

# Limits to Arbitrage and Hedging: Evidence from Commodity Markets

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## Abstract

We build an equilibrium model of commodity markets in which speculators are capital constrained, and commodity producers have hedging demands for commodity futures. Increases in producers' hedging demand or speculators' capital constraints increase hedging costs via price-pressure on futures, which affect producers' equilibrium hedging and supply decision inducing a link between a financial friction in the futures market and commodity spot prices. Consistent with the model, measures of producers' propensity to hedge forecasts futures returns and spot prices in oil and gas market data from 1979-2010. The component of the commodity futures risk premium associated with producer hedging demand rises when speculative activity reduces. We conclude that limits to financial arbitrage generate limits to hedging by producers, and affect equilibrium supply and commodity prices.

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# Limits to Arbitrage and Hedging: Evidence from Commodity Markets

## **Abstract**

We build an equilibrium model of commodity markets in which speculators are capital constrained, and commodity producers have hedging demands for commodity futures. Increases in producers' hedging demand or speculators' capital constraints increase hedging costs via price-pressure on futures, which affect producers' equilibrium hedging and supply decision inducing a link between a financial friction in the futures market and commodity spot prices. Consistent with the model, measures of producers' propensity to hedge forecasts futures returns and spot prices in oil and gas market data from 1979-2010. The component of the commodity futures risk premium associated with producer hedging demand rises when speculative activity reduces. We conclude that limits to financial arbitrage generate limits to hedging by producers, and affect equilibrium supply and commodity prices.

# 1 Introduction

The neoclassical theory of asset pricing (Debreu (1959)) has been confronted by theory and evidence highlighting the numerous frictions faced by financial intermediaries in undertaking arbitrage, and the consequent price effects of such frictions (see, for example, Shleifer and Vishny (1997)). These price effects appear to be amplified in situations in which financial intermediaries are substantially on one side of the market, e.g., when intermediaries bear the prepayment and default risk of households in mortgage markets or when providing catastrophe insurance to households, as in Froot (1999).

In this paper, we consider an implication of such limits to arbitrage for commodity spot and futures prices. Our main point is that when speculators are constrained in their ability to deploy capital in the commodity futures market, commodity producers experience *limits to hedging*. In other words, limits on the risk-taking capacity of speculators imply a price impact arising from aggregate producer hedging behaviour. These hedging costs arising from producer hedging demands affect the equilibrium supply of the commodity, which in turn affects the commodity spot price. This mechanism means that limits to arbitrage can affect asset prices, i.e., commodity futures prices, but perhaps more surprisingly, they can also impact prices in the underlying product market.

We present a model that formalizes the above argument, in which we derive the effects of the interaction between producer hedging demand and speculator capital constraints on commodity spot and futures prices and expected price changes. To understand the comparative statics generated by the model, consider the following scenario: assume that producers as a whole need to hedge more by shorting futures contracts, say, on account of their rising default risk. Given that speculators are limited in their ability to take positions to satisfy this demand, this increased demand depresses current futures prices and thus makes hedging more expensive. Consequently, producers scale back on the amount of inventory they carry forward. As this inventory hits the spot market, it depresses current spot prices, but increases future expected spot prices. In this case, the futures risk premium and the expected percentage change in the spot price have a common driver – the hedging demand of producers. Increases in speculators’ capital constraints have similar effects.

This simple scenario is based on a partial equilibrium version of the model, in which the demand for the commodity is exogenous. In general equilibrium the intuition is somewhat more subtle – for instance, the relevant metric determining spot price changes is equilibrium supply of the commodity *relative* to the supply of other goods in the economy, in which the latter also depends on the costs of hedging. Therefore, in our general equilibrium model, inventory is not a sufficient statistic for spot prices. However, for a wide range of relevant parameters in the more complex model, increased producer hedging desire or arbitrageur risk-aversion does depress current spot prices relative to future spot prices, which is consistent with the intuition derived from the simpler partial equilibrium scenario presented given above.

To test the implications of the model, we employ data on spot and futures prices for heating oil, crude oil, gasoline and natural gas over the period 1979 to 2010. We pair these data with two sets of micro data on individual commodity producer hedging. First, we hand collect Crude Oil and Natural Gas (SIC code 1311) producing firms' reported hedging policies from their FAS 133 disclosures from 2000Q1 to 2010Q4. Second, we employ two different measures of the default risk of oil and gas producers in our work: a balance-sheet based measure – the Zmijewski (1984) score – and a measure that combines market data with balance-sheet data – KMV's expected default frequency. We use these measures of default risk to identify changes in commodity producers' propensity to hedge, an identification strategy driven by extant theoretical and empirical work on hedging.<sup>1</sup>

Using the FAS 133 disclosures, we document that most producers hedge part of their inventory and future production. We also find that the propensity of commodity producers to hedge using commodity derivatives is strongly and positively related to their default risk – when *firm-specific* default risk is high, these firms are more likely to hedge. Second, an increase in measures of the *aggregate* default risk of commodity producers forecasts a statistically and economically significant increase in the excess returns on short-term futures of the relevant commodities. A one standard deviation increase in aggregate commodity-specific producer default risk is on average associated with a 4% increase in the respective commodity's quarterly futures risk premium.<sup>2</sup> Third, this effect of aggregate default risk on futures risk premia increases with the volatility of the corresponding commodity prices, which is consistent with a downward-sloping speculator demand curve. Fourth, we find that the fraction of the futures risk premium attributable to producers' default risk is higher in periods in which broker-dealer balance-sheets are shrinking.<sup>3</sup> In other words, when speculator risk tolerance is low, hedging pressure has a larger impact on the futures risk premium. Finally, increases in the default risk of oil and gas producers positively predict commodity spot price changes. This is consistent with the prediction from our model that when producers' inclination to hedge increases, current spot prices will be depressed relative to future spot prices.

We check the robustness of our results, and verify that they are driven by changes in producer hedging demand in a number of different ways. First, we control for the possibility that default risk of commodity producers may be related to business-cycle conditions that also drive risk premiums. In particular, we add into our forecasting regressions variables commonly employed to predict the

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<sup>1</sup>A 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), 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)). Fehle and Tsyplakov (2005) argue, both theoretically and empirically, that firms hedge more actively when default risk is higher.

<sup>2</sup>Futures risk premia are identified through standard forecasting regressions as in Fama and French (1987).

<sup>3</sup>The broker-dealer balance sheet measure that we employ was proposed as an inverse measure of speculator capital constraints by Adrian and Shin (2008) and, as shown by Etula (2010), it strongly predicts commodity futures returns – a finding that our model also predicts.

equity premium, such as changes in forecasts of GDP growth, the risk-free rate, and the aggregate default spread, and confirm that our results are unaffected by this addition. Second, we try to account for the possibility that producer default risk - an endogenous variable - is related to future supply uncertainty caused by the likelihood of inventory stock-outs or other production shocks that might affect the futures risk premium.<sup>4</sup> We do so by employing commodity-specific controls such as the futures basis and the realized variance of futures returns in our regressions, and we find that default risk, our proxy for the hedging desire of producers, survives the introduction of these controls. Third, we employ a “matching” approach to determine that the predictive power that we identify is driven *only* by the default risk of firms that hedge, and *not* by the default risk of firms that do not hedge. In particular, using the FAS 133 disclosure data, we separate the sample of producers into those firms that state they significantly hedge their commodity price exposure using derivatives, versus those that do not hedge. We show that our results are driven only by the default risk of the former set. Finally, using data on executive compensation, we also find that what matters in our results is the default risk of producers whose management is effectively “risk-averse” (for instance, CEOs with above-median dollar value of stock holdings relative to base salary, but below-median dollar value of stock option holding relative to base salary).

To summarize, our model implies that limits to arbitrage in the financial market 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 also affect spot prices in underlying product markets. Our empirical results are consistent with the implications of the model and are robust to a number of alternative explanations.

The remainder of the introduction relates our paper to the literature. Section 2 introduces our model. Section 3 presents our empirical strategy. Section 4 establishes the link between the hedging demand of commodity producers and measures of their default risk at the individual firm level. Section 5 discusses our aggregate empirical results. Section 6 concludes.

## 1.1 Related Literature

There are two classic views on the behavior of commodity forward and futures prices. The *Theory of Normal Backwardation* (Keynes (1930)), states that speculators, who take the long side of a commodity futures position, require a risk premium for hedging the spot price exposure of producers. Thus, this theory relies on market segmentation between other asset markets and the commodity futures market. The risk premium on long forward positions is thus increasing in the amount of demand pressure from hedgers and should be related to observed hedger and speculator positions in

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<sup>4</sup>Note that supply uncertainty will tend to *decrease* the variance of commodity prices, as a supply disruption due to a negative economic shock would in general decrease supply. Negative demand shocks are therefore offset by negative supply shocks, which would lead to lower price variance than if these demand shocks were not accompanied by a supply disruption. In other words, supply uncertainty would tend to make the futures risk premium *smaller* as it is the long side of the trade that benefits from supply shortages.

the commodity forward market. Carter, Rausser and Schmitz (1983), Chang (1985), Bessembinder (1992), and de Roon, Nijman, and Veld (2000) empirically link this “hedging pressure” to futures excess returns, the basis and the convenience yield, providing evidence in support of this theory.

The *Theory of Storage* (Kaldor (1939), Working (1949), and Brennan (1958)), on the other hand, postulates that forward prices are driven by optimal inventory management. In particular, this theory introduces the notion of a *convenience yield* to explain the holding of inventory in periods in which spot prices are expected to decline. Tests of the theory include Fama and French (1987) 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.<sup>5</sup> An important contribution is that of Gorton, Hayashi, and Rouwenhorst (2007), who provide evidence that futures risk premia are related to inventory levels, as predicted by this theory.

The two theories are not mutually exclusive, and our model incorporates both features. 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. In the data, we find that hedgers are net short forwards on average, while speculators are net long, which indicates that producers do have hedging demands. In support of this view, Haushalter (2000, 2001) surveys 100 oil and gas producers over the 1992 to 1994 period and finds that close to 50 percent of them hedge, in the amount of approximately a quarter of their production each year.

