorst (2007)

find that this measure of hedger demand does not significantly forecast forward risk premiums, while De Roon, Nijman and Veld (2000) find that they hold some forecasting power for futures risk premia. The CFTC hedging classification has significant short-comings – in particular, anyone that reasonably can argue that they have a cash position in the underlying can obtain a hedger classification. This includes consumers of the commodity, and more prominently, banks that have offsetting positions in the commodity (perhaps on account of holding a position in the swap market). The line between a hedge trade or a speculator trade, as defined by this measure, is therefore blurred. We note these issues with this measure as they may help explain why hedging pressure is a contentious forecasting variable for futures risk premia, while our measures of default risk do seem to explain futures risk premia. Nevertheless, we use the CFTC data as a check that our measures of producers’ hedging demand is in fact reflected in futures positions as noted by the CFTC.

The Hedger Net Positions data are obtained from Pinnacle Inc., which sources data directly from the Commodity Futures Trading Commission (CFTC). Classification into Hedgers, Speculators and Small traders is done by the CFTC, and the reported data are the total open positions, both short and long, of each of these trader types across all maturities of futures contracts. We measure the net position of all hedgers in each period as:

$$HedgersNetPosition_t = \frac{(HedgersShortPosition_t - HedgersLongPosition_t)}{(HedgersShortPosition_{t-1} + HedgersLongPosition_{t-1})}. \quad (25)$$

This normalization means that the net positions are measured relative to the aggregate open interest of hedgers in the previous quarter. Summary statistics on these data are shown in Table I. First, the hedger positions are on average positive, which means investors classified as “hedgers” are on average short the commodity forwards. However, the standard deviations are relatively large, indicating that there are times when the CFTC classified “hedgers” are actually net long commodity futures contracts.

3.6 Other Controls

In our empirical tests, we use controls to account for sources of risk premia that are not due to hedging pressure. In a standard asset pricing setting, time-varying aggregate risk aversion and/or aggregate risk can give rise to time-variation in excess returns. This is reflected in the pricing kernel, Λ , of equity-holders in the model. To capture this source of variation, therefore, we include business cycle variables that have been shown to forecast excess asset returns in previous research. We include the Default Spread: the yield spread between Baa and Aaa rated corporate bond yields, which proxies for aggregate default risk in the economy and has been shown to forecast excess returns on stocks and bonds (see, e.g., Fama and French (1989), and Jagannathan and Wang (1996)). We also include the Payout Ratio, which is defined as $\ln(1 + \text{Net Payout} / \text{Market Value})$. Here Net Payout is the aggregate equity market cash dividends plus repurchases minus

equity issuance, while Market Value is the aggregate market value of outstanding equity. In a recent paper, Boudoukh, Michaely, Richardson, and Roberts (2007), show that this measure of the aggregate dividend yield dominates the cash-dividend-only aggregate dividend yield that is commonly used to forecast aggregate equity market returns.

We also include business cycle and production variables in our regressions, to account for time-varying expected commodity spot demand, as well as to capture variation in supply that is exogenous to the model. In particular, we use a forecast of quarterly GDP growth, obtained from the Philadelphia Fed’s survey of professional forecasters, as well as OPEC production growth. Finally, we use growth in Broker-Dealer assets relative to Household assets, obtained from the Flow of Funds data, as a measure of the aggregate capital available to commit to positions by commodity speculators (see Etula (2009)).

4 Individual Producer’s Hedging Behavior

While the main tests in the paper concern the relationship between spot and futures commodity prices and the commodity sector’s *aggregate* fundamental hedging demand, we first investigate the available micro evidence of producer hedging behavior. While Haushalter (2000, 2001) provides useful evidence of the cross-sectional determinants of hedging behavior among oil and gas firms, his evidence pertains to a smaller sample than ours, over the period from 1992 to 1994.¹⁹ A natural question for our purposes is to what extent the oil and natural gas producing firms in our sample actually do engage in hedging activity, and if so, in which derivative instruments and using what strategies. In this section, we use the publicly available data from firm accounting statements in the EDGAR database to ascertain the extent and nature of individual commodity producer hedging behavior.

4.1 Summary of Producer Hedging Behavior

The EDGAR database has available quarterly or annual statements for 231 of the 525 firms in the sample. In part, the smaller EDGAR sample is due to the fact that derivative positions are only reported in accounting statements, in our sample, from 1998 onwards.²⁰ We determine whether

¹⁹Another notable study of firm-level hedging behavior in commodities is Tufano (1996), who relies on proprietary data from gold mining firms.

²⁰Since the introduction of Financial Accounting Standards Board’s 133 regulation (Accounting for Derivative Instruments and Hedging Activities), effective for fiscal years beginning after June 15, 2000, firms are required to measure all financial assets and liabilities on company balance sheets at fair value. In particular, hedging and derivative activities are usually disclosed in two places. Risk exposures and the accounting policy relating to the use of derivatives are included in “Market Risk Information.” Any unusual impact on earnings resulting from accounting for derivatives should be explained in the “Results of Operations.” Additionally, a further discussion of risk management activity is provided in a footnote disclosure titled “Risk Management Activities & Derivative Financial Instruments.” Some firms, however, provided some information on derivative positions also before this date.

each firm uses derivatives for hedging commodity price exposure or not by reading at least two quarterly or annual reports per firm. Panel A in Table II shows that out of the 231 firms, there are 172 that explicitly state that they use commodity derivatives, 20 that explicitly state that they do *not* use commodity derivatives, and 39 that do not mention any use of derivatives. Of the 172 firms that use commodity derivatives, Panel B shows that 146 explicitly state that they use derivatives *only* for hedging purposes, while 16 firms say they both hedge and speculate. For the remaining 10 firms, we cannot tell. In sum, 74% of the producers in the EDGAR sample state that they use commodity derivatives, while a maximum of 26% of the firms do not use commodity derivatives. Of the firms that use derivatives, 85% are, by their own admission, pure hedgers.

Panel C of Table II shows the instruments the firms use and their relative proportions. Forwards and futures are used in 29% of the firms, while swaps are used by 52% of the firms. Options and strategies, such as put and call spreads and collars, are used by 20% and 33% of the firms, respectively. Most options positions are not strong volatility bets. In particular, low-cost collars that are long out-of-the-money put and short out-of-the-money calls are the most common option strategy for producers – a position that is very similar to a short futures position. Thus, derivative hedging strategies that are linear, or close to linear, in the underlying are by far the most common.

We focus on short-term commodity futures - the most liquid derivative instruments in the commodity markets - in our empirical analysis. However, quite a bit of the hedging is done with swaps, which are provided by banks over-the-counter, and often are longer term. On the one hand, this indicates that a significant proportion of producer’s hedging is done outside the futures markets that we consider. On the other hand, banks in turn hedge their aggregate net exposure in the underlying futures market and in the most liquid contracts. For instance, it is common to hedge long-term exposure by rolling over short-term contracts (e.g., Metallgesellschaft). A similar argument can be made for the net commodity option imbalance held by banks in the aggregate. Thus, producers’ aggregate net hedging pressure is therefore likely to be reflected in trades in the underlying short-term futures market.

4.2 The Time-Series Behavior of Producer Hedging

Information about hedging positions from accounting statements could potentially be used directly to assess the impact of time-varying producer hedging demand on commodity returns. However, there are significant data limitations for such use. First, FAS 133 requires the firms to report mark-to-market values of derivative positions, which are not directly informative of the underlying price exposure. There is no agreed upon reporting standard or requirement for providing information on effective price exposure for each firm’s derivative positions, which leads to either no, or very different, reporting of such information. For instance, firms sometimes report notional outstanding or number of barrels underlying a contract, but not the direction of the position or the actual derivative instruments and contracts used, the 5%-, 10%-, or 20%-delta with respect to the underlying, or

Value-at-Risk measures (again sometimes without mention of direction of hedge). We went through *all* the quarterly and annual reports available for the firms with SIC codes 2910 and 2911 (50 firms) in the EDGAR database to attempt to extract (a) whether the firms were long or short the underlying, and (b) the extent of exposure in each quarter or year as measured by sensitivity to price changes in the underlying commodity futures price (i.e., a measure of Delta).

Panel D in Table I reports that of the 34 firms with these SIC codes that we could find in EDGAR, only 19 (56%) gave information about the direction of the hedge (long or short the underlying). Of these, on average 80% of the firm-date observations were noted as short the underlying commodity. Since commodity producers are naturally long the commodity, one would expect that the producers' derivative hedge positions are always short the underlying. However, there are complicating factors. First, some firms do take speculative positions. Second, there are cases where hedging demand could manifest itself in long positions in the futures market. For instance, a pure refiner may have an incentive to go long crude oil futures to hedge its input costs, but short, say gasoline futures to hedge its production. This suggests that it might be fruitful to separate producers and producer refiners (such as Marathon Oil) from pure refiners (such as Valero) in the analysis.

Of the 19 firms that reported whether they were long or short in the futures markets, we could only extract a reliable, and relatively long, time-series of actual derivative position exposure to the underlying commodity price for 4 firms: Marathon Oil, Hess Corporation, Valero Energy Corporation, and Frontier Oil Corporation. Consequently, the data is not rich enough to provide a measure of *aggregate* producer hedging positions based on direct (self-reported) observations of producers' futures hedging demand, even for the relatively short period for which EDGAR data is available. Nevertheless, we show the relationship between the time series of hedging behavior and default risk for the 4 firms for which we were able to extract this information. This represents an interesting insight into the time-series variation in hedging, which complements existing analyses (such as Haushalter (2000, 2001)) of the cross-sectional relation between hedging behavior and default risk measures.

4.3 Observed Hedging Demand and Default Risk

From the quarterly and annual reports of these four firms, we extract a measure of each firm's \$1 delta exposure to the price of crude oil (i.e., how does the value of the company's derivative position change if the price of the underlying increases by \$1). This measure of each firm's hedging position is constructed from, for instance, value-at-risk numbers that are provided in the reports by assuming log-normal price movements and using the historical mean and volatility from the respective commodity futures returns. In other cases, firms report delta's based on 5%, 10% and 20% moves in the underlying price, which are then used to construct the \$1 delta number as a measure of hedging demand.

We next compare the time-series of each of the firms' commodity derivatives hedging demand to each firm's Zmijewski-score and 3-year lagged stock return throughout the EDGAR sample. There are too few observations per firm to compare with the naive-EDF scores, which is only provided to us until the end of 2003. Figure 3a shows the negative of the imputed delta and the Zmijewski-score for each of the four companies. Both variables are normalized to have mean zero and unit variance. The figure shows that there is a strong, positive correlation between the level of default risk, as measured by the Zmijewski-score and the amount of short exposure to crude oil using derivative positions for Marathon Oil, Hess Corp., and Valero Energy Corp. For Frontier Oil Corp., the hedging activity is strongly negatively correlated with the Zmijewski-score. The same pattern can be seen in Figure 3b, where each firm's hedging activity is plotted against the negative of its 3-year average stock returns. Marathon Oil and Hess both extract and refine oil and so it is natural that as default risk and hedging demand increases, these firms increase their short crude oil positions. Valero, however, is a pure refining company that one might argue should go more *long* crude oil as default risk increases. This does not happen, however, because Valero in fact holds inventory of its input, crude oil, as well as for refined products. This was inferred by reading Valero's quarterly reports, and is anecdotally quite a common happenstance for refiners. Thus, an increase in the demand for hedging leads to increasing hedge of both the input and output good inventories. Frontier Oil, however, behaves more as one might naively expect of a refiner, as the company does not hold significant crude inventory in this sample, and decreases its short crude positions as default risk increases.

In sum, in these four firms, which constituted the best sample available in EDGAR of the producer firms, it is clear that hedging activity indeed is time-varying and related to the proposed proxies for fundamental hedging demand. However, the graphs highlight that one must take care when inferring expected hedging activity from whether a firm is involved only with extraction, or extraction and refining, or a pure refiner. Essentially, all firms are to some extent naturally long crude oil, but for pure refiners one can expect this to be less the case than for companies that engage in both extraction and refining - this echoes the analysis in Ederington and Lee (2002). We now turn to our analysis of the aggregate relationships between our proxies for fundamental hedging demand, spot returns and futures risk premia in the oil and gas markets.

5 Aggregate Empirical Analysis

In this section, we employ the aggregate measures of producer hedging demand, for which we reported summary statistics in the Data section, to test the empirical predictions of the model documented in Section 2. The main novel prediction of our model is that aggregate commodity sector fundamental hedging demand should be positively related to the respective commodity's futures risk premium. We have argued that a proximate determinant of hedging demand is default

risk, in particular, high default risk on average leads to higher hedging demand. Further, there should be a common component in the expected change in the spot price and the futures risk premium, and so the default risk measures should also predict changes in commodity spot prices. Our model shows that this common component is why the basis, as shown in previous research (e.g., Fama and French (1986)), is not a strong forecaster of the time-series of commodity futures risk premiums, but instead should be more tightly linked to fluctuations in inventory, as shown by Gorton, Hayashi, and Rouwenhorst (2007).

Before we test these predictions of the model, however, we perform one additional check of our aggregate measures of producers’ fundamental hedging demand by relating them to the CFTC measures of aggregate net hedging demand. We further use the CFTC measure to substantiate a split of the sample of producing firms into firms that state they hedge versus firms that are self-stated likely non-hedgers. This split is then used as a robustness check throughout the analysis to facilitate the interpretation of the regression results as arising from fundamental hedging demand rather than from any omitted variable in our empirical model.

5.1 CFTC Hedging Positions and Producer Hedging Demand

As previously explained in the Data section, the aggregate CFTC data on hedger positions is noisy. However, a noisy measure of hedger positions should still contain information about the underlying true producer hedging demand. Therefore, we regress the CFTC hedger positions on our aggregate default risk measure as an additional test of the validity of our measures of fundamental hedging demand.

We construct the hedger net position variables from the CFTC data as the net *short* position, so we should expect a positive relation between the default risk and CFTC hedger positions. We use our default risk measures to predict one-quarter ahead CFTC hedger positions to account for the possibility that there are lags between the desire for hedging and the implementation of the hedge, as well as to establish causality.

Table III reports the results of the regression:

$$HedgerNetPos_{i,t+1} = \beta_i DefRisk_{i,t} + ControlVariables_t + u_{i,t+1}, \quad (26)$$

where i denotes the relevant commodity (crude oil, heating oil, gasoline, or natural gas). The controls in these regressions are the lagged aggregate stock market dividend-price ratio, the aggregate default spread, GDP growth forecast, each commodity’s aggregate inventory and basis, net hedger positions, and quarterly dummy variables. The moniker “*DefRisk*” denotes in this, and all following regressions, the aggregate Zmijewski-score, Naive EDF, or the *negative* of the 3-year average producer stock returns (so as to make the expected regression coefficient, β_i , positive in all specifications). Table III shows that the regression coefficient β_i is indeed positive for all the

default risk measures and across all the commodities. The right-most column of the table gives the β -coefficient from a pooled regression across all commodities. For all three default risk measures, β is positive and statistically significant at the 5% level or greater.²¹

5.1.1 Hedgers Versus Non-Hedgers.

Next, we split the producers into two groups based on whether a producer is a stated hedger or non-hedger, according to the data we gathered in Section 3 on individual firms' disclosures about their hedging policies. If our model is correct, hedging pressure should be driven by the increase in default risk only for those firms that engage in hedging, and not when the default risk increases for firms that do not engage in hedging. This split also helps assuage concerns that our default risk measures are a consequence of an unobservable factor that simultaneously drives defaults and the commodity futures risk premium.

To implement the split, we must implicitly extrapolate the behavior of the sample firms backwards in time. This is because the EDGAR data only contains information back to 1998. Panel A of Table II identifies 20 firms as stated non-hedgers, while 59 firms are likely non-hedgers, and 146 firms are stated hedgers. We construct aggregate Zmijewski-scores, Naive EDF's, and 3-year average returns based on these three definitions. One concern that arises in this context is that hedging firms tend to be quite a bit larger than the non-hedgers. In particular, the average market value of the hedgers is \$3,035 million versus only \$701 million for likely non-hedgers, and \$313 million for stated non-hedgers. Furthermore, the sample of hedging firms is larger, which reduces the idiosyncratic noise in aggregate measures constructed for this group of firms.

To facilitate comparisons that are not driven by these differences, we identify a matched sample of self-described hedging producer firms, by removing the firms with the largest market values until the number of firms in the hedger sample is 59 – the same as in the likely non-hedger sample. The average market value of the matched hedgers is \$373 million, with a comparable standard deviation to that of the non-hedgers, and we run our tests also using this matched sample.

Table IV gives the results of regressions, where the hedger positions are pooled across commodities, that are run for each of the three default risk measures:

$$\begin{aligned} HedgerNetPos_{t+1} = & \beta_1 (DefRisk_Hedgers_t + DefRisk_NonHedgers_t) \dots \\ & + \beta_2 DefRisk_NonHedgers_t + ControlVariables_t + u_{t+1}. \end{aligned} \quad (27)$$

A significant $\beta_2 < 0$ in these regressions would indicate that the regression coefficient on the default risk measure of non-hedging producers is significantly smaller than the regression coefficient on the

²¹Note that in all individual-commodity regressions in this paper, standard errors are constructed using the Newey-West (1987) method, which is robust to heteroskedasticity and autocorrelation of the error terms, and in all pooled regressions, we employ Rogers (1983, 1993) errors that are robust to heteroskedasticity, own and cross-autocorrelation and contemporaneous correlation across all commodities in each quarter.

default risk measure of hedging producers. Table IV shows that in all the regressions the sign of β_1 is strongly positive, while the sign on β_2 is significantly negative 10 out of 12 times. Inspecting the magnitude of the regression coefficients, the implied regression coefficient on the non-hedgers' default risk measure ($\beta_1 + \beta_2$) is, as expected, close to zero. Thus, it is the default risk of producers that hedge their exposure, and not default risk in general, that drives aggregate hedging pressure. In our analysis to follow, we continue to use these splits of firms into hedging and non-hedging producers as additional robustness checks.

5.2 Commodity Futures Returns

In this section we evaluate the first part of Proposition 1, namely that increases in fundamental hedging demand are associated with higher futures risk premia. To do so, we run a standard forecasting regression for excess commodity futures return, using our default risk proxy for fundamental hedging demand. In particular, we regress quarterly (excess) futures returns on one quarter lagged measures of default risk (*DefRisk*):

$$ExcessReturns_{i,t+1} = \beta_i DefRisk_{i,t} + ControlVariables_t + u_{i,t+1}, \quad (28)$$

where i denotes the commodity and t denotes time measured in quarters. The controls are: aggregate commodity inventory and basis; the aggregate stock market dividend-price ratio; the aggregate default spread; the GDP growth forecast; and quarterly dummy variables. All regressions include quarterly dummy variables to control for the seasonal variation in inventory, basis and returns.

Table V shows the results of the above regression across the four commodities considered, as well as a pooled regression across all commodities. First, we note that in all cases, the regression coefficients have the predicted sign: an increase in default risk forecasts higher futures returns over the next quarter. For ease of interpretation, the default risk measures are in all cases normalized to have unit variance, and thus the regression coefficients give the expected futures return response to a one standard deviation change in the aggregate default risk measure. The average expected return response is highly economically significant at 4% per quarter across the commodities. The standard deviation of quarterly futures returns of Crude Oil, Heating Oil, and Gasoline is 20% per quarter, and so the implied quarterly R^2 from the effect of the producer fundamental hedging demand alone is 4% for these commodities. This is a significant number for quarterly forecasting regressions, considering the high persistence of the predictive default risk variables.²²

The pooled regressions show that the effect of producer hedging demand is significant at the 5% level or greater for all the default measures. In the individual regressions, the evidence is strongest for Crude Oil and Heating Oil and somewhat weaker for Gasoline and Natural Gas. However,

²²The default risk measures are also significant predictors of futures returns in simple univariate regressions (not reported).

the two latter have the shortest time-series of 84 and 64 quarters, respectively, which potentially explains the lower significance. Furthermore, Haushalter (2000, 2001) points out that hedging for Natural Gas producers in particular is less prevalent and more risky since there is substantial basis risk depending on the location of the producer relative to the location at which the benchmark price is set.²³ This may also be responsible for the somewhat weaker results we see for this commodity.