In closely related work, Hirshleifer (1988, 1989, 1990) considers the interaction between hedgers and arbitrageurs. In particular, Hirshleifer (1990) observes that in general equilibrium there must be a friction to investing in commodity futures in order for hedging demand to affect prices and quantities. In our model, this friction arises due to limited movement of capital, motivated by the ‘limits to arbitrage’ literature, and hedging demand of producers, motivated by a principal-agent problem (as the commodity firm is ultimately owned by the consumers). Furthermore, our analysis, unlike Hirshleifer’s, is also empirical. As a useful consequence, in addition to providing evidence for our model, we are able to confirm many of the propositions of Hirshleifer’s (1988, 1989, 1990) theoretical models, using a different approach than the one followed by Bessembinder (1992). Another related paper is by Bessembinder and Lemmon (2002), who show that hedging demand affects spot and futures prices in electricity markets when producers are risk-averse. They highlight that the absence of storage is what allows for predictable intertemporal variation in equilibrium prices. We show in this paper that price impact can arise even in the presence of storage – in oil

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<sup>5</sup>There is a large literature on reduced form, no-arbitrage modeling of commodity futures prices (e.g., Brennan (1991), Schwartz (1997), Cassasus and Collin-Dufresne (2005)). General equilibrium models of commodity pricing include Cassasus, Collin-Dufresne, and Routledge (2009), and Johnson (2009).

and gas markets.

Finally, it has proven difficult to explain unconditional risk premiums on commodity futures using traditional asset pricing theory (see Jagannathan, (1985) for an earlier effort). Although conditional risk premiums on commodity futures do appear to be reliably non-zero (see Bessembinder (1992)), Bessembinder and Chan (1992) document that the forecastability of price changes in commodity futures is based on different asset pricing factors than those in equity markets. Furthermore, in a recent paper, Tang and Xiong (2009) show that the correlation between commodity and equity markets increases in the amount of speculator capital flowing to commodity markets. These results are consistent with our assumption of time-varying market segmentation between equity and commodity markets.

## 2 The Model

We present a two-period model of commodity spot and futures price determination that includes optimal inventory management, as in Deaton and Laroque (1992), and hedging demand, similar to the models of Anderson and Danthine (1980, 1983) and Hirshleifer (1988, 1990). 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 commodity futures, along with the futures hedging demand of producers, determine the commodity futures price.<sup>6</sup>

### 2.1 Consumption, Production and the Spot Price

Let commodity consumers' inverse demand function be given by:

$$S_t = \omega \left( \frac{C_t}{Q_t} \right)^{1/\varepsilon}, \quad (1)$$

where  $S_t$  is the commodity spot price,  $Q_t$  is the equilibrium commodity supply,  $C_t$  is the consumption of other goods, and  $\omega$  and  $\varepsilon$  are positive constants. Let the representative consumer's intertemporal marginal rates of substitution across states between period 0 and 1 be denoted  $\Lambda$ . We will soon endogenize both the inverse demand function and  $\Lambda$ . However, we first consider a partial equilibrium setting in which  $\Lambda$  is unaffected by frictions in the commodity market and where  $C_t$  represents an exogenous demand shock, which we assume is lognormally distributed with

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<sup>6</sup>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). However, net speculative capital (e.g., in hedge funds) has historically been allocated to long positions in commodity futures, indicating that the sign of net hedger demand for futures is consistent with our assumption.

$E[\ln C_t] = \mu$  and  $Var[\ln C_t] = \sigma^2$ . This shock captures changes in demand arising from sources such as technological changes in the production of substitutes and complements for the commodity, weather conditions, or other shocks that are not explicitly accounted for in the model.

The consumers are the equity holders in the economy and they own the commodity producing firms. Thus, the initial period's cum-dividend value of a commodity producing firm in this economy is:

$$V_0 = D_0 + E_0[\Lambda D_1], \quad (2)$$

where  $D_t$  denotes the net profits of the firm. Let aggregate commodity inventory and production be denoted  $I_t$  and  $G_t$ , respectively. Further, let  $\delta$  be the cost of storage; that is, 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 commodity spot price is determined by market clearing, which demands that incoming aggregate inventory and current production,  $G_t + (1 - \delta)I_{t-1}$ , equals current consumption and outgoing inventory,  $Q_t + I_t$ .

## 2.2 Producers

There are an infinite number of commodity producing firms in the model, with mass normalized to one. Each firm 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 0, 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  $S_1(i(1 - \delta) + g_1) + h_p(F - S_1)$ , where  $F$  is the futures price and  $g_1$  is supply in period 1.<sup>7</sup>

We assume that managers of commodity producing firms act as if they are risk averse – they maximize the value of the firm subject to a penalty for the variance of next period's earnings. This variance penalty generates hedging demand, and is a frequent assumption when modeling commodity producer behavior (see, for example, Bessembinder and Lemmon (2002)). The literature on corporate hedging provides several justifications for this modeling choice, which 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). Hedging demand could result from managers being underdiversified (Amihud and Lev (1981), Stulz (1984)), or better informed about the risks faced by the firm (Breedon and Viswanathan (1990), DeMarzo and Duffie (1995)). Managers could also be averse to variance on account of private costs suffered upon distress (Gilson (1989)), for reasons to do with costs of external financing (Froot, Scharfstein, and Stein (1993)), or because the firm may face deadweight costs of financial distress, as argued by Smith and Stulz (1985). We

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<sup>7</sup>Note 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. For simplicity of exposition, we assume that extraction is costless.

therefore write the manager's problem as:<sup>8</sup>

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

subject to:

$$i \geq 0. \tag{3}$$

The parameter  $\gamma_p$  thus determines the manager's fundamental hedging demand. The first order condition with respect to inventory holding  $i$  yields:

$$i^* (1 - \delta) = \frac{(1 - \delta) E [\Lambda S_1] - S_0 + \lambda}{(1 - \delta) \gamma_p \sigma_S^2} - g_1 + h_p, \tag{4}$$

where  $\lambda$  is the Lagrange multiplier on the inventory constraint and  $\sigma_S^2$  is the variance of the period 1 spot price.

As can be seen from Equation (4), managers use inventories to smooth demand shocks. If, however, 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 can sell at a temporarily high price. This is the *Theory of Storage* aspect of our model, as in Deaton and Laroque (1992).<sup>9</sup> Importantly, inventory is increasing in the amount hedged in the futures market,  $h_p$ : 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:

$$h_p^* = i^* (1 - \delta) + g_1 - \frac{E [\Lambda (S_1 - F)]}{\gamma_p \sigma_S^2}, \tag{5}$$

Note that if the futures price  $F$  is such that  $E [\Lambda (S_1 - F)] = 0$ , there are no gains or costs to consumers of the manager's hedging activity in terms of expected, risk adjusted profits. The producer will therefore simply minimize the variance of period 1 profits by hedging fully. In this case,

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<sup>8</sup>In an Online Appendix, we solve a version of the model where hedging demand of producers is induced due to a deadweight loss upon default. While this model is closer in spirit to the empirical analysis, which makes use of firm default risk as a measure of hedging demand, it does not yield a closed-form, easily interpretable expression for the risk premium, and the empirical implications of that model, given reasonable parameters, are qualitatively the same as the model we present here. Given this, we have opted to present the simpler mean-variance framework to make the intuition as clear as possible.

<sup>9</sup>In 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)).

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 complete markets.

If, however, the futures price is lower than what is considered fair from the consumers’ 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 other words, in this situation, the hedge is costly due to perceived mispricing in the commodity market, and it is no longer optimal to hedge the period 1 price exposure fully. This entails shorting fewer futures contracts. Note that an increase in the manager’s risk aversion  $\gamma_p$  decreases this implicit speculative futures position, all else equal.

**The Basis.** The futures basis is defined as:

$$basis \equiv \frac{S_0 - F}{S_0} = y - \frac{r + \delta}{1 - \delta}, \quad (6)$$

where  $y$  is the *convenience yield* and  $r$  is the net risk-free rate which in the model is equal to  $1/E[\Lambda]-1$ . Combining the first order conditions of the firm (Equations (4) and (5)), the convenience yield is given by:

$$y = \frac{\lambda}{S_0} \frac{1 + r}{1 - \delta}. \quad (7)$$

The convenience yield can only differ from zero if the shadow price of the inventory constraint ( $\lambda$ ) is positive. 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.

The basis is not a good measure of the futures risk premium when inventories are positive. 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. This prediction of the model is largely borne out in our empirical results, and is consistent with the findings of Fama and French (1987).

### 2.3 Speculators

Speculators 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 trading desks). As a consequence of this superior investment technology, we assume investors 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. In our case, the payoff to the fund manager per long futures contract is therefore  $E[\Lambda(S_1 - F)]$ .

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).<sup>10</sup> Commodity funds are assumed to behave competitively, and we assume the existence of a representative fund with objective function:

$$\max_{h_s} h_s E[\Lambda(S_1 - F)] - \frac{\gamma_s}{2} \text{Var}[h_s(S_1 - F)] \quad (8)$$

↓

$$h_s^* = \frac{E[\Lambda(S_1 - F)]}{\gamma_s \sigma_S^2}, \quad (9)$$

where  $\gamma_s$  is the severity of the capital constraint, and  $h_s$  is the aggregate number of *long* speculator futures positions. If commodity funds were not subject to any constraints (i.e.,  $\gamma_s = 0$ ), 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, and the futures risk premium would be independent of the level of managerial risk-aversion. With  $\gamma_s, \gamma_p > 0$ , 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 speculators' objective function is different from that of the consumers, who are the equity-holders of the commodity firms.

## 2.4 Equilibrium

The futures contracts are in zero net supply and therefore  $h_s = h_p$ , in equilibrium. From equations (5) and (9) we obtain:

$$E[\Lambda(S_1 - F)] = \frac{\gamma_s \gamma_p}{\gamma_s + \gamma_p} \sigma_S^2 Q_1, \quad (10)$$

where the variance of the spot price is  $\sigma_S^2 \equiv \omega^2 Q_1^{-2/\varepsilon} \left( e^{(\sigma/\varepsilon)^2} - 1 \right) e^{2\mu/\varepsilon + (\sigma/\varepsilon)^2}$ , and where period 1 supply is  $Q_1 = I^*(1 - \delta) + g_1$ . From the expression for the basis,  $(S_0 - \lambda) \frac{1+r}{1-\delta} = F$ . We have that:

$$E[\Lambda S_1(I^*)] - (S_0(I^*) - \lambda(I^*)) / (1 - \delta) = \frac{\gamma_s \gamma_p}{\gamma_s + \gamma_p} k Q_1 (I^*)^{1-2/\varepsilon}, \quad (11)$$

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<sup>10</sup>Such a constraint is also assumed by Etula (2009) who finds empirical evidence to support the role of speculator capital constraints in commodity futures pricing. 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.

where  $k \equiv \omega^2 \left( e^{(\sigma/\varepsilon)^2} - 1 \right) e^{2\mu/\varepsilon + (\sigma/\varepsilon)^2}$ . Equation (11) implicitly gives the solution for  $I^*$ . Since  $F = (S_0(I^*) - \lambda(I^*)) \frac{1+r}{1-\delta}$ , the equilibrium supply of short futures contracts can be found using equation (5).

Equation (10) can be rewritten in terms of the futures risk premium. In particular, defining  $\sigma_f = \sigma_S/F$  as the standard deviation of the futures return,  $\frac{S_1-F}{F}$ , we have that:

$$E \left[ \frac{S_1 - F}{F} \right] = -(1+r) \text{Corr}(\Lambda, S_1) \text{Std}(\Lambda) \sigma_f + \frac{\gamma_p \gamma_s}{\gamma_p + \gamma_s} (1+r) \sigma_f^2 F Q_1. \quad (12)$$

The first term on the right hand side is the usual risk adjustment term due to covariance with the equity-holders' pricing kernel. However, the the producers and the speculators are the marginal investors in the commodity futures market, rather than the equity-holders (consumers). The second term, which arises due to the combination of limits to arbitrage and producer hedging demand, has four components:  $FQ_1$ , the forward dollar value of the hedging demand,  $\sigma_f^2$ , the variance of the futures return,  $\gamma_p$ , producers' risk-aversion, and  $\gamma_s$ , speculator risk aversion. Note that Equation (12) holds for *any* consumer preferences (inverse demand functions).

## 2.5 Partial Equilibrium Model Predictions

Here, we consider the predictions of the partial equilibrium model just presented, where equity holders' marginal rate of substitution ( $\Lambda$ ) is exogenous and unaffected by the frictions in the commodity market. With this model we can show analytically that a number of comparative statics can be signed for all parameters. We will, after this, consider a general equilibrium version of the model that we calibrate and solve numerically.

We are interested in comparative statics with respect to producers' propensity to hedge,  $\gamma_p$  (which we refer to henceforth as producers' *fundamental hedging demand*), and the degree of the capital constraint on speculators,  $\gamma_s$ . The partial equilibrium model, where we have assumed that the consumption of other goods and the consumers' intertemporal rates of substitution are not affected by the frictions in the commodity market (i.e.,  $\gamma_p$  and  $\gamma_s$ ), allows us to determine the sign of the comparative statics without any parametric assumptions. The proof of the following Proposition is relegated to the Appendix.

**Proposition 1** (a) *The futures risk premium and the expected percentage spot price change are increasing in producers' fundamental hedging demand,  $\gamma_p$ :*

$$\frac{d}{d\gamma_p} \frac{E[S_1 - F]}{F} > 0 \quad \text{and} \quad \frac{d}{d\gamma_p} \frac{E[S_1 - S_0]}{S_0} > 0, \quad (13)$$

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

(b) The futures risk premium and the expected percentage spot price change are increasing in the severity of speculators' capital constraints,  $\gamma_s$ :

$$\frac{d}{d\gamma_s} \frac{E[S_1 - F]}{F} > 0 \quad \text{and} \quad \frac{d}{d\gamma_s} \frac{E[S_1 - S_0]}{S_0} > 0, \quad (14)$$

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

(c) The convenience yield is constant if there is not a stock-out, but increasing in producers' fundamental hedging demand,  $\gamma_p$ , and speculators' capital constraints,  $\gamma_s$ , if there is a stock out:

$$\frac{d}{d\gamma_p} \frac{S_0 - F}{F} \Big|_{I_0=0} > 0 \quad \text{and} \quad \frac{d}{d\gamma_s} \frac{S_0 - F}{F} \Big|_{I_0=0} > 0. \quad (15)$$

(d) The optimal inventory is decreasing in both producer and speculator hedging demand, unless there is a stock-out.

The intuition for these results is as follows. When producers' fundamental hedging demand ( $\gamma_p$ ) increases, the manager's sensitivity to the risk of holding unhedged inventory increases. In response to this, the manager reduces inventory and increases the proportion of future supply that is hedged. The former means that more of the commodity is sold on the spot market, which depresses current spot prices and raises future spot prices. The latter leads to a higher variance-adjusted demand for short futures contracts, which is accommodated by increasing the futures risk premium. An increase in speculator capital constraints,  $\gamma_s$ , has similar effect. The cost of hedging now increases as the speculators require a higher compensation per unit of risk. The direct effect of this is to decrease the number of short futures positions. However, this leaves the producer more exposed to period 1 spot price risk, and to mitigate this effect, optimal inventory also decreases. In a stock-out, the inventory is constant (at zero) and consequently so are the expected spot price and its variance. In that case, the only effect of an increase in producer (or speculator) risk-aversion is the direct effect on the futures risk premium, as the marginal cost of hedging increases.

## 2.6 General Equilibrium Model Predictions

In general equilibrium, the consumers' consumption of other goods will typically be affected by the frictions in the commodity market. Thus, both the commodity 'demand' shocks,  $C_t$ , and the marginal intertemporal rate of substitution will be affected when varying the frictions in the commodity market. Further, a general equilibrium model allow us to calibrate the model to gauge the likely magnitudes of the effect of the model's frictions.

We follow the same setup as in the partial equilibrium model just given, but now also solve the

consumers' problem. Let consumers' preferences be given by:

$$V = u(C_0, Q_0) + \beta E_0 [u(C_1, Q_1)], \quad (16)$$

where the felicity function is of the constant elasticity of substitution (CES) form:

$$u(x, y) = \frac{1}{1-\gamma} \left\{ \left( x^{(\varepsilon-1)/\varepsilon} + \omega y^{(\varepsilon-1)/\varepsilon} \right)^{\varepsilon/(\varepsilon-1)} \right\}^{1-\gamma}, \quad (17)$$

where  $\varepsilon$  is the intratemporal elasticity of substitution and  $\gamma$  is the level of relative risk-aversion. The standard intratemporal first order condition implies that the equilibrium commodity spot price  $S_t$  is given by:

$$S_t = \omega \left( \frac{C_t}{Q_t} \right)^{1/\varepsilon}, \quad (18)$$

as assumed earlier in the partial equilibrium version of the model. However, in the general equilibrium case we assume that the consumers own a Lucas tree producing the numeraire good  $A_t$ , as well as the commodity producing firms which produce the aggregate supply of the commodity  $Q_t$ . However, the consumers must hire managers to manage the firms (their inventory and hedging decisions). The manager's objective function is as in the partial equilibrium case (see Equation (3)).<sup>11</sup> Consumers can also invest in the commodity futures markets, but only through specialized funds who provide an aggregate number of contracts  $h_s$  as the solution to the problem given earlier in Equation (8). Denote the cost charged per contract by these funds as  $c$ . We assume the costs are incurred at time 0. The consumers' equilibrium consumption of other goods in the first period will equal  $C_0 = A_0 - c \times h^*$ , where  $h^*$  is the equilibrium open interest in the futures market, while in the last period  $C_1 = A_1$ .

In equilibrium, consumers' net present value of a marginal investment in a commodity futures must be zero and so we have that  $c = E[\Lambda(S_1 - F)]$ . Therefore, the aggregate loss due to intermediation is  $h^* E[\Lambda(S_1 - F)]$ . Given the optimal position in futures contracts from Equation (9), we have that the equilibrium aggregate cost is  $\frac{E[\Lambda(S_1 - F)]^2}{\gamma_s \sigma_s^2}$ . The reason the consumers are willing to incur this cost is the utility gain from moving to more optimal  $Q_0$  and  $Q_1$  as the futures price affects the commodity producers' inventory decisions. In equilibrium, we have that  $E[\Lambda(S_1 - F)] = \frac{\gamma_p \gamma_s}{\gamma_s + \gamma_p} \sigma_s^2 Q_1$  and so, substituting out  $\sigma_s^2$ , we have:

$$\text{Aggregate cost} = c \times h^* = \frac{1}{\gamma_s} \left( \frac{\gamma_p \gamma_s}{\gamma_s + \gamma_p} \right)^2 \omega^2 Q_1^{2(1-1/\varepsilon)} k, \quad (19)$$

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<sup>11</sup>We do not model the managers' consumption, but instead argue that this is a reasonable abstraction as there are very few managers relative to the total population and so their consumption is a minuscule component of aggregate consumption.

where  $k$  is a positive constant defined earlier. In sum, *both the supply of the commodity and consumption of other goods are affected by the combination of hedging demand and limits to arbitrage.* It is clear then that the intertemporal marginal rate of substitution for consumers is explicitly a function of *both* equilibrium inventory and the frictions that give rise to hedging demand and costly intermediation in the futures market:

$$\Lambda(I, \gamma_p, \gamma_s) = \beta \left( \frac{C_1}{C_0} \right)^{-\gamma} \left( \frac{1 + \omega \left( \frac{Q_1}{C_1} \right)^{(\varepsilon-1)/\varepsilon}}{1 + \omega \left( \frac{Q_0}{C_0} \right)^{(\varepsilon-1)/\varepsilon}} \right)^{(1/\gamma - \varepsilon)/((\varepsilon-1)/\gamma)}, \quad (20)$$

where equilibrium consumption of other goods is  $C_0 = A_0 - \frac{1}{\gamma_s} \left( \frac{\gamma_p \gamma_s}{\gamma_s + \gamma_p} \right)^2 \omega^2 Q_1^{2(1-1/\varepsilon)} k$  and  $C_1 = A_1$ .