In terms of the controls, aggregate measures of investor risk aversion do not play a greatly important role when producer default risk is accounted for. Consistent with the model, the basis does not appear to be a good predictive variable for the commodity futures risk premium (with the exception of gasoline) in our regressions. We do not find inventory to be a significant predictor once producer hedging demand and the other controls are included in the regression.

In sum, we conclude that there is strong evidence that commodity producers' fundamental hedging demand is positively related to the expected return of commodity futures, consistent with the model in Section 2. This evidence is robust to the inclusion of a range of standard control variables that capture variation in investor risk aversion. Additionally, at the end of this section, we report the robustness of our results to the introduction of alternative controls such as variables that proxy for speculator risk tolerance and consumer hedging demand.

5.2.1 Hedgers Versus Non-Hedgers.

Next, we consider the forecasting power of default risk measures based on producers that state they are hedgers versus producers that are non-hedgers, parallel to the analysis conducted for the CFTC hedger positions. In particular, Table VI gives the results of futures returns forecasting regressions, where the hedger positions are pooled across commodities, that are run for each of the three default risk measures:

$$\begin{aligned} ExcessReturns_{t+1} = & \beta_1 (DefRisk_Hedgers_t + DefRisk_NonHedgers_t) \dots \\ & + \beta_2 DefRisk_NonHedgers_t + ControlVariables_t + u_{t+1}. \end{aligned} \quad (29)$$

Table VI shows that for the Zmijewski-score and the Naive EDF, the β_1 -coefficients are positive and significant at the 1% level or greater, while the β_2 -coefficients are negative and significant at the 5% level or greater. In this case, the default risk measures are not individually normalized to have unit variance, as this would invalidate the interpretation of β_2 as a test of the significance of the difference in impact of hedger versus non-hedger default risk. Yet again, the implied coefficient on non-hedger default risk is close to zero in these specifications. While the 3-year lagged return does not yield a significantly different coefficient between hedgers and non-hedgers, in the pooled

²³He mentions, for example, that in 1993 the correlation between the prices of natural gas sold at Wheeling Ridge Hub in California and gas sold at Henry Hub in Louisiana (the benchmark for prices on NYMEX contracts) was slightly less than 30%

regression, the signs are consistent with that of the other measures.

5.3 Commodity Spot Returns

The model predicts a strong common component in spot and futures returns as arising from the producers' fundamental hedging demand. Table VII shows forecasting regressions of quarterly spot returns on the baseline lagged default risk measures, analogous to the regressions in Table V for the case of the futures returns. In particular, the regression is:

$$SpotReturns_{i,t+1} = \beta_i DefRisk_{i,t} + ControlVariables_t + u_{i,t+1}, \quad (30)$$

where the control variables are the same as before. Table VII shows that there is a clear positive relation between default risk and spot returns on commodities. In particular, all the default risk measures are significant at the 5% level or better in the pooled regressions. The regression coefficients are very close to those found in the futures returns forecasting regressions, as predicted by the model. That is, the common component in the expected futures and spot returns are of a similar size. Unlike in the results for futures returns, however, the basis is highly significant in the pooled regressions. This is also consistent with the model, which predicts that the basis will indeed be more informative about future spot prices than futures risk premia.

In the model, a decrease in the futures risk premium leads to an increase in the spot price as producers are willing to hold more inventory when the cost of hedging is lower. The spot regressions are consistent with this result, as an increase in the spot price all else equal leads to a lower expected spot return. To the extent that the massive increase in speculator demand for long commodity futures positions over the recent years led to a decrease in the futures risk premium, we should expect to have seen an increase in the spot price. This effect is due to the increased risk-sharing between producers and speculators enabled on account of the lower futures risk premium. Note that an increase in spot prices can occur through this channel even if there are no changes in the fundamentals of the commodity spot market.

5.4 Robustness and Additional Model Implications

5.4.1 Speculators, Consumers, and Other Producers.

The model (Proposition 3) also predicts that changes in the capital constraints of speculators will have an impact on expected futures and spot returns. In particular, with more capital flowing to commodity funds, $\tilde{\gamma}_s$ should decrease and thus so should futures risk premium. Following Etula (2009), we use the growth in aggregate broker-dealer asset growth relative to household asset growth as a proxy for this speculator constraint (see Etula (2009) for details on the construction of this variable using the Flow of Funds data). In addition to this, we add three other controls to address

effects that might be important for the futures risk premium, but that are outside the model. First, consumer hedging demand may also impact the futures risk premium. Consumers, however, are a more difficult group to pinpoint. First, several different industries have oil and gas products as one of their factor inputs. The basis risk in terms of hedging in these markets are likely larger for these agents exactly because energy is just one of several factors influencing profits, as opposed to the case of producers, where the source of risk is relatively clear. Nevertheless, we create an aggregate Zmijewski-score based on airlines (SIC code 4512), as a proxy for consumer hedging demand analogous to our measures for producers. Second, we add the conditional volatility of the commodity futures returns obtained from a GARCH(1,1) model to control for time-variation in return volatility. Third, we use OPEC production growth to control for production changes of producers outside the model that influence the price of oil.

Table VIII shows the results of pooled forecasting regressions of the futures returns, using the above variables as well as the controls applied in the previous regressions. All the measures of producer fundamental hedging demand are still significant. Notably, the measure of speculator investment constraint comes in strongly significant in all regressions with the sign predicted by our model, consistent with the findings in Etula (2009). None of the other controls are strongly significant. In sum, the main result of the paper is robust to these controls, and the fact that the measure of the extent of capital available to the speculators is significant in addition to standard measures of investor risk appetite (the payout ratio and the default spread) supports the assumptions that underpin our model.

Figure 4 presents the estimated Crude Oil quarterly futures risk premium based on all the variables employed in Table VIII versus the estimated risk premium based on the Zmijewski-score alone, in one case just for hedging producers and in the other case just for non-hedging producers. The producer hedging demand based on hedgers can be seen to be an economically significant component of the futures risk premium. In particular, it accounts for 34% of the total estimated variation in the futures risk premium. In contrast, the producer hedging demand based on non-hedgers is essentially flat and has little explanatory power for the futures risk premium.

5.4.2 Inventory

Finally, we check whether the specific mechanism predicted by the theory operates correctly, i.e., whether changes in default risk translate into changes in discretionary holdings of inventory. Again, rather than a contemporaneous regression, we run a forecasting regression for changes in aggregate inventory, in the event there is some friction preventing hedgers from immediately implementing their strategies and to establish causality:

$$Inventory_{i,t+1} = \beta_i DefRisk_{i,t} + \sum_{k=1}^4 \gamma_i ChangeInventory_{i,t-k} + ControlVariables_t + u_{i,t+1}, \quad (31)$$

We augment the set of controls with four lagged values of changes in inventory, in case there are seasonalities in changes in inventory that are not captured by the quarterly dummy variables. Table IX shows the signs are as predicted in all but three of the regressions - an increase in default risk decreases the level of inventory. Moreover, the joint test results all have the predicted sign and they are statistically significant for *AVG3Y* and Naive EDF. For *AVGZm*, the *t*-statistic for the joint test results is 1.52. Natural Gas is the culprit for the weaker evidence here, as for this commodity the sign is in fact positive. This again raises the possibility that the high location-specific basis risk identified by Haushalter (2000, 2001) for natural gas producers in particular, is clouding our inferences in this case. If the pooled regressions exclude Natural Gas, the sign is negative and significant at the 5% level or better for all the measures. This evidence suggests that the mechanism we identify in the paper connecting discretionary changes in inventory with measures of default risk is a reasonable one.

As in the model, the empirical results presented in this paper confirm that the primitive driving force is producers' fundamental hedging demand: An increase in default risk leads to a subsequent decrease in the optimal inventory holding, which in turn lowers the current spot price and increases future expected spot prices. The increase in default risk also increases commodity producers' demand for hedging in the futures market, which in turn increases the futures risk premium.

5.4.3 Splitting the Sample and Producers versus Refiners²⁴

When splitting the sample, all the pooled regression coefficients indicate a positive relation between producer fundamental hedging demand and the futures risk premium in the first half of the sample. However, only for the 3 year lagged return measure is this effect statistically significant. The predictability evidence is stronger in the second half of the sample. Here all the pooled regressions are significant at the 1% level or better. The magnitude of the regression coefficients are, however, comparable across the samples.

We also performed a split of the sample of producers into pure refiners versus producer-refiners, as given by the information in accounting statements in EDGAR. The idea is that refiners are less likely to hold short futures positions in crude oil as their natural hedging position, as crude oil is an input to these firms' production. As discussed in Section 4, however, this hypothesis is complicated by the fact that many pure refiners hold significant inventories of crude oil. We find that the predictive power of producer-refiners' default measure tends to be stronger than that of pure refiners. In particular, the producer versus pure refiner split does lead to a significantly different impact on the CFTC measure of aggregate hedger activity in the crude oil commodity market. The split leads to a significant difference in the forecasting regression coefficients across refiners and producers only in the case of the return measure. The other two default risk measures

²⁴These results are not reported, but they are available upon request.

yield an insignificant difference in the effect. This is not unexpected, however, given that some pure refiners do hold inventory of crude oil to hedge input purchase costs and, as explained in Section 4, therefore sometimes hedge by going short crude oil futures, just as a producer would.

6 Conclusion

In this paper, we build a theoretical model in which the interaction between commodity producers who are averse to price fluctuations, and capital constrained speculators investing in commodity markets, determines commodity spot prices and commodity futures risk premia in equilibrium. Using a theoretically and empirically motivated proxy for the fundamental hedging demand of commodity producers - their default risk - we find evidence to support the predictions of the model in the oil and gas markets.

Our main insight is that the hedging demand of producers is an important channel through which trading in commodity futures markets can affect spot prices. This occurs in our model because futures markets allow producers' inventory holdings to better adjust to current and future demand shocks, reminiscent of the Litzenberger and Rabinowitz (1995) model in which the optimal adjustment of production schedules is the main focus. Our model allows us to shed light on an important recent debate – whether speculative activity in the oil futures market has been responsible for the gyrations in oil spot prices. The model reveals that changes in speculative positions change the costs of hedging for producers, which in turn change inventory holdings and thus spot prices. Empirically we verify this line of reasoning - the default risk of oil and gas producers (a proxy for their fundamental hedging demand) is a significant determinant of producers' hedging demand in oil and gas futures markets, and in turn, of spot and futures prices and futures risk premia.