This analysis shows that the frictions assumed in this paper (limits to arbitrage and producer hedging demand) in general equilibrium also affect the consumption of other goods and the equity market pricing kernel. Thus, the covariance term in Equation (12) is affected, not only through the volatility of the commodity price as in the partial equilibrium model in the main text, but also through the dynamics of the pricing kernel ( $\Lambda$ ). However, the identifying component of the frictions lies in the risk compensation of the second term in Equation (12), which is related to the magnitude of desired hedging and the total volatility (including any idiosyncratic components) of the futures price.

To illustrate the model implications, we calibrate the model using key moments of the data: in particular, the volatility of the commodity futures returns, commodity expenditure relative to aggregate endowment (GDP) and aggregate endowment growth. All moments are quarterly, corresponding to the empirical exercise in the next section. We calibrate the demand shock  $A_1$  to roughly correspond with aggregate GDP growth and set  $\mu = 0.004$ ,  $\sigma = 0.02$  and the initial demand shock  $A_0 = 1$ . We set the depreciation rate,  $\delta$ , to 0.01 and the coefficient of relative risk-aversion,  $\gamma$ , to 2.5 which is within the range typically used in macro economic models. Next, we calibrate the intratemporal elasticity of substitution  $\varepsilon$  and the constant  $\omega$  jointly such that the standard deviation of futures returns  $(S_1 - F)/F$  is about 20% per quarter, as in the data, and the average commodity expenditure is about 10% of expenditures on other goods. Given the volatility of demand shocks, this is achieved when  $\varepsilon = 0.1$  and  $\omega = 0.01$ . That is, consumers are relatively inelastic in terms of substituting the commodity good for other goods, which is reasonable given our focus on oil and gas in the empirical section.<sup>12</sup> We let period 0 and period 1 production,  $g_0$  and  $g_1$ , be 0.8 and 0.75, respectively, such that inventory holdings are positive as in the data.

The severity of the model's frictions are increasing in the variance aversion of producers and speculators,  $\gamma_p$  and  $\gamma_s$ . As we posit mean-variance preferences, the values of these coefficients do not

<sup>12</sup>This also justifies our implicit model assumption that price risk outweighs quantity risk for the producers. As pointed out by, e.g., Hirshleifer (1988), if the opposite is the case, producers would hedge by going *long* the futures contract.

directly correspond to easily interpretable magnitudes (such as might be the case with relative risk-aversion). We therefore use the following two economic measures to calibrate a reasonable range for each of these parameters. First, we let the loss to the firm from hedging,  $h^* E[\Lambda(S_1 - F)]$ , be between 0.1% and 1% of firm value and, second, we let the abnormal quarterly Sharpe ratio earned by speculators be between 0.05 and 0.25. The variation in these quantities is shown in the two top graphs of Figure 1a, where  $\gamma_p \in \{2, 4, \dots, 20\}$  on the horizontal axis and  $\gamma_s \in \{8, 40\}$  is shown as a dashed line for high speculator risk-aversion and a solid line for low speculator risk-aversion.

The remaining plots in Figure 1a show that the futures risk premium is indeed increasing in producer and speculator risk-aversion, while the spot price and inventory are decreasing. The calibration implies economically significant variation in both spot and futures risk premiums. In particular, for high speculator risk-aversion (corresponding to their earning a quarterly Sharpe ratio of about 0.25) and high hedging demand (corresponding to a loss of about 0.8% of firm value due to hedging), the abnormal quarterly futures risk premium is about 6%, whereas for low producer hedging demand and speculator risk-aversion (Sharpe ratio of about 0.05 and loss from hedging of about 0.1% of firm value), the abnormal futures risk premium is less than 1%. The standard risk component of the futures risk premium, captured by the covariance term in Equation (12), shows a much more modest increase in response to changes in  $\gamma_p$  and  $\gamma_s$ , indicating an important role for market specific variables that capture the constraints in the model that will not be captured by standard controls for time-varying risk premiums. The decrease in inventory is about a 1% to 9% change in the level. The effect on percentage spot price changes is about the same as that for the futures risk premium, since the cost of carry relation holds when there is no stock-out. In sum, reasonable levels of the costs of hedging and required risk compensation leads to economically significant abnormal returns in the futures market, and concomitant changes in inventory and spot prices that are consistent with the intuition from the partial equilibrium model.

Figure 1a also illustrates an intuitive interaction between speculator risk tolerance and producer hedging demand. In particular, the response of the abnormal futures risk premium to changes in producer hedging demand is smaller when speculator risk tolerance is high. These are times when speculators are willing to meet the hedging demand of producers with small price concessions. If, conversely, speculators are more risk-averse, the price concession required to meet an additional unit of hedging demand is high.

Figure 1b shows a slightly different calibration of the model that sets  $\varepsilon = 0.08$  and  $\omega = 0.012$ . While the futures risk premium and spot price implications qualitatively are the same, the figure shows that equilibrium inventory in some cases in fact *increases* when producers' fundamental hedging demand increases, contrary to the intuition in the partial equilibrium model. This happens even though the spot price is still decreasing in producers' fundamental hedging demand as before. The reason for this is that it is the ratio of  $C_t$  to  $Q_t$  that matters for spot prices and that  $C_t$  in the general equilibrium case is endogenous and also a function of the magnitude of the frictions in the

futures market. We have checked a large variety of reasonable parameter configurations and, with the exception of the inventory prediction, the predictions of the model with respect to the futures risk premium and the link to the spot price are robust and as described above.

### 3 Empirical Strategy

In our empirical analysis we test the main predictions of the model, as laid out in Proposition 1. To do so, we need proxies for  $\gamma_p$  and  $\gamma_s$  - the fundamental hedging demand and risk aversion of producers and speculators, respectively.

It is worth noting here that from equation (12), to identify time-variation in the futures risk premium from hedging pressure and limits to speculative capital, we must control for the covariance of the futures return with the equity pricing kernel. We therefore apply a substantial set of controls and robustness checks in the empirical analysis in order to establish that our findings arise on account of the interaction of producer hedging demand and limited arbitrage capital, rather than on account of an omitted variable related to the usual covariance term.

#### 3.1 Commodity Producer Sample

To construct proxies for fundamental producer hedging demand, we employ data on public 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 is a large enough set of 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. The full sample of producers is all firms with SIC code 1311 (Crude Petroleum and Gas Extraction) with quarterly data from 1979Q3 to 2010Q4 (400 firms). We also use data on these firms' descriptions of their hedging activities when available in quarterly and annual reports in the EDGAR database from 2000Q1 to 2010Q4 (94 firms). The data on direct hedging positions is for a smaller sample of firms and, as we will discuss, quite coarse. Also, in equilibrium the hedging positions taken are not only related to the *desire* to hedge, as captured by  $\gamma_p$ , but also to arbitrageur capital constraints, the amount of future production and inventory, as well as the variance of the spot price and the covariance of futures returns with the stochastic discount factor. These reasons all suggest that we require a more fundamental measure of hedging demand.

#### 3.2 Proxying 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 2008.

We propose that variation in the aggregate level of fundamental hedging demand,  $\gamma_p$ , can be proxied for by measures of aggregate commodity producer default risk. 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 that we focus on 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) propose general aversion of managers to cash flow variance 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: e.g., Coughlan and Schmidt (1985), Warner et al. (1988) and Weisbach (1988) provide evidence that top management turnover is predicted by declining stock market performance. 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, and that firms that are highly leveraged or in default on their debt experience higher top management turnover than their counterparts. Gilson further documents that following their resignation from firms in default, managers are not subsequently employed by another exchange-listed firm for at least three years - consistent with managers experiencing large personal costs when their firms default. Finally, Haushalter (2000, 2001) in a 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 use more debt financing also hedge a greater fraction of their production, and he interprets this 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 Altman's (1968) Z-score, and the methodology employed to calculate the Zmijewski-score was developed by identifying the firm-level balance-sheet variables that help to "discriminate" whether a firm is likely to default or not. The market-based measure we employ is the expected default frequency (or EDF) computed by KMV.

Each firm’s Zmijewski-score is calculated as:

$$\begin{aligned} Zmijewski\text{-score} = & -4.3 - 4.5 * NetIncome/TotalAssets + 5.7 * TotalDebt/TotalAssets \\ & - 0.004 * CurrentAssets/CurrentLiabilities. \end{aligned} \quad (21)$$

We obtain each firm’s EDF directly from KMV. The EDF from the (simple) 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,  $\sigma_V$  is the volatility of the firm’s value,  $\mu$  is an estimate of the expected annual return of the firm’s assets, and  $T$  is the time period (in our case, one year). The KMV data includes 120 firms with SIC code 1311 (producers). We use the same sample of firms when constructing the Zmijewski scores.

In the next section, we first confirm Haushalter’s (2000, 2001) results in our sample of firms – i.e., that our default risk measures are indeed related to individual producer firms’ hedging activity. We then aggregate (equal-weight) these firm-specific measures within each commodity sector to obtain measures of fundamental producer hedging demand, which are used to test the pricing implications of the model.<sup>13</sup> While our sample of firms goes back until 1979, 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. Figure 2 shows the resulting time-series of aggregate Zmijewski-score and EDF. The Zmijewski-score, which is based on the Compustat sample, is available until Q4 of 2010, while we were only able to obtain the EDF data from KMV up until Q4 of 2009. For ease of comparison, the series have been normalized to have zero mean and unit variance. Both measures are persistent, but stationary (the latter is confirmed using unit root tests for both measures). As expected, the aggregate Zmijewski-scores and EDFs are positively correlated. Table 2 reports the mean, standard deviation and quarterly autocorrelation of the aggregate hedging measures.