Much work remains to be done in order to understand these relationships fully, especially from an empirical standpoint. First, even though aggregate default risk proxies are hard to come by for other commodities due to the paucity of identifiable producers, it would be interesting to see if our results are verified for a broader set of commodities than oil and gas. Second, in recent times, demand shocks to commodity markets have largely arisen from increased demand for commodities from fast developing countries like India and China. An interesting avenue for further research would be to investigate the role of such global demand shifts on commodity inventories and spot and futures prices. Exploring the role of such demand shocks in a model such as ours would open the possibility of understanding their contribution to the recent volatility in commodity prices, relative to the contribution of increased speculative activity in futures markets.

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7 Appendix

7.1 Proofs of results given in the main body of paper

It is useful to establish some preliminary results. Note that for the futures market to clear when $\tilde{\gamma}_p, \tilde{\gamma}_s > 0$, the condition $E[\Lambda(S_1 - F)] > 0$ must be satisfied (see Equation (16)). Since this implies that $h_p^* < I(1 - \delta) + g_1$ (see Equation (8)), we have from Equation (5) that $E[\Lambda S_1] - S_0/(1 - \delta) > 0$ when there is no stock-out ($\lambda = 0$).

Proof of Proposition 1

It is, for ease of exposition, useful to define speculator and producer risk tolerance as $\gamma_s \equiv 1/(\tilde{\gamma}_s \sigma^2)$ and $\gamma_p \equiv 1/(\tilde{\gamma}_p \sigma^2)$, respectively.²⁵ We first consider the effect an increase in producer risk tolerance, γ_p , has on inventory.

First, consider the case of no stock-out, $\lambda = 0$. In this case, we have from the equilibrium condition given in Equation (17) that:

$$(\gamma_s + \gamma_p) (E[\Lambda S_1(I^*)] - S_0(I^*)/(1 - \delta)) = I^*(1 - \delta) + g_1. \quad (32)$$

Then

$$(E[\Lambda S_1(I)] - S_0(I)/(1 - \delta)) + (\gamma_s + \gamma_p) \frac{dI}{d\gamma_p} \left(E \left[\Lambda \frac{dS_1}{dI} \right] - \frac{dS_0}{dI}/(1 - \delta) \right) = \frac{dI}{d\gamma_p} (1 - \delta) \quad (33)$$

$$\Downarrow$$

$$(E[\Lambda S_1(I)] - S_0(I)/(1 - \delta)) \left(1 - (\gamma_s + \gamma_p) \left(E \left[\Lambda \frac{dS_1}{dI} \right] - \frac{dS_0}{dI}/(1 - \delta) \right) \right)^{-1} = \frac{dI}{d\gamma_p} (1 - \delta) \quad (34)$$

Remember that $S_0 = a_0 + f(-I)$ and $S_1 = a_1 + f(I)$. Thus, since $f' < 0$, we have that $\frac{dS_0}{dI} > 0$, and $\frac{dS_1}{dI} < 0$, and $E \left[\Lambda \frac{dS_1}{dI} \right] - \frac{dS_0}{dI}/(1 - \delta) < 0$. Since $E[\Lambda S_1] - S_0/(1 - \delta) > 0$, it follows that $\frac{dI}{d\gamma_p} > 0$. In the case of an inventory stock-out, we have trivially that $\frac{dI}{d\gamma_p} = 0$.

The derivative of the expected spot return with respect to producer risk tolerance is then:

$$\frac{d}{d\gamma_p} \frac{E[S_1] - S_0}{S_0} = \frac{\left(E \left[\frac{dS_1}{dI} \frac{dI}{d\gamma_p} \right] - \frac{dS_0}{dI} \frac{dI}{d\gamma_p} \right) S_0 - (E[S_1] - S_0) \frac{dS_0}{dI} \frac{dI}{d\gamma_p}}{S_0^2} \quad (35)$$

$$= \frac{E \left[\frac{dS_1}{dI} \right] S_0 - E[S_1] \frac{dS_0}{dI}}{S_0^2} \frac{dI}{d\gamma_p} < 0. \quad (36)$$

Thus, the expected spot return is increasing in the producers' risk aversion, $\tilde{\gamma}_p$, as stated in the proposition. If there is a stock-out, there is no change in the expected spot return, since in this case $\frac{dI}{d\gamma_p} = 0$.

Next, we turn to the futures risk premium. Consider the impact on the futures risk premium of a change in inventory in the case of no stock-out, when $F = S_0 \frac{1+r}{1-\delta}$ (using Equations (9) and (12)):

$$\frac{\partial}{\partial I} \left(\frac{E[S_1] - S_0 \frac{1+r}{1-\delta}}{S_0 \frac{1+r}{1-\delta}} \right) = \frac{\left(E \left[\frac{\partial S_1}{\partial I} \right] - \frac{\partial S_0}{\partial I} \frac{1+r}{1-\delta} \right) S_0 - \left(E[S_1] - S_0 \frac{1+r}{1-\delta} \right) \frac{\partial S_0}{\partial I}}{S_0^2 \frac{1+r}{1-\delta}} \quad (37)$$

$$= \frac{S_0 E \left[\frac{\partial S_1}{\partial I} \right] - E[S_1] \frac{\partial S_0}{\partial I}}{S_0^2 \frac{1+r}{1-\delta}} < 0. \quad (38)$$

²⁵This transformation of variables does not affect the sign of the derivatives other than in the obvious way (tolerance versus aversion means it is flipped) as the price volatility is constant in this model.

Since $E\left[\frac{\partial S_1}{\partial I}\right] < 0$, and $\frac{\partial S_0}{\partial I} > 0$, we have that the sign on the change in the futures risk premium relative to the aggregate inventory level is negative. Since $\frac{dI}{d\gamma_p} > 0$, the futures risk premium is increasing in producer risk aversion ($\tilde{\gamma}_p$) if there is no stock-out: $\frac{d\frac{E(S_1)-F}{d\tilde{a}_p}}{d\tilde{a}_p} > 0$.

Next, consider the case of a stock-out. Now, price in period 0 and expected price in period 1 stay constant. In this case the futures price can be written: $F = S_0 \frac{1+r}{1-\delta} - \lambda \frac{1+r}{1-\delta}$. The futures risk premium is then:

$$\frac{E[S_1] - F}{F} = \frac{E[S_1] - S_0 \frac{1+r}{1-\delta} + \lambda \frac{1+r}{1-\delta}}{S_0 \frac{1+r}{1-\delta} - \lambda \frac{1+r}{1-\delta}}. \quad (39)$$

From Equation (17), we have that:

$$(\gamma_s + \gamma_p) (E[\Lambda S_1(I^*)] - (S_0(I^*) - \lambda(I^*)) / (1 - \delta)) = I^* (1 - \delta) + g_1. \quad (40)$$

First consider the derivative of λ with respect to γ_p :

$$\begin{aligned} & (E[\Lambda S_1(I)] - S_0(I) / (1 - \delta) + \lambda / (1 - \delta)) + \dots \\ & (\gamma_s + \gamma_p) \left(\frac{\partial E[\Lambda S_1(I)]}{\partial I} \frac{dI}{d\gamma_p} - \frac{\partial S_0(I) / (1 - \delta)}{\partial I} \frac{dI}{d\gamma_p} + \frac{d\lambda}{d\gamma_p} / (1 - \delta) \right) = \frac{dI}{d\gamma_p} (1 - \delta). \end{aligned} \quad (41)$$

Since in a stock-out $\frac{dI}{d\gamma_p} = 0$, we have that

$$\begin{aligned} & (E[\Lambda S_1(I)] - S_0(I) / (1 - \delta) + \lambda / (1 - \delta)) + (\gamma_s + \gamma_p) \frac{d\lambda}{da_s} / (1 - \delta) = 0 \\ & \frac{d\lambda}{da_s} = -E[\Lambda(S_1 - F)] (1 - \delta) / (\gamma_s + \gamma_p). \end{aligned} \quad (42)$$

Since we only achieve market clearing in the futures market if $E[\Lambda(S_1 - F)] > 0$, it must be that $\frac{d\lambda}{da_s} < 0$. Given this, the derivative of the futures risk premium in the case of a stock-out is:

$$\frac{d}{da_s} \frac{E[S_1] \frac{1-\delta}{1+r} - S_0 + \lambda}{S_0 - \lambda} = \frac{\frac{d\lambda}{da_s} (S_0 - \lambda) + \left(E[S_1] \frac{1-\delta}{1+r} - S_0 + \lambda \right) \frac{d\lambda}{da_s}}{(S_0 - \lambda)^2} < 0, \quad (43)$$

since $E[S_1] \frac{1-\delta}{1+r} - S_0 + \lambda > 0$, $S_0 - \lambda > 0$, and $\frac{d\lambda}{da_s} < 0$.

Proof of Corollary 2

The basis is defined as $\frac{S_0 - F}{S_0}$ in this paper. Combining the producers' first order conditions given in equations (5) and (8), we have that:

$$S_0 - (1 - \delta) E[\Lambda S_1] - (1 - \delta) E[\Lambda(F - S_1)] = \lambda \quad (44)$$

\Downarrow

$$S_0 - \frac{1 - \delta}{1 + r} F = \lambda, \quad (45)$$

where we have used the fact that $1 + r = 1/E[\Lambda]$. Manipulating the above expression, we obtain:

$$\frac{S_0 - F}{S_0} = \frac{\lambda}{S_0} - \frac{F}{S_0} \frac{\delta + r}{1 + r} \quad (46)$$

$$= \frac{\lambda}{S_0} - \frac{S_0 \frac{1+r}{1-\delta} - S_0 y}{S_0} \frac{\delta + r}{1 + r} \quad (47)$$

$$= \frac{\lambda}{S_0} - \frac{\delta + r}{1 - \delta} + y \frac{\delta + r}{1 + r}, \quad (48)$$

where we used the no-arbitrage relation $F = S_0 \frac{1+r}{1-\delta} - S_0 y$ from Equation (9). Since the convenience yield is given by $y = \frac{\lambda}{S_0} \frac{1+r}{1-\delta}$, we can write the basis as:

$$\frac{S_0 - F}{S_0} = \frac{\lambda}{S_0} \frac{1 + r}{1 - \delta} - \frac{\delta + r}{1 - \delta}. \quad (49)$$

The basis reflects storage δ and interest r costs, as expected. Otherwise, the basis only reflects the shadow price of the inventory constraint, which is only positive in an inventory stock-out in this model. Thus, the basis is not a good signal of time-variation in the futures risk premium. This is because of the common component in the spot and futures returns, as implies by equation (44) above.

Proof of Proposition 3.

Here we consider the effect of speculator risk aversion. We focus on $\gamma_s \equiv 1/(\tilde{\gamma}_s \sigma^2)$ as it simplifies the exposition.

First, we note that the market clearing level of aggregate inventory is increasing in speculator risk tolerance unless there is an inventory stock-out, for which case it remains at zero. Consider the case of no stock-out, $\lambda = 0$. In this case, we have from the equilibrium condition given in Equation (17) that:

$$(\gamma_s + \gamma_p) (E[\Lambda S_1(I^*)] - S_0(I^*)/(1 - \delta)) = I^*(1 - \delta) + g_1. \quad (50)$$

Then

$$(E[\Lambda S_1(I)] - S_0(I)/(1 - \delta)) + (\gamma_s + \gamma_p) \frac{dI}{da_s} \left(E \left[\Lambda \frac{dS_1}{dI} \right] - \frac{dS_0}{dI}/(1 - \delta) \right) = \frac{dI}{da_s} (1 - \delta) \quad (51)$$

$$\Downarrow$$

$$(E[\Lambda S_1(I)] - S_0(I)/(1 - \delta)) \left(1 - (\gamma_s + \gamma_p) \left(E \left[\Lambda \frac{dS_1}{dI} \right] - \frac{dS_0}{dI}/(1 - \delta) \right) \right)^{-1} = \frac{dI}{da_s} (1 - \delta) \quad (52)$$

Remember that $S_0 = a_0 + f(-I)$ and $S_1 = a_1 + f(I)$. Thus, since $f' < 0$, we have that $\frac{dS_0}{dI} > 0$, and $\frac{dS_1}{dI} < 0$, and $E \left[\Lambda \frac{dS_1}{dI} \right] - \frac{dS_0}{dI}/(1 - \delta) < 0$. Since $E[\Lambda S_1] - S_0/(1 - \delta) > 0$, it follows that $\frac{dI}{da_s} > 0$. In the case of an inventory stock-out, we have trivially that $\frac{dI}{da_s} = 0$. Given this and the results established in the proof of Proposition 1, it follows that the expected spot return and futures risk premium are both increasing in speculator risk aversion.

Table I
Summary Statistics

This table reports summary statistics (mean, standard deviation, and the first autocorrelation coefficient AR(1)) of the variables AVGZm (cross-sectional average quarterly Zmijewski-score); AVG3Y (cross-sectional average of the time-series average stock return per producer-firm over the past three years, each quarter); cross-sectional average naïve EDF (expected default frequency) from Bharath and Shumway (2008); basis (standard deviation and AR(1) computed for the deseasonalized series); spot returns; futures excess returns; net change in hedger's short positions and the change in aggregate inventory (standard deviation and AR(1) computed for the deseasonalized series), all measured quarterly as specified in the Data section. These statistics are computed for each of Crude Oil, Heating Oil, Gasoline and Natural Gas.

	Crude Oil	Heating Oil	Gasoline	Natural Gas
AVGZm				
<i>Mean</i>	-2.689	-2.727	-2.692	-2.587
<i>StdDev</i>	0.318	0.323	0.329	0.417
<i>AR(1)</i>	0.951	0.939	0.969	0.702
AVG3Y				
<i>Mean</i>	0.009	0.009	0.009	0.004
<i>StdDev</i>	0.010	0.010	0.010	0.013
<i>AR(1)</i>	0.930	0.930	0.953	0.923
Naïve EDF				
<i>Mean</i>	0.037	0.040	0.036	0.099
<i>StdDev</i>	0.030	0.032	0.029	0.073
<i>AR(1)</i>	0.726	0.743	0.719	0.829
Basis				
<i>Mean</i>	0.018	0.026	0.040	-0.039
<i>StdDev</i>	0.059	0.131	0.081	0.136
<i>AR(1)</i>	0.462	0.146	0.390	0.342
Spot Return				
<i>Mean</i>	0.031	0.033	0.039	0.042
<i>StdDev</i>	0.170	0.179	0.175	0.226
<i>AR(1)</i>	-0.132	-0.143	-0.137	-0.194
Futures Excess Return				
<i>Mean</i>	0.043	0.044	0.067	0.025
<i>StdDev</i>	0.206	0.200	0.210	0.298
<i>AR(1)</i>	-0.123	-0.078	-0.183	0.035
Hedgers Net Position				
<i>Mean</i>	0.003	0.080	0.069	0.067
<i>StdDev</i>	0.072	0.114	0.099	0.068
<i>AR(1)</i>	0.135	-0.010	0.256	0.206
Change in Inventory				
<i>Mean</i>	-0.001	0.002	0.001	-0.004
<i>StdDev</i>	0.044	0.088	0.035	0.156
<i>AR(1)</i>	0.551	0.506	0.138	0.415

Table II
Producer Hedging – Summary Statistics

The data in this table is taken from 10-Q and 10-K filings in the Edgar database of firms with SIC codes 1310, 1311 (mainly Natural Gas), and 2910 and 2911 (mainly Crude Oil and Refined Products). The Edgar files have only been obtained for firms that are verified to be crude oil or natural gas producers, oil refiners, and oil refined product marketers.

Panel A:

	<i>Number</i>	<i>Proportion</i>
Firms in CompuStat sample (SIC 1310, 1311, 2910, 2911)	570	
Firms where Edgar filings could be found	231	
- # firms where cannot tell if use commodity derivatives	39	17%
- # firms that do not use commodity derivatives	20	9%
- # firms that use commodity derivatives	172	74%

Panel B:

Hedging vs. Speculation

	<i>Number</i>	<i>Proportion</i>
Firms that hedge	146	85%
Firms that both speculate and hedge	16	9%
Firms that do not specify	10	6%
	172	100%

Panel C:

Instruments

	<i>Number</i>	<i>Proportion</i>
Futures	47	20%
Forwards	21	9%
Options	48	20%
Swaps*	124	52%
Strategies**	80	33%
Not Specified	9	4%

* Mainly of two types: Price Swaps and Spread Swaps

** Usually Collars, sometimes Put Spreads, Call Spreads

Panel D:

Commodity Class and Direction (SIC 2910, 2911)	<i>Firms in Edgar where direction of hedge is known</i>	<i>Proportion of all Edgar firms</i>	<i># of time-series obs.</i>	<i># of obs. where firm is short</i>	<i>Proportion of all time-series observations</i>
Crude Oil*	7	88%	113	98	87%
Natural Gas*	3	50%	42	32	76%
Crude Oil + Natural Gas**	2	100%	2	2	100%
Refined Products***	4	44%	50	41	82%
Various****	3	33%	20	8	40%
<i>All Commodity classes</i>	19	56%	227	181	80%

* Including positions reported as dominated by, but not exclusively comprising, this class

** Where reported as a combined class

*** Includes Gasoline, Diesel, Heating Oil, Jet Fuel and Asphalt

**** Where firms report all or some of the above classes together, sometimes combined with other classes such as electricity

Table III
CFTC Hedger Position Forecasting Regressions

The independent variables are CFTC aggregate net short hedger positions in Crude Oil, Heating Oil, Gasoline, and Natural Gas. The measures of fundamental hedging demand are the average Zmijewski-score (avgZm), the average Naive EDF (avgEDF), and the negative of the average returns the last 3 years (-avg3yr) for the sample of producers in each commodity. These dependent variables are normalized to have unit variance. The data is quarterly and the dependent variables are lagged one quarter relative to the independent variables. The controls are GDP forecast, the dividend yield, the default spread, the relevant commodity basis and inventory. For the case of hedging positions, lagged net hedging positions are also included. Heteroskedasticity and autocorrelation consistent standard errors (using 3 lags) are given in parentheses; *** means p-value < 0.01, ** p < 0.05, * p < 0.1.

	Crude Oil	Heating Oil	Gasoline	Natural Gas	Pooled Regression
avgZm	0.226* (0.122)	0.287*** (0.075)	0.070 (0.086)	0.326** (0.166)	0.176** (0.088)
R ²	13.2%	31.4%	29.0%	34.0%	12.3%
# obs	79	91	82	52	304
avgEDF	0.243* (0.131)	0.252** (0.073)	0.227*** (0.095)	0.099 (0.079)	0.213*** (0.050)
R ²	15.2%	33.9%	30.7%	29.4%	13.8%
# obs	69	81	72	42	264
-avg3yr	0.141 (0.109)	0.300*** (0.090)	0.034 (0.076)	0.257*** (0.082)	0.159** (0.073)
R ²	12.6%	31.7%	35.5%	32.7%	13.8%
# obs	79	91	82	52	304
Controls?	yes	yes	yes	yes	yes

Table IV
Forecasting CFTC Hedger Positions with FAS 133 Classified Hedgers and Non-Hedgers

The independent variables is CFTC aggregate net short hedger positions in Crude Oil, Heating Oil, Gasoline, and Natural Gas. The regressions are pooled across the commodity classes. The measures of fundamental hedging demand are the average Zmijewski-score (avgZm), the average Naive EDF (avgEDF), and the negative of the average returns the last 3 years (-avg3yr) for the sample of producers in each commodity. These dependent variables are calculated for both hedgers and non-hedgers and, unlike in Table III, the values are not normalized. The data is quarterly and the dependent variables are lagged one quarter relative to the independent variables. The controls are GDP forecast, the dividend yield, the default spread, the relevant commodity basis and inventory, and lagged net hedging positions. Heteroskedasticity and autocorrelation consistent standard errors (using 3 lags) are given in parentheses; *** means p-value < 0.01, ** p < 0.05, * p < 0.1.