## 4 Producers’ Hedging Behavior

While the main tests in the paper concern the relationship between spot and futures commodity prices and commodity sector *aggregate* fundamental hedging demand, we begin by investigating the available *micro* evidence of producer hedging behavior. Haushalter (2000, 2001) provides useful evidence of the cross-sectional determinants of hedging behavior among oil and gas firms, but his

<sup>13</sup>We drop the 10% highest and 10% lowest observations of both Zmijewski score and EDF in the cross-section at each time  $t$  to control for outliers.

evidence pertains to a smaller sample than ours, over the period from 1992 to 1994.<sup>14</sup>

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 they do, to identify the derivative instruments and strategies that they employ. We also wish to verify that hedging behavior is indeed significantly related the state of the firm, as measured by its default risk. 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 contains quarterly or annual statements for 94 firms with SIC code 1311 for the period from Q1 of 2000 to Q4 of 2010. This sample period is chosen based on the introduction of the Financial Accounting Standards Board's (FAS) 133 regulation "Accounting for Derivative Instruments and Hedging Activities" in June 1998. The reports are available for fiscal years ending after 15th of June 2000.

Since the introduction of FAS 133, 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."

While firms are required to recognize derivative positions as assets or liabilities on their balance sheet given this accounting standard, the current market value of a derivative in most cases does not allow one to infer the notional exposure or even the direction of trade (for example, consider an exchange traded futures contract). Thus, it is necessary to read the management's notes on hedging behavior which gives qualitative information of the amount and nature of hedging. Our 94 firm sample required the reading of around 2,500 quarterly and annual reports over the sample period. To make the onerous task of manually reading and deciphering all of these reports manageable and also to quantify the qualitative information given in the reports, we created a set of fields to be filled out for each firm quarter with a "0" for "no", a "1" for "yes" and missing if there is no clear information in the report. The fields we employ in the paper are shown in Panel A of Table 1.

The first question is simply "Does the firm allow for using derivatives to manage risk?" There are 2,400 firm-quarter reports where we were able to determine from the report whether they did, and these firm-quarters constitute the main sample. In 88% of the firm-quarters the answer was affirmative. Note that this does not necessarily mean that a firm is using derivatives that quarter

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<sup>14</sup>Another notable study of firm-level hedging behavior in commodities is Tufano (1996), who relies on proprietary data from gold mining firms and shows that hedging behavior is driven in part by managerial risk-aversion.

– it may just mean that the management wrote in the report a generic statement that the firm *may* use derivatives to manage risk. Furthermore, in 47.7% of the firm-quarters forwards or futures were used, in 80.6% of the firm-quarters swaps were used, and in 81.8% of the firm-quarters options (typically a short collar position) were used.

The dominant commodity exposure hedged by firms is Crude Oil. We therefore concentrate our efforts on determining whether the firm had a significant long or short position in Crude Oil derivatives. In some cases, the actual notional positions in the derivatives were given, and in such cases, we specify that a significant position is one in which the management hedged at least 25% of production. In many cases, however, we infer the existence of a significant position from management statements that ‘most’ or ‘a large part of’ the production is hedged using a particular type of derivatives position.

In 69.8% (1%) of the firm-quarters in which we could determine whether the firm had initiated a Crude Oil derivatives position, firms had significant short (long) Crude Oil derivatives positions. In sum, Panel A of Table 1 shows that producers in the oil and gas sector do typically hedge a significant part of their production by going short in the Crude Oil derivatives market, consistent with the assumptions in our model.

## 4.2 The Time-Series and Cross-section of Producer Hedging

Next, we turn to the determinants of firm hedging in both the time-series and the cross-section, based on the data collected from the EDGAR reports. In particular, we run pooled panel regressions, in which the left-hand-side variable gives a value of 1 to a firm-quarter with a ‘Yes’ response to the ‘Significant Crude Hedging?’ question, otherwise 0. We regress this binary variable on the corresponding firm-quarter Zmijewski-score and log EDF, as well as time and firm fixed effects.<sup>15</sup>

Panel B of Table 1 shows these regressions, estimated both using probit regressions as well as standard OLS. The standard errors are clustered by time, and allow for heteroskedasticity of the residuals across both firm and time. We estimate the specifications with time fixed effects, with firm fixed effects, and finally with both time and firm fixed effects.

Across all regressions, the propensity to engage in significant short Crude Oil derivatives hedging is positively related to the default risk measures. In 11 out of 12 cases, the relation is significant at the 1% level, and the 12th is significant at the 5% level. With both firm and time fixed effects, the regressions explain about 30% of the total variation in the binary firm-quarter hedging variable as given by the overall regression  $R^2$  statistics. The regressions with firm and time fixed effects, in particular, show that the non-systematic component of the variation in a firm’s hedging decision is significantly related to the firm’s non-systematic component of default risk, ruling out that firm hedging is driven only by aggregate fluctuations such as business cycles or the conditional futures

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<sup>15</sup>We use the log of the EDF to alleviate issues with outliers at the individual firm-quarter level.

risk premium. Thus, this is a particularly strong tests of the assumption that default risk is a driver of producer hedging demand.

While Panel *B* of Table 1 provides formal tests of the relation between firm default risk and hedging behavior, Figure 3 provides a visual representation of the aggregate relation between firm hedging and default risk. In particular, the figure shows average firm hedging, as given by the ‘Significant Crude Hedging?’ fraction in each quarter plotted against the median Zmijewski-score of the corresponding firms in the EDGAR sample. This plot just shows the raw numbers (no firm or time fixed effects applied). The correlation between the two series is 0.34, which is significant at the 5% level.

In sum, from a thorough data gathering exercise involving soft information in all the quarterly and annual reports over the period 2000Q1 to 2010Q4 for firms in EDGAR with SIC code 1311, we conclude that firm default risk is indeed significantly related to firm short Crude Oil derivatives positions. The commodity producers typically hedge a significant fraction of their commodity exposure with swaps and option collars as the most common positions. This is worth taking a moment to explain – as our analysis primarily comprises exchange traded futures prices for reasons of data availability – it is important to note that the net counterparty exposure from the producer over-the-counter derivatives is likely hedged in the futures markets. Moreover, there are strong no-arbitrage relations between swaps and futures that make price pressure in one market likely to manifest itself in both markets in equilibrium.

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. We will, however, use the data from the micro-analysis using the FAS 133 data to later perform robustness checks for our aggregate results.

## 5 Aggregate Empirical Analysis

In this section, we employ the aggregate measures of producer hedging demand, for which we reported summary statistics in Section 3, to test the empirical predictions of the model described in Section 2.

### 5.1 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 fourth quarter of 1979 until the fourth quarter of 2010 (125 quarters; heating 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, i.e., 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. Summary statistics for the quarterly futures returns are presented in Table 2, and the returns themselves are shown in Figure 4. Table 2 shows that the excess returns are on average positive for all oil commodities, ranging from 3.75% to 6.29% per quarter, with relatively large standard deviations (in excess of 20%). Natural Gas, however, has a slightly negative return of  $-0.28\%$  per quarter, with a standard deviation of almost 30%. 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):

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

## 5.2 Inventory

For all four energy commodities, aggregate U.S. inventories 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.”

## 5.3 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. For example, 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 shortcomings; in particular, anyone that can reasonably 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 and a speculative trade, as defined by this measure, is therefore blurred. We note these issues with the measure as they may help explain why the forecasting power of hedging pressure for futures risk premia is debatable, while our measures of default risk do seem to explain futures risk premia. Nevertheless, we use the CFTC data to relate our measures of producers' hedging demand to hedger (commercial trader) futures positions as recorded by the CFTC.

The Hedger Net Positions data are obtained from the Commodity Futures Trading Commission (CFTC) website. 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.

## 5.4 Aggregate 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 equity holders' marginal rate of intertemporal substitution,  $\Lambda$ . In particular, Equation (12) shows that the risk premium is related to the conditional covariance with this pricing kernel (as usual), in addition to the component coming from the fundamental hedging demand of producers. To capture the first 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 difference between the 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)). Following Ang and Bekaert (2009), we also include the risk-free rate (3M T-bill rate), which has been shown to be a robust, out-of-sample predictor of equity market excess returns. We do not include the aggregate dividend yield, as this variable has no forecasting power for commodity returns (results not shown). Finally, to account for time-varying expected commodity spot demand, we use a forecast of quarterly GDP growth, obtained as the median forecast from the Philadelphia Fed's survey of professional forecasters.

## 5.5 Commodity Specific Controls

We also include controls that are specific to each commodity. As emphasized in Routledge and Seppi (2000), the basis is related to (the probability) of an inventory stock-out, and so is expected to have predictive power mainly for the spot return, but can also be informative of the conditional variance and skewness of futures returns. When there is ample inventory, however, the basis is not expected to be informative about spot or futures returns, and so our model predicts that it should not drive out predictability that arises from producer hedging demand. We will also use realized quarterly variance of futures returns as a simple control for time-variation in the quantity of risk, effectively then assuming the correlation with the pricing kernel is constant. The realized variance is calculated as the sum of squared daily log futures price changes over the quarter.<sup>16</sup> Finally, we include quarterly dummy variables in all the regressions as both the independent and many of the dependent variables in the regressions exhibit seasonalities.

## 5.6 Empirical Results

The main predictions of the model are with respect to the expected commodity futures and spot return, which we test next. After this we consider the relation between default risk and aggregate commodity inventory, CFTC hedger positions, and the spot-futures basis. We also provide some evidence that managerial risk-aversion is indeed a factor for determining hedging demand, as our model strictly speaking is assuming. In the following, the moniker *ControlVariables<sub>t</sub>* in a regression means the inclusion of aggregate and commodity specific controls in the regression.