	All hedgers + Stated non-hedgers	All hedgers + Likely non-hedgers	Matched hedgers + Stated non-hedgers	Matched hedgers + Likely non-hedgers
HedgeZm + NoHedgeZm	0.024*** (0.005)	0.025*** (0.005)	0.022*** (0.005)	0.021*** (0.004)
NoHedgeZm	-0.023*** (0.006)	-0.026*** (0.005)	-0.019*** (0.005)	-0.017*** (0.004)
R ²	20.5%	20.5%	21.8%	21.7%
# obs	304	304	304	304
HedgeEDF + NoHedgeEDF	0.088*** (0.024)	0.094*** (0.025)	0.058*** (0.020)	0.051** (0.025)
NoHedgeEDF	-0.091** (0.042)	-0.104** (0.047)	-0.043 (0.041)	-0.025 (0.051)
R ²	15.8%	15.8%	14.9%	15.0%
# obs	264	264	264	264
-Hedge3yr - NoHedge3yr	0.507** (0.228)	0.710*** (0.257)	0.452*** (0.180)	0.688*** (0.203)
-NoHedge3yr	-0.761** (0.371)	-1.267*** (0.486)	-0.717** (0.351)	-1.352*** (0.453)
R ²	12.2%	12.9%	12.6%	13.9%
# obs	304	304	304	304
Controls?	yes	yes	yes	yes

Table V
Forecasting Commodity Futures Returns

The independent variables are excess returns of futures on Crude Oil, Heating Oil, Gasoline, and Natural Gas. The measures of fundamental hedging demand are the average Zmijewski-score (avgZm), the average Naive EDF (avgEDF), and the negative of the average returns the last 3 years (-avg3yr) for the sample of producers in each commodity. These dependent variables are normalized to have unit variance. The data is quarterly and the dependent variables are lagged one quarter relative to the independent variables. The controls are GDP forecast, the dividend yield, the default spread, the relevant commodity basis and inventory. Heteroskedasticity and autocorrelation consistent standard errors (using 3 lags) are given in parentheses; *** means p-value < 0.01, ** p < 0.05, * p < 0.1.

	Hedging Demand Measures			Commodity Variables		Other Return predictors			N	R ²
	avgZm	avgEDF	-avg3yr	Inventory	Basis	ΔGDP forecast	Dividend yield	Default Spread		
Crude Oil	1	0.043** (0.019)		0.523 (0.508)	-0.235 (0.667)	0.016 (0.015)	-0.015 (0.061)	-0.018 (0.078)	91	12.3%
	2		0.045*** (0.018)	0.780 (0.565)	-0.104 (0.681)	0.006 (0.016)	0.035 (0.059)	-0.041 (0.078)	77	13.6%
	3		0.040** (0.019)	0.697 (0.508)	-0.140 (0.654)	0.009 (0.015)	0.016 (0.066)	-0.015 (0.082)	91	11.8%
Heating Oil	4	0.035*** (0.014)		-0.116 (0.172)	-0.016 (0.191)	0.010 (0.008)	-0.004 (0.081)	-0.020 (0.036)	108	9.3%
	5		0.034*** (0.013)	-0.041 (0.175)	0.022 (0.196)	0.008 (0.008)	0.026 (0.076)	-0.061* (0.032)	93	8.1%
	6		0.036*** (0.013)	-0.040 (0.169)	-0.000 (0.173)	0.008 (0.008)	0.010 (0.082)	-0.038 (0.036)	108	9.5%
Gasoline	7	0.026 (0.018)		0.123 (0.734)	0.654*** (0.220)	0.026** (0.013)	-0.036 (0.052)	0.025 (0.071)	84	14.4%
	8		0.061*** (0.014)	-0.447 (0.696)	0.626*** (0.231)	0.018 (0.013)	0.029 (0.048)	-0.002 (0.067)	70	21.8%
	9		0.027 (0.019)	0.158 (0.722)	0.632*** (0.210)	0.023* (0.013)	-0.014 (0.060)	0.030 (0.076)	84	14.5%
Natural Gas	10	0.070* (0.042)		0.072 (0.233)	0.221 (0.195)	0.065 (0.040)	-0.094 (0.193)	0.112 (0.135)	64	11.3%
	11		0.011 (0.031)	0.118 (0.298)	0.063 (0.310)	0.076* (0.044)	-0.114 (0.197)	0.148 (0.172)	50	10.6%
	12		0.085** (0.036)	0.179 (0.235)	0.147 (0.226)	0.065* (0.039)	-0.059 (0.182)	0.080 (0.147)	64	14.0%
Pooled regression	13	0.038** (0.016)		0.038 (0.070)	0.117 (0.106)	0.019* (0.012)	-0.031 (0.076)	-0.019 (0.042)	347	8.2%
	14		0.039*** (0.008)	0.042 (0.085)	0.119 (0.108)	0.014 (0.012)	-0.002 (0.073)	-0.046 (0.034)	290	7.2%
	15		0.040** (0.016)	0.067 (0.072)	0.114 (0.099)	0.015 (0.011)	-0.005 (0.072)	-0.029 (0.049)	347	8.5%

Table VI
Forecasting Futures Returns With FAS 133 Classified Hedgers and Non-Hedgers

The independent variable is excess returns of futures on Crude Oil, Heating Oil, Gasoline, and Natural Gas. The regressions are pooled across the commodity classes. The measures of fundamental hedging demand are the average Zmijewski-score (avgZm), the average Naive EDF (avgEDF), and the negative of the average returns the last 3 years (-avg3yr) for the sample of producers in each commodity. These dependent variables are calculated for both hedgers and non-hedgers and, unlike in Table VII, the values are not normalized. The controls are GDP forecast, the dividend yield, the default spread, the relevant commodity basis and inventory. For the case of hedging positions, lagged net hedging positions are also included. Heteroskedasticity and autocorrelation consistent standard errors (using 3 lags) are given in parentheses; *** means p-value < 0.01, ** p < 0.05, * p < 0.1.

	All hedgers + Stated non-hedgers	All hedgers + Likely non-hedgers	Matched hedgers + Stated non-hedgers	Matched hedgers + Likely non-hedgers
HedgeZm + NoHedgeZm	0.148*** (0.049)	0.490*** (0.155)	0.106*** (0.035)	0.308*** (0.069)
NoHedgeZm	-0.138** (0.059)	-0.392** (0.192)	-0.083* (0.045)	-0.191** (0.094)
R ²	9.6%	9.4%	8.8%	8.7%
# obs	347	347	347	347
HedgeEDF + NoHedgeEDF	0.770*** (0.231)	0.439*** (0.073)	0.533*** (0.088)	0.292*** (0.048)
NoHedgeEDF	-1.060** (0.439)	-0.323*** (0.115)	-0.690*** (0.224)	-0.155** (0.074)
R ²	7.8%	7.9%	7.7%	7.7%
# obs	290	290	290	290
-Hedge3yr - NoHedge3yr	2.942 (2.417)	0.056 (0.322)	1.618 (1.601)	-0.097 (0.328)
-NoHedge3yr	-2.245 (3.389)	0.148 (0.321)	-0.470 (2.495)	0.295 (0.337)
R ²	8.7%	9.6%	8.3%	9.7%
# obs	347	347	347	347
Controls?	yes	yes	yes	yes

Table VII
Forecasting Commodity Spot Returns

The independent variables are percentage price changes in spot Crude Oil, Heating Oil, Gasoline, and Natural Gas. The measures of fundamental hedging demand are the average Zmijewski-score (avgZm), the average Naive EDF (avgEDF), and the negative of the average returns the last 3 years (-avg3yr) for the sample of producers in each commodity. These dependent variables are normalized to have unit variance. The data is quarterly and the dependent variables are lagged one quarter relative to the independent variables. The controls are GDP forecast, the dividend yield, the default spread, the relevant commodity basis and inventory. Heteroskedasticity and autocorrelation consistent standard errors (using 3 lags) are given in parentheses; *** means p-value < 0.01, ** p < 0.05, * p < 0.1.

	Hedging Demand Measures			Commodity Variables		Other Return Predictors			N	R ²
	avgZm	avgEDF	-avg3yr	Inventory	Basis	ΔGDP forecast	Dividend yield	Default Spread		
Crude Oil	1	0.035*		0.683	-0.885	0.013	-0.007	-0.020	91	19.6%
		(0.019)		(0.494)	(0.616)	(0.013)	(0.058)	(0.074)		
	2		0.038**	0.944*	-0.744	0.004	0.034	-0.034	77	21.7%
		(0.016)		(0.541)	(0.621)	(0.014)	(0.055)	(0.070)		
	3		0.033*	0.830*	-0.812	0.008	0.019	-0.018	91	19.5%
			(0.019)	(0.509)	(0.608)	(0.014)	(0.062)	(0.076)		
Heating Oil	4	0.020		0.136	-0.297***	0.012	0.010	-0.043	108	17.5%
		(0.015)		(0.158)	(0.086)	(0.008)	(0.063)	(0.037)		
	5		0.027**	0.235	-0.247***	0.009	0.030	-0.063**	93	20.1%
		(0.013)		(0.148)	(0.084)	(0.008)	(0.059)	(0.029)		
	6		0.017	0.173	-0.286***	0.010	0.018	-0.053*	108	17.4%
			(0.012)	(0.160)	(0.079)	(0.008)	(0.064)	(0.034)		
Gasoline	7	0.018		0.660	-0.077	0.018	-0.026	-0.020	88	19.9%
		(0.015)		(0.485)	(0.187)	(0.120)	(0.052)	(0.068)		
	8		0.048***	0.306	-0.121	0.010	0.024	-0.039	74	21.7%
		(0.014)		(0.456)	(0.200)	(0.012)	(0.048)	(0.067)		
	9		0.013	0.682	-0.078	0.015	-0.014	-0.016	88	19.4%
			(0.014)	(0.483)	(0.185)	(0.012)	(0.058)	(0.072)		
Natural Gas	10	0.055		0.156	-0.279*	0.060*	-0.104	0.117	64	15.3%
		(0.035)		(0.227)	(0.157)	(0.036)	(0.175)	(0.086)		
	11		0.008	0.190	-0.417*	0.067	-0.124	0.148	50	17.0%
		(0.026)		(0.284)	(0.232)	(0.043)	(0.192)	(0.110)		
	12		0.072**	0.237	-0.346**	0.061*	-0.072	0.094	64	17.8%
			(0.030)	(0.225)	(0.178)	(0.035)	(0.159)	(0.095)		
Pooled regression	13	0.028**		0.007	-0.397***	0.016	-0.016	-0.021	351	11.5%
		(0.013)		(0.068)	(0.059)	(0.010)	(0.053)	(0.044)		
	14		0.031***	0.009	-0.406***	0.011	0.004	-0.035	294	12.6%
		(0.008)		(0.087)	(0.036)	(0.010)	(0.058)	(0.031)		
	15		0.026**	0.029	-0.394***	0.013	0.001	-0.028	351	11.4%
			(0.011)	(0.071)	(0.053)	(0.010)	(0.050)	(0.047)		