### 5.6.1 Commodity Futures and Spot Returns

With reference to the discussion in Section 2 and in particular to Equation (12), we recall that the model has the following robust implications that are new to the literature:

1. The futures risk premium and expected percentage change in the underlying spot price are increasing in producers' fundamental hedging demand, where the latter is proxied by measures of aggregate producer default risk.
2. This relation is stronger when the variance of the futures return is high and when arbitrageurs have low risk capacity.

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<sup>16</sup>In an online Appendix, we account for time-varying correlations with the pricing kernel, as well as capturing time-variation in the market segmentation between equity and commodity markets, by using the realized covariance between each futures returns and the Fama and French (1993) factors. The realized covariance between each futures and factor is calculated as the sum of the product of the futures return and the return on the relevant factor over the quarter.

To test (1), we run standard forecasting regressions for excess commodity futures return or changes in the percentage spot price, using our default risk proxies for fundamental hedging demand. In particular, Panel A of Table 3 shows the results of the following regression:

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

where  $i$  denotes the commodity and  $t$  denotes time measured in quarters. DefRisk is either the aggregate Zmijewski-score or the aggregate EDF as described in Section 3. The regression is run for each of the four commodities in our sample, as well as a pooled regression across all commodities. First, 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 about 4% or more 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, which is relatively high for a quarterly forecasting regression, considering the high persistence of the predictive default risk variables.<sup>17</sup>

The pooled regressions show that the effect of producer hedging demand is significant at the 5% level or greater for both 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, the latter two have fewer time-series observations, with Natural Gas with the least number (79 and 82 quarters when using the EDF or the Zm-score, respectively), which potentially explains the lower power of these regressions. 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.<sup>18</sup> This may be the reason for the somewhat weaker results we see for this commodity throughout the paper.

Panel B of Table 3 show the same regressions, but with the change in the percentage spot price as the left-hand-side variable:

$$SpotReturns_{i,t+1} = \beta_i DefRisk_{i,t} + ControlVariables_t + u_{i,t+1}, \quad (27)$$

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<sup>17</sup>The default risk measures are also significant predictors of futures returns in simple univariate regressions (not reported).

<sup>18</sup>He 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%.

where the control variables are the same as before. The spot return is as defined in Section 3, i.e., the change in the price of the nearest to maturity contract relative to its previous value. Panel *B* of Table 3 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 and imply that a one standard deviation increase in aggregate commodity producer default risk increases the expected spot price by about 4%.

The regression coefficients are very close to those found in the futures returns forecasting regressions, as predicted by the model – the common component in the expected futures and spot returns are of a similar size. Thus, the hedging pressure leading to changes in the futures risk premium indeed has real implications in that current spot prices are lower relative to future spot prices when the default risk is high.

In sum, we conclude that there is strong evidence that commodity producers’ fundamental hedging demand, as proxied by the producer default risk measures, is positively related to the expected return of commodity futures, as well as the spot price change, consistent with the model in Section 2. These results are robust to standard, aggregate forecasting variables, as well as to the covariance with standard risk factors (the latter is reported in an Online Appendix). Before we turn to tests of item (2) above, we consider two other robustness tests of this main result.

### 5.6.2 Hedger versus non-hedger sample partitions and out-of-sample performance

As a robustness check, we consider the forecasting power of default risk measures based only on producers that state they are hedgers, and contrast these measures with measures derived from producers that are stated non-hedgers. We classify producers into hedgers or non-hedgers based on the analysis in Section 4 using the quarterly and annual reports from the EDGAR database. Of these, we were able to identify whether or not firms had ‘significant’ positions in 72% of the total number firm-quarters. Of these, Panel A of Table 1 shows that in about 70% of the firm-quarters, firms have significant short positions in the derivative market relative to their exposure to future spot prices, leaving 30% of firms which do not have significant hedges in place.

We construct the within-group average Zmijewski-score and EDF for each of the groups. The sample is the same as for the EDGAR data (2000 to 2010) and so significantly shorter than that for the full sample regressions reported in Table 3. Panel A of Table 4 shows the results of the pooled futures return forecasting regressions across all four commodity classes:

$$\begin{aligned}
 ExcessReturns_{i,t+1} = & \beta_1 DefRisk\_Hedgers_{i,t} + \beta_2 DefRisk\_NonHedgers_{i,t} \dots \\
 & + ControlVariables_t + u_{i,t+1}.
 \end{aligned}
 \tag{28}$$

The hedgers’ default risk measures predict commodity futures excess returns with a coefficient between 5.2% and 9.6%, which is higher than the roughly 4% for all producer firms found in Panel

A of Table 3. In all cases, the regression coefficient is statistically significantly different from zero at the 5% level or better. The regression coefficients on non-hedger default risk, however, lie between  $-3.2\%$  and  $-0.4\%$  and are always statistically insignificant. In fact, the  $p$ -value of a test that the regression coefficient of hedgers is larger than that of non-hedgers is always less than 0.03. This indicates that it is the default risk of firms that actually do hedge that matters for the futures risk premium, rather than default risk per se.

Panel B of Table 4 shows out-of-sample results for the futures return regressions across the four commodities over the period 2006Q1 to 2010Q4. This period saw large gyrations in the commodity prices not seen earlier in the sample and therefore is of particular interest. The regressions here are univariate in order to focus purely on the predictive power of the default risk measures and not on that of the other controls.

The top row shows the regression  $R^2$ 's for the univariate futures forecasting regressions using data from the beginning of each futures contract's sample until 2005Q4. The estimated intercept and slope coefficient on the relevant default risk measure is then used to perform out-of-sample forecasts of the futures risk premium in the period 2006Q1 to 2010Q4 (2009Q4 in the case of the EDF due to its somewhat shorter sample availability). The out-of-sample  $R^2$  is defined relative to the historical in-sample mean, following Campbell and Thompson (2008):

$$R_{out-of-sample}^2 = 1 - \frac{\sum_{j=1}^N \left( r_{t+j,t+j+1} - \hat{\alpha}_t - \hat{\beta}_t DefRisk_{t+j} \right)^2}{\sum_{j=1}^N \left( r_{t+j,t+j+1} - \hat{\mu}_t \right)^2}, \quad (29)$$

where  $t$  is the final date of the in-sample estimation,  $\{\hat{\alpha}_t, \hat{\beta}_t\}$  are the OLS estimates from the in-sample estimation window, and  $\hat{\mu}_t$  is the sample mean of the commodity's return in the in-sample estimation window. According to this measure and with the exception of the EDF for Natural Gas, the out-of-sample  $R^2$ 's are all positive and often higher than the in-sample  $R^2$ 's.

### 5.6.3 Volatility Interaction

From the expression for the futures risk premium in Equation (12), the model implies an interaction between fundamental hedging demand ( $\gamma_p$ ) and the variance of the commodity futures return. In particular, a change in fundamental hedging demand has a larger impact on the futures risk premium if the variance is high. We test this relation by running the following pooled regression across all four commodities:

$$\begin{aligned} ExcessReturns_{i,t+1} = & \beta_1 RV_{i,t} + \beta_2 DefRisk_{i,t} + \beta_3 RV_{i,t} \times DefRisk_{i,t} \dots \\ & + ControlVariables_t + u_{i,t+1}, \end{aligned} \quad (30)$$

where  $i$  denotes the commodity,  $t$  denotes time measured in quarters, and  $RV_{i,t}$  is a measure of the conditional variance at time  $t$  of futures returns from time  $t$  to  $t + 1$  for commodity  $i$  (the realized variance). The model predicts a positive coefficient on the interaction term ( $\beta_{i,3}$ ). Since volatility also appears in the covariance term in Equation (12), we include its direct effect. Further, the conditional volatility of futures returns is an indirect control for supply uncertainty (probability of inventory stock-out or other production shocks) that may be correlated with default risk.

The estimate of the conditional variance we use is the realized average squared daily futures returns from time  $t - 1$  to  $t$ . Panel A of Table 5 shows the results of the above pooled regression, where all the independent variables are normalized to have zero mean and unit variance. Including the volatility interaction term sees the average response at 3.6% and 3.3% for the EDF and the Zmijewski-score, respectively. If the variance is one standard deviation above its average value, this sensitivity increases to 5.8% (EDF) and 4.8% (Zm). Thus, in a high volatility environment, the sensitivity of the futures risk premium to producers fundamental hedging demand increase by 45% – 60%. This effect is significant at the 5% level for both measures of default risk.

Panel A of Table 5 also shows the results for the same regressions as in Equation (30), but where the dependent variable is the change in the spot price from  $t$  to  $t + 1$  relative to the spot price at time  $t$ . In this case the direct effect of default risk is 3.4% – 3.6%, depending on the measure, increasing to 5.5% – 6.2% if the return variance is one standard deviation higher than normal. Again, the interaction coefficient is significant at the 5% level or better for both measures. In other words, for both spot and futures returns the sensitivity of the expected return to default risk is strongly increasing in the variance of the spot price, consistent with the model.

#### 5.6.4 Speculator Risk Tolerance Interaction

From the expression for the futures risk premium in Equation (12), the model also implies an interaction between fundamental hedging demand ( $\gamma_p$ ) and the risk tolerance of speculators ( $\gamma_s^{-1}$ ). In particular, a change in fundamental hedging demand has a larger impact on the futures risk premium if speculator risk tolerance is low. Following Adrian and Shin (2009) and Etula (2010), we use the growth in intermediaries’ (aggregate Broker-Dealer) assets relative to household asset growth as a measure of speculators’ ease of access to capital in aggregate ( $\gamma_s^{-1}$ ). This data is constructed from the U.S. Flow of Funds data. Etula (2009) shows that high relative growth in Broker-Dealer asset predicts low subsequent commodity futures returns, consistent with a relaxation of capital constraints leading to a lower commodity futures risk premium. The Broker-Dealer data is available quarterly for the full sample period.

The novel prediction of our model is the effect on the spot and futures returns of the interaction of the broker-dealer variable with the default risk measures: if speculators have ample capital, they are willing to cheaply take the opposite side of producers’ hedge-motivated futures demand, while if speculator capital is scarce, the compensation required (the futures risk premium) is large. We

test this relation by running the following pooled regression across the four commodities:

$$ExcessReturns_{i,t+1} = \beta_1 BD_t + \beta_2 DefRisk_{i,t} + \beta_3 BD_t \times DefRisk_{i,t} + ControlVariables_t + u_{i,t+1}, \quad (31)$$

where  $i$  denotes the commodity,  $t$  denotes time measured in quarters, and  $BD_{i,t}$  is the Broker-Dealer measure. The model predicts a negative coefficient on the interaction term ( $\beta_{i,3}$ ). Since Broker-Dealer asset growth may be correlated with the volatility of the equity market pricing kernel, it is important to include its direct effect.

Panel *B* of Table 5 shows the results of the above regression, where all the independent variables are normalized to have zero mean and unit variance. First, note that the Broker-Dealer measure of speculator risk tolerance strongly predicts commodity futures returns with a negative sign, documented by Etula (2010). More importantly for our model, the interaction of default risk and speculator risk tolerance has a negative sign across all commodities and for both default risk measures. Including the Broker-Dealer interaction term sees the average response at about 3%, with a decrease of 1.5% to 2.8% if Broker-Dealer relative growth is one standard deviation above its average value. Thus, in a high speculator risk tolerance environment, the sensitivity of the futures risk premium to producers fundamental hedging demand decrease by 50% – 75%. This effect is significant at the 5% level or better for both default risk measures.

Finally, Panel *C* of Table 5 adds the realized variance and the interaction between realized variance and default risk to the pooled regressions. In this case, both interaction terms have the predicted signs and are significant at the 10% level or better for the futures return and 5% level or better in 3 out of 4 cases for the spot returns. Thus, both the volatility and the speculator risk tolerance interaction effects are distinct and jointly present in the data, as predicted by the model.

**Interaction of limits to arbitrage and limits to hedging: visual evidence.** As an alternative approach to identify the interaction between the risk capacity of speculators in the commodity market and hedging demand of producers, we consider the realized covariance between the futures risk premium and the default risk measures versus the Broker-Dealer measure of Adrian and Shin (2009). In particular, we construct such an annual realized covariance as:

$$Covar_t = \sum_{j=0}^3 r_{t+1-j}^{crude} \times DefRisk_{t-j}, \quad (32)$$

where the realized future excess return from  $t$  to  $t + 1$  is used as a proxy for the risk premium at time  $t$ . We focus on the crude oil return in these plots. To measure the marginal effect of default risk after controlling for other standard predictors, in the above measure of the covariance, we use the Zmijewski-score and the EDF orthogonalized to the standard control variables used in the regression. We then plot this estimated annual covariance against the corresponding four quarter

moving average of the Broker-Dealer measure in Figure 5.

Changes in hedging demand should have little effect, and thus low covariance, with the risk premium if speculator risk capacity is high. Thus, the two measures should be negatively correlated. Figure 5 shows that there is a striking negative correlation over the sample for both default risk measures. For the EDF, the correlation is  $-0.50$  and significant at the 1% level, while for the covariance measure based on the Zmijewski-score the correlation is  $-0.35\%$  and significant at the 5% level. consistent with the model.

In sum, the evidence presented indicates that time-varying market segmentation, due to time-variation in the severity of limits to arbitrage for speculators, impacts futures and spot commodity prices through the hedging demand of producing firms. In particular, there is an intuitive interaction between speculator capital and the impact of producer hedging demand and market prices that, in addition to being strongly significant at the quarterly frequency, is also visually striking when we consider annual measures of hedging demand and speculator capital supply.

## 5.7 Other tests

In this final section, we first consider the relation between CFTC reported commercial trader positions, inventory, and the commodity basis spread versus the default risk measures. Second, we consider whether managerial risk aversion, as we assume in the model, is in fact linked to firm hedging in our sample. We test this by merging our micro data on firm hedging with data on executive compensation from the ExecuComp database.

### 5.7.1 CFTC Hedging Positions and Producer's Desire to Hedge

As discussed earlier in the paper, the CFTC measures of commercial trader positions have significant limitations for our use. In fact, even theoretically the equilibrium open interest need not be one for one with measures of producers' fundamental hedging demand, as open interest depends also on the abnormal returns earned by speculators relative to the variance of those returns, as well as speculator risk-aversion. For example, Chen, Kirilenko, and Xiong (2011) show that during the financial crisis in the fall of 2008, there were large shocks to long speculators' risk capacity as commodity prices plummeted that forced these investors to reduce their long positions. By market clearing this implies that the shorts also reduced their short positions even though default risk rose also for producers over this period. Nevertheless, the micro hedger analysis conducted in this paper shows that the propensity to hedge is indeed increasing in default risk. Since we construct the hedger net position variables from the CFTC data as the net *short* position, we might therefore expect a positive contemporaneous relation between the default risk and CFTC hedger positions.

The first two columns with results in Table 6 show the regression coefficient on the default risk

measures in the following pooled regression:

$$HedgerNetPos_{i,t} = \beta \times DefRisk_{i,t} + \gamma_i HedgerNetPos_{i,t-1} + ControlVariables_t + u_{i,t+1}, \quad (33)$$

where we note that the  $\beta$ -coefficient is pooled across the four commodities. Table 6 shows that the relation is positive and significant at the 5% level or better. To get a sense of the magnitude, note that the hedger variable has also been normalized to have unit variance. Thus, a one standard deviation movement in the default risk measures increases net short hedger positions by 10% to 15% of its standard deviation, controlling for business cycle fluctuations as well as lagged net short hedger positions.<sup>19</sup> This indicates that there is a large component of the variation of the CFTC hedger demand that is not accounted for by the default risk measures. The Online Appendix to this paper shows the results of this regression commodity by commodity, and finds in all cases (other than Gasoline, using EDF, for which it is insignificant) that the regression coefficient is positive and of a similar magnitude.

### 5.7.2 Inventory

We next turn to the implications for variation in the default risk measures on aggregate commodity inventory levels. The impact of producers' inventory decision of increased fundamental hedging demand is typically negative, but per the discussion of the general equilibrium model in Section 2, this implication does not hold for all reasonable parameterizations of the model. Thus, the sign here is an empirical question.

An instrumental variables approach is needed to answer this question. In particular, transitory demand shocks (the  $A_t$ 's in the model) will affect both measures of default risk and inventory with opposite signs, even if there is no causal relation between the two. For instance, a transitory negative shock to demand will increase inventory holdings even in a frictionless model such as Deaton and Laroque (1992). At the same time, the resulting lower spot price typically decreases producer firm values, which in turn will affect the measures of default risk. Thus, we need an instrument for default risk at time  $t + 1$  that's unrelated to the demand shock at time  $t + 1$ , but related to the inventory decision at time  $t + 1$ . Since the default risk measures are quite persistent, with use the fitted measure of default risk from an AR(1) as the instrumented default risk variable:  $DefRisk_{i,t+1}^{IV} = \hat{\alpha}_i + \hat{\beta}_i DefRisk_{i,t}$  where  $\hat{\alpha}_i$  and  $\hat{\beta}_i$  are the AR(1) regression coefficients obtained from the full sample regression and adjusting the  $\hat{\beta}_i$  for the well-known small-sample bias in the AR(1) coefficient. Finally, we run the pooled regression:

$$\Delta i_{i,t+1} = \beta \times DefRisk_{i,t+1}^{IV} + \sum_{j=1}^3 \gamma_{i,j} \Delta i_{i,t+1-j} + ControlVariables_t + u_{i,t+1}, \quad (34)$$

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<sup>19</sup>Since the regression is pooled across different commodities, we normalize the left hand side variable for each commodity to have mean zero and unit variance.

where  $i$  is the log inventory level and  $\Delta$  denotes the first difference operator. The two middle columns of Table 6 shows that high default risk indeed is associated with lower levels of inventory. For both default risk measures, the effect is significant at the 5% level. A one standard deviation increase in aggregate default risk decreases the inventory by 7% to 10% of its standard deviation, which in turn tends to depress current spot prices and increase future spot prices, consistent with the forecasting results shown in Table 3.

### 5.7.3 The Basis Spread

The commodity basis spread, defined in our setting as the difference between the spot price and the futures price relative to the spot price  $\left(\frac{S_t - F_t^{(\tau)}}{S_t}\right)$ , is often used as an indicator of future expected spot prices and also of expected returns in the futures market. In particular, Hong and Yogo (2010) show that the aggregate basis across all commodities has some forecasting power for future commodity returns. Gorton, Hayashi, and Rouwenhorst (2010) show that the basis is a powerful predictor of the cross-section of commodity returns. The model in Section 2, however, predicts that the individual commodity basis is not affected by the commodity sector default risk unless there is an inventory stock-out. This prediction is a bit stark and comes from the two period set up. Routledge, Seppi, and Spatt (2000) show that the probability of a stock-out does affect the basis in a multiperiod setting.

To investigate whether the default risk measures can help explain the commodity basis spread, we apply the same instrumental variables approach as we did for the inventory regressions. We run the pooled regression:

$$basis_{i,t+1} = \beta \times DefRisk_{i,t+1}^{IV} + \gamma_i basis_{i,t} + ControlVariables_t + u_{i,t+1}. \quad (35)$$

The final two columns of Table 6 shows that for the EDF measure, the basis indeed increases by 14% of its standard deviation for a one standard deviation in aggregate default risk, significant at the 5% level. For the Zmijewski-score, the estimated increase is 15%, but this number is not significant at conventional levels. Thus, there is a positive relation, but again a significant fraction of the variation in the basis is not related to variation in producer default risk, consistent with the model.

### 5.7.4 Managerial risk-aversion and hedging

Our final results relate back to the micro analysis of producer hedging behavior. In the model, managers are assumed to be risk-averse. This assumption is meant as a reduced-form way of capturing many different motives for hedging, such as deadweight costs of default, convex taxes, and indeed managerial risk-aversion itself. In particular, in the Online Appendix we show that a

model with explicit costly default has qualitatively the same predictions as the model with risk-averse managers. Nevertheless, it is of interest to see if the data supports an interpretation of managerial hedging behavior being driven, at least in part, by managerial risk-aversion.