Table VIII
Forecasting Futures Returns with Speculator and Consumer Demand

The independent variable is excess returns of futures on Crude Oil, Heating Oil, Gasoline, and Natural Gas. The regressions are pooled across the commodity classes. The measures of fundamental hedging demand are the average Zmijewski-score (avgZm), the average Naive EDF (avgEDF), and the negative of the average returns the last 3 years (-avg3yr) for the sample of producers in each commodity. In addition lagged conditional volatility from a GARCH(1,1) estimation for each commodity, a measure of consumers (Airlines) aggregate Zmijewski-score, OPEC production growth, as well as speculator capital (growth in Broker-Dealer assets; BD_growth) are included as lagged independent variables. The other controls are GDP forecast, the dividend yield, the default spread, the relevant commodity basis and inventory. For the case of hedging positions, lagged net hedging positions are also included. Heteroskedasticity and autocorrelation consistent standard errors (using 3 lags) are given in parentheses; *** means p-value < 0.01, ** p < 0.05, * p < 0.1.

	Specification		
	1	2	3
avgZm	0.025* (0.015)		
naiveEDF		0.029*** (0.005)	
-avg3yr			0.035*** (0.014)
CondVol	-0.012 (0.017)	-0.019 (0.018)	-0.020 (0.017)
OPEC_Prod	-0.006 (0.025)	-0.004 (0.024)	-0.007 (0.025)
Cons_Zm	0.019 (0.022)	0.014 (0.031)	0.021 (0.023)
BD_growth	-0.056*** (0.012)	-0.053*** (0.013)	-0.058*** (0.010)
R2	15.0%	13.8%	16.0%
# obs	345	288	345
Controls?	yes	yes	yes

Table IX
Inventory Forecasting Regressions

The independent variables are aggregate inventory above trend value in Crude Oil, Heating Oil, Gasoline, and Natural Gas. The measures of fundamental hedging demand are the average Zmijewski-score (avgZm), the average Naive EDF (avgEDF), and the negative of the average returns the last 3 years (-avg3yr) for the sample of producers in each commodity. These dependent variables are normalized to have unit variance. The data is quarterly and the dependent variables are lagged one quarter relative to the independent variables. The controls are GDP forecast, the dividend yield, the default spread, the relevant commodity basis and inventory. For the case of hedging positions, lagged net hedging positions are also included. Heteroskedasticity and autocorrelation consistent standard errors (using 3 lags) are given in parentheses; *** means p-value < 0.01, ** p < 0.05, * p < 0.1.

	Crude Oil	Heating Oil	Gasoline	Natural Gas	Pooled regression	Pooled regression ex Nat. Gas
avgZm	-0.062 (0.067)	-0.016 (0.043)	-0.017 (0.086)	0.103** (0.046)	-0.061 (0.051)	-0.085** (0.041)
R ²	51.8%	73.5%	15.0%	92.0%	34.2%	29.3%
# obs	91	108	88	64	351	287
avgEDF	-0.138 (0.092)	-0.143** (0.074)	-0.315** (0.135)	0.106*** (0.035)	-0.188* (0.109)	-0.240** (0.122)
R ²	52.8%	76.5%	24.8%	92.7%	35.8%	32.3%
# obs	77	93	74	50	294	244
-avg3yr	-0.176** (0.077)	-0.086 (0.050)	-0.023 (0.109)	0.028 (0.046)	-0.125** (0.058)	-0.156** (0.062)
R ²	54.0%	74.3%	17.6%	91.4%	35.2%	30.8%
# obs	91	108	88	64	351	351
Controls?	yes	yes	yes	yes	yes	yes

Figure 1a

This figure shows how futures and spot prices change in response to an increase in fundamental hedging demand ($\tilde{\gamma}_p$) in the case of no inventory stock-out. The solid lines denote equilibrium values before the change. Here the basis before the change is noted on the vertical axis: Basis = $S_0 - F$. The dashed lines denote equilibrium values with higher hedging demand.

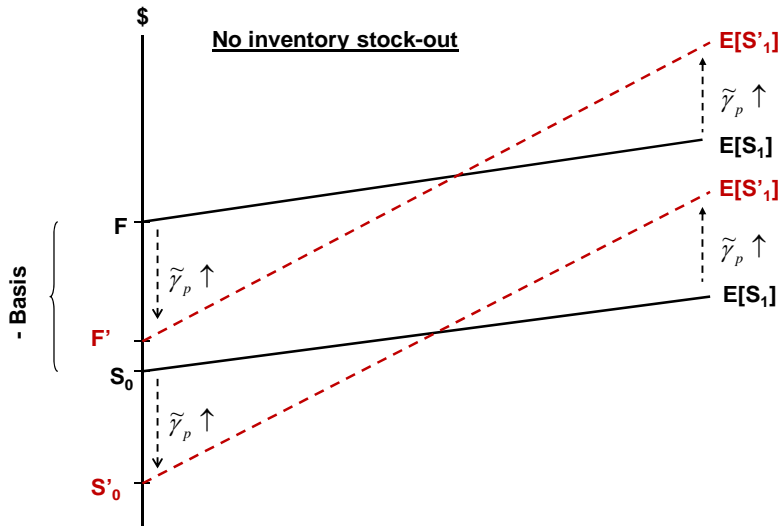


Figure 1b

This figure shows how futures and spot prices change in response to an increase in fundamental hedging demand in the case of an inventory stock-out. The solid lines denote equilibrium values before the change. Here the basis before the change is noted on the vertical axis: Basis = $S_0 - F$. The dashed lines denote equilibrium values with higher hedging demand.

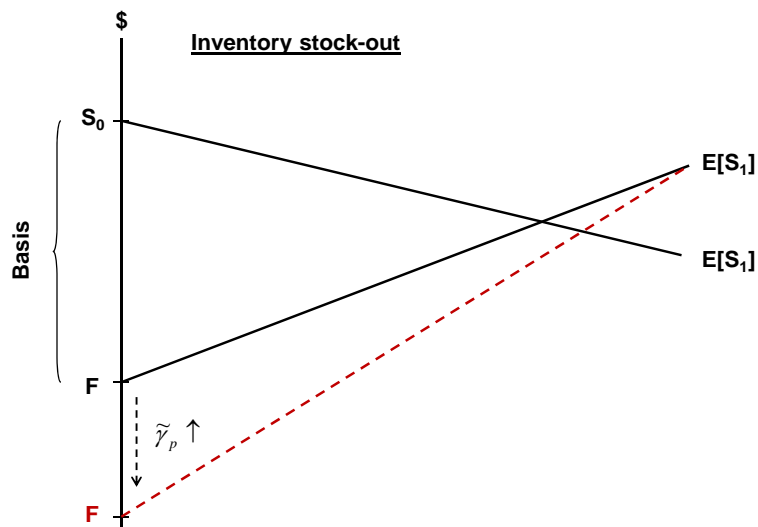


Figure 2a

This figure plots the default risk measures (AVG3Y, AVGZm and Naïve EDF) for Crude Oil, Heating Oil and Gasoline (the series used for all three commodities are the same, since the producer firms are in the same SIC classification codes). The series are normalized by subtracting their means and dividing by their standard deviations for ease of plotting.

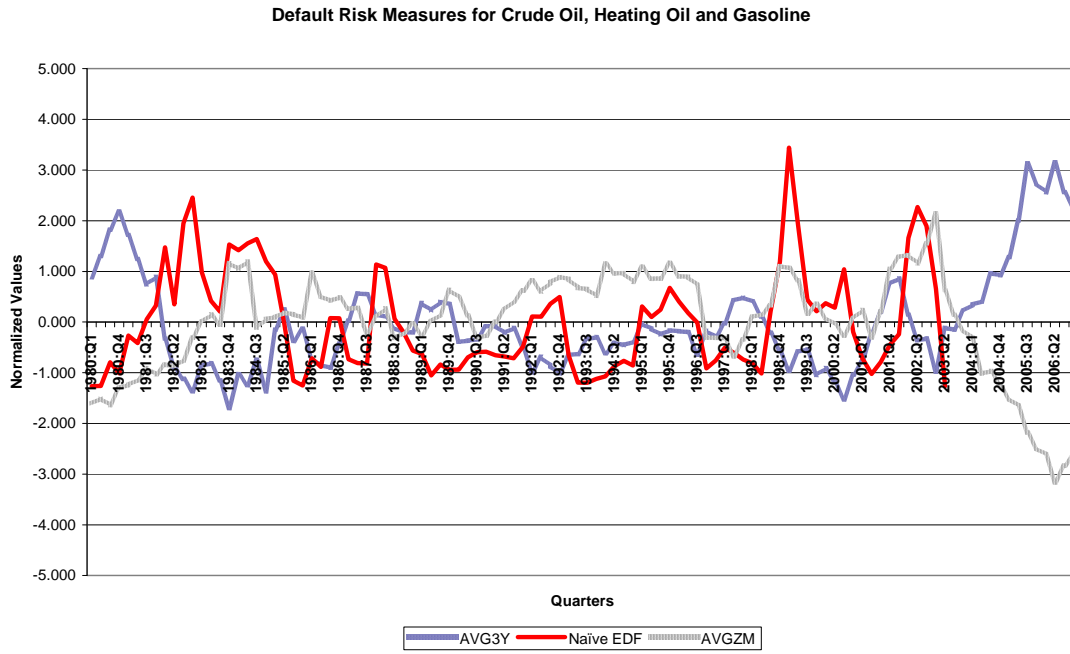


Figure 2b

This figure plots the default risk measures (AVG3Y, AVGZm and Naïve EDF) for Natural Gas producers. The series are normalized by subtracting their means and dividing by their standard deviations for ease of plotting.

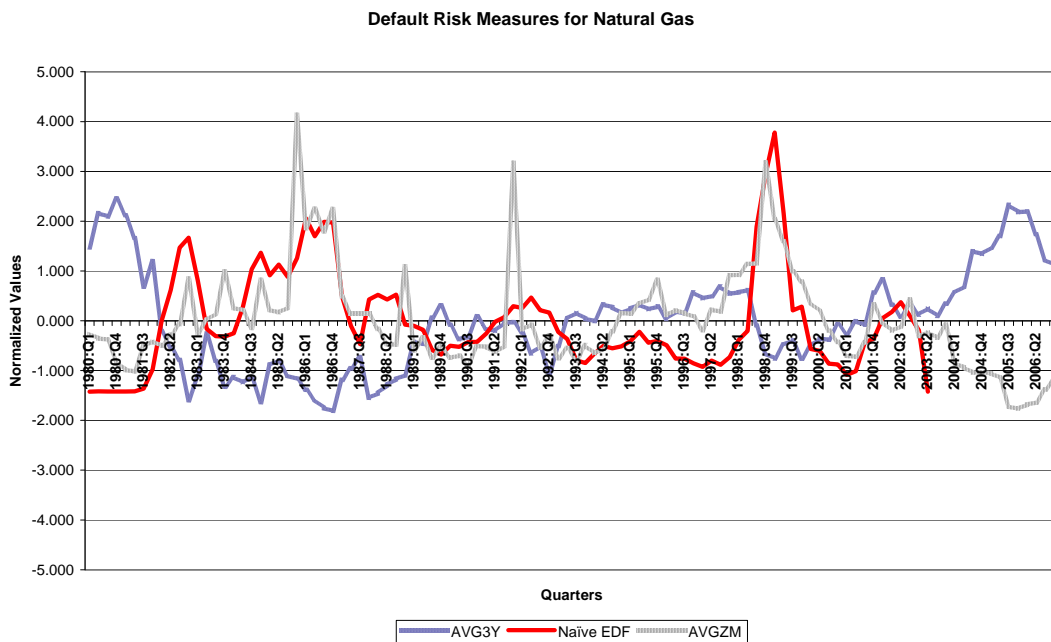


Figure 3a – Firm Crude Oil Hedging and the Zmijewski-score

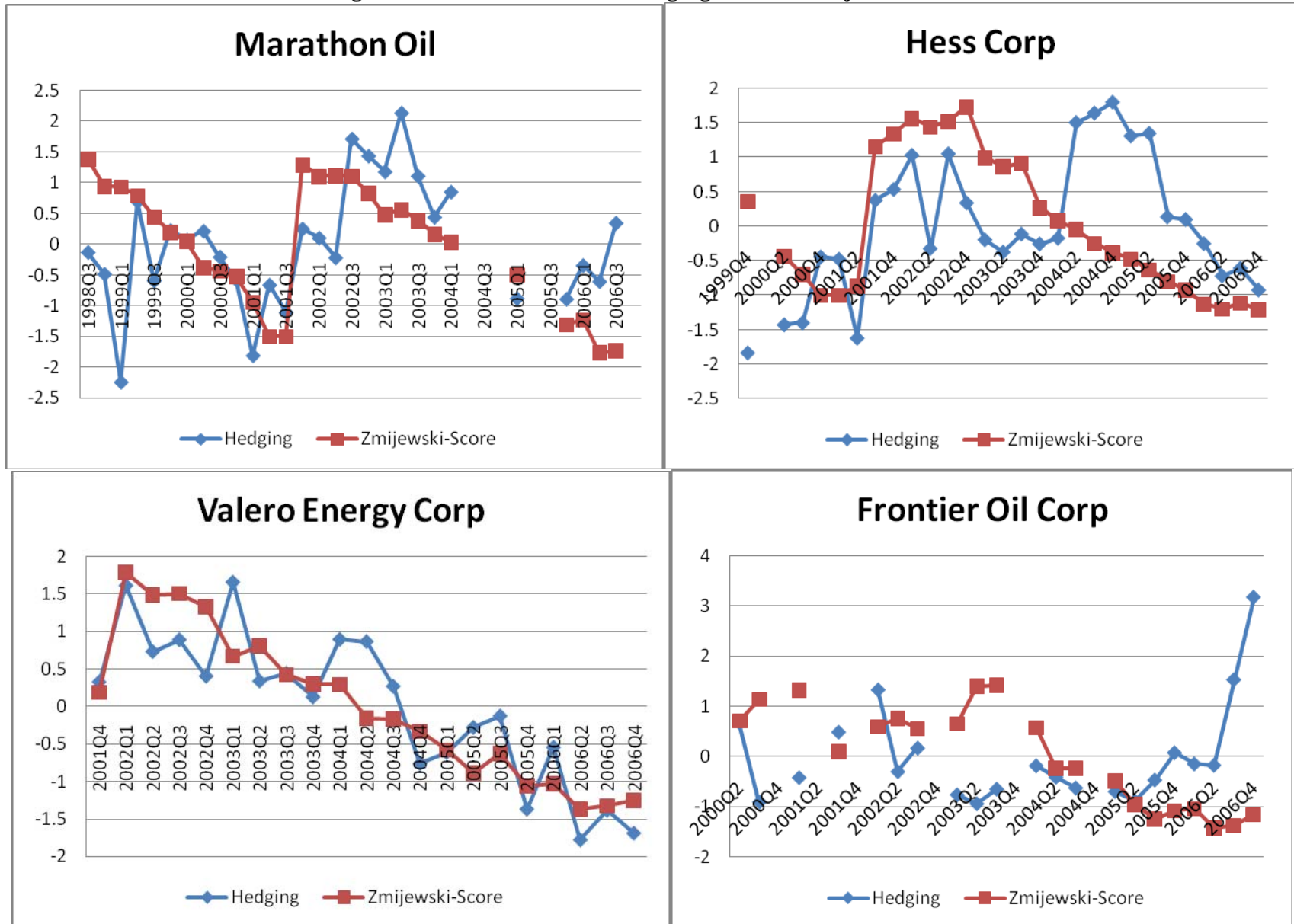


Figure 3b – Firm Crude Oil Hedging and the Negative of the 3 Year Average Stock Return

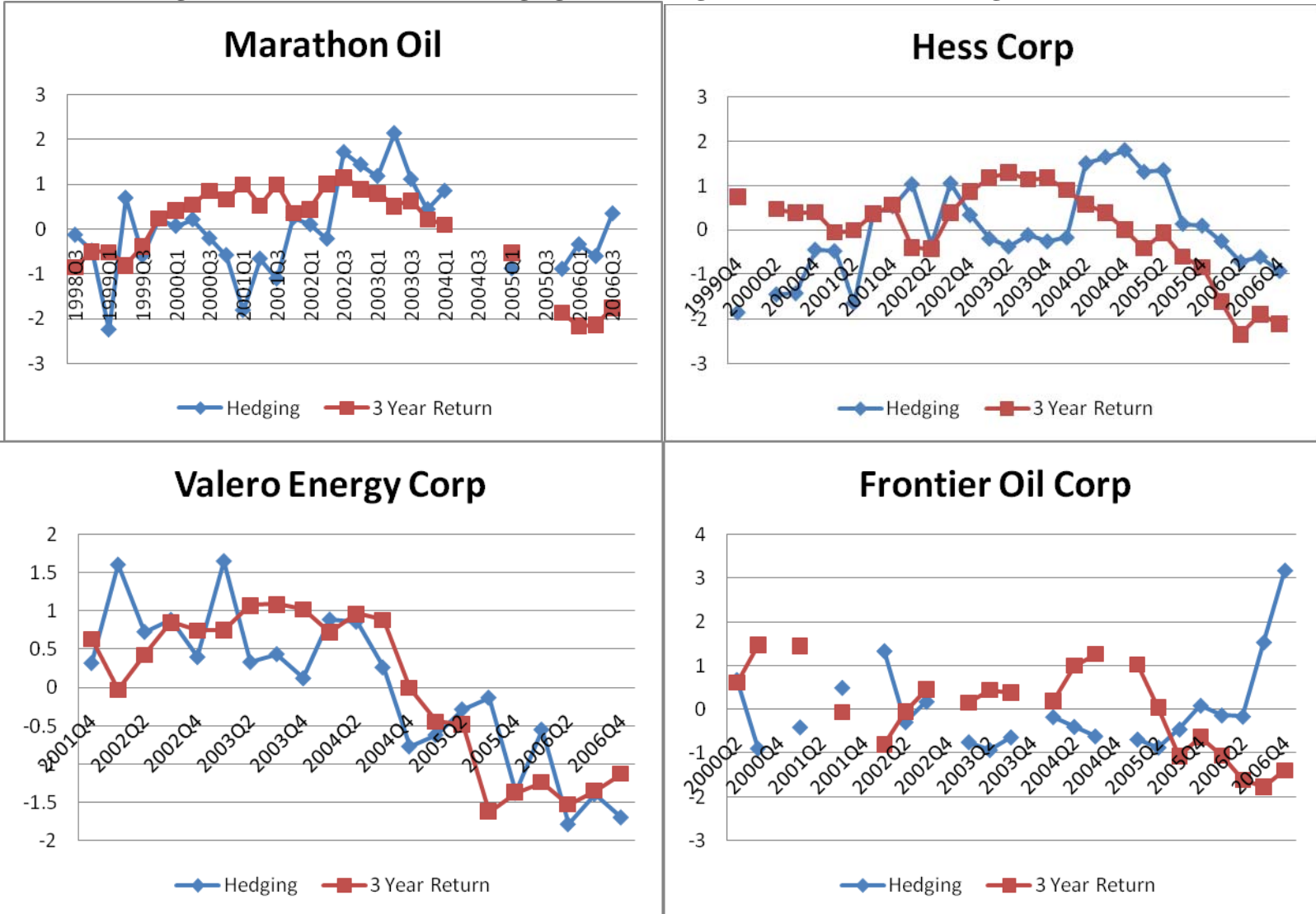


Figure 4 – Crude Oil Futures Risk Premium