To investigate the hypothesis that managerial risk-aversion affects firm hedging, we merge the micro data obtained from the EDGAR reports and discussed in Section 3, with data on CEO compensation from ExecuComp for oil and gas producers (SIC 1311). The latter data are annual from 1992 to 2010. For each manager in each year, we create the ratio of dollar firm stock holdings to base salary and the ratio of the dollar value of stock option holdings to the base salary.<sup>20</sup> We then perform an annual cross-sectional sort on each of these variables. If a variable is in the top half of the stock holding measure, but in the bottom half of the option holding measure, we designate this manager as ‘risk-averse’. If, on the other hand, the manager has compensation that puts him/her in the bottom half of all firms in terms of the stock holding measure and the top half in terms of the option holdings measure, we designate the manager as ‘risk-tolerant’.<sup>21</sup>

In our tests, the firms with a risk-averse manager is given a 1, and the firms with a risk-tolerant manager is given a 0. All other firms are given a missing value. Next, we perform panel regressions in which the dependent variable is the binary variable representing whether the firm has a significant derivatives hedge in play (we discussed this variable in Section 3). This firm-quarter variable is made into a firm-year variable by taking the average over the year in order for it to correspond to the ExecuComp-based managerial risk-aversion variable, which is the independent variable. We also examine specifications in which firm size is employed as a control, as well as a specification with time fixed effects. We do not use CEO fixed effects as cross-sectional CEO-level variation is exactly what we are trying to exploit in this analysis. However, we do cluster the standard errors at the CEO level.

Panel *A* of Table 7 shows the results of these panel regressions. In all the regressions, a risk-averse manager is about 20% more likely to hedge than a risk-tolerant manager. The effect is significant at the 5% level when firm size (log market value of equity) is used as a control. This control comes in with a negative sign, indicating that managers of large firms hedge less. The  $R^2$  of the regression with time fixed effects and size as controls, in addition to the managerial risk-aversion variable, is 29.2%. Thus, we do find statistically significant evidence that managers with more downside compensation exposure to the firms’ profits tend to hedge more.

Next, we sort firms based on whether the manager of the firm is designated as risk-averse or risk-tolerant in each quarter in the sample covered by the ExecuComp data from 1992 to 2010.

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<sup>20</sup>We normalize by base salary to a control for the wealth level of the manager, which is unobserved, and also to make the size of the firm less important in our sorting procedure.

<sup>21</sup>These sorts are motivated by the empirical literature on managerial incentives and risk-taking. For instance, Coles, Daniel and Naveen (2006) document that after controlling for CEO stock holdings, greater options-based compensation leads to greater risk-taking in firm policies: “[H]igher sensitivity of CEO wealth to stock volatility (vega) implements riskier policies, including relatively more investment in R&D, less investment in PPE (property, plants and equipment), more focus, and higher leverage.”

Based on these sorts, we create corresponding average Zmijewski-scores and EDFs for the each group. Then, we run the pooled futures return forecasting regressions as before, using the average default risk measure of each sub-group. Panel *B* of Table 7 shows that it is the default risk of the firms which have managers that are designated as risk-averse that are the significant predictors of excess futures returns. The coefficients on the default risk of the risk-tolerant firms are close to zero and all insignificant. Thus, the pattern clearly shows a difference between the effect on futures returns of the default risk of highly risk-averse managers and that of the rest. Of course, the annual nature of the ExecuComp data makes these specifications somewhat low-powered, so it is difficult to confirm the statistical significance of this difference.

In sum, the results given in Table 7 document a relation between producer hedging and managerial risk-aversion as a determinant of such hedging behavior. Further, the table shows that it is the default risk of the firms with ‘risk-averse’ managers that is the driver of the predictability. We acknowledge that executive compensation is endogenously determined and in part designed exactly to overcome frictions related to managerial preferences. Further, managerial compensation and firm default risk may be correlated and so the regressions presented here may suffer from an omitted variable bias. Nevertheless, assuming that contracts are not perfect at each point in time, the evidence presented at least points to managerial risk-aversion as a plausible channel for hedging behavior. This evidence should be viewed together with the alternate model presented in the Online Appendix, which addresses concerns that are perhaps more directly related to default risk.

## 6 Conclusion

We build a theoretical model in which the interaction between commodity producers who are averse to price fluctuations, and capital constrained speculators that invest 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 – and data from oil and gas markets, we find evidence to support the predictions of the model. 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. Taken together, our theoretical model and empirical results provide support for the notion that limits to arbitrage in financial markets can have real impacts – through limits to hedging imposed on producers of real commodities.

Our analysis provides a useful lens through which to view an important debate about 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.<sup>22</sup> While these trends occurred concurrently, some market practitioners and economists vehemently argued that the speculative investments 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. This trend has increased current spot prices, and should stabilize prices going forward.

Our results are most consistent with the third explanation above for the rise in spot prices. This explanation (and our model’s prediction) is also consistent with the decline in commodity spot prices during the sub-prime crisis in 2008, which increased speculator risk-aversion and simultaneously raised producer default risk which. Indeed, we show that the default risk of producers also predicts commodity futures returns out-of-sample over this particularly interesting recent period. More work is warranted, however, to explain the full *magnitude* of the recently witnessed rise and fall in oil prices.

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<sup>22</sup>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)

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## Appendix

### Proof of Proposition 1

It is useful to establish some preliminary results. Note that for the futures market to clear when  $\gamma_p, \gamma_s > 0$ , the condition  $E[\Lambda(S_1 - F)] > 0$  must be satisfied (see Equation (10)). Since this implies that  $h_p^* < I(1 - \delta) + g_1$  (see Equation (5)), we have from Equation (4) that  $E[\Lambda S_1] - S_0/(1 - \delta) > 0$  when there is no stock-out ( $\lambda = 0$ ).

The consumer demand function is given by

$$S_t = \omega \left( \frac{A_t}{Q_t} \right)^{1/\varepsilon} = \omega Q_t^{-1/\varepsilon} e^{\frac{1}{\varepsilon} a_t}. \quad (36)$$

where the log of the demand shock  $A_t$  ( $a_t$ ) is distributed  $N(\mu, \sigma^2)$  and where  $Q_t$  is the equilibrium commodity supply at time  $t$ . Since  $Q_t$  is predetermined, the variance of the period 1 spot price conditional on period 0 information is:

$$\sigma_S^2 = Q_1^{-2/\varepsilon} k, \quad (37)$$

where  $k \equiv \omega^2 \left( e^{(\sigma/\varepsilon)^2} - 1 \right) e^{2\mu/\varepsilon + (\sigma/\varepsilon)^2}$ .

First, consider the case of no stock-out,  $\lambda = 0$ . In this case, we have from the equilibrium condition given in Equation (11) that:

$$Q_1^{2/\varepsilon} (E[\Lambda S_1(I^*)] - S_0(I^*)/(1 - \delta)) = \frac{\gamma_p \gamma_s}{\gamma_p + \gamma_s} k Q_1. \quad (38)$$

Taking the total derivative of Equation (38) with respect to producer default risk, we have:

$$\begin{aligned} & \frac{2}{\varepsilon} Q_1^{2/\varepsilon - 1} \frac{\partial Q_1}{\partial I} \frac{dI}{d\gamma_p} (E[\Lambda S_1] - S_0/(1 - \delta)) + Q_1^{2/\varepsilon} \left( E \left[ \Lambda \frac{\partial S_1}{\partial I} \frac{dI}{d\gamma_p} \right] - \frac{\partial S_0}{\partial I} \frac{dI}{d\gamma_p} / (1 - \delta) \right) \\ & \dots = \frac{\gamma_s^2}{(\gamma_p + \gamma_s)^2} k Q_1 + \frac{\gamma_p \gamma_s}{\gamma_p + \gamma_s} k \frac{\partial Q_1}{\partial I} \frac{dI}{d\gamma_p}. \end{aligned} \quad (39)$$

$\Updownarrow$

$$\frac{-\frac{\gamma_s^2}{(\gamma_p + \gamma_s)^2} k Q_1}{\frac{\gamma_p \gamma_s}{\gamma_p + \gamma_s} k (1 - \delta) - Q_1^{2/\varepsilon} \left( E \left[ \Lambda \frac{\partial S_1}{\partial I} \right] - \frac{\partial S_0}{\partial I} / (1 - \delta) \right) - \frac{2}{\varepsilon} Q_1^{2/\varepsilon - 1} (1 - \delta) [E[\Lambda S_1] - S_0/(1 - \delta)]} = \frac{dI}{d\gamma_p}. \quad (40)$$

In this calculation, we are assuming that the pricing kernel  $\Lambda$  is not affected by changes in inventory. Given the inverse demand function,  $\frac{dS_1}{dI} < 0$  and  $\frac{dS_0}{dI} > 0$ , and therefore  $E \left[ \Lambda \frac{dS_1}{dI} \right] - \frac{dS_0}{dI} / (1 - \delta) < 0$ . Also, as noted in the preliminary results above,  $E[\Lambda S_1] - S_0/(1 - \delta) > 0$ . Since  $S_t = \omega Q_t^{-1/\varepsilon} e^{\frac{1}{\varepsilon} a_t}$ , and since  $Q_0 = G_0 - I$  and  $Q_1 = G_1 + (1 - \delta)I$ , we have that:

$$\frac{\partial S_1}{\partial I} = -\frac{1}{\varepsilon} \omega e^{\frac{1}{\varepsilon} a_1} Q_1^{-1/\varepsilon - 1} (1 - \delta) < 0, \quad (41)$$

$$\frac{\partial S_0}{\partial I} = \frac{1}{\varepsilon} \omega e^{\frac{1}{\varepsilon} a_0} Q_0^{-1/\varepsilon - 1} > 0. \quad (42)$$

Thus,

$$E \left[ \Lambda \frac{\partial S_1}{\partial I} \right] - \frac{\partial S_0}{\partial I} / (1 - \delta) = -\frac{1}{\varepsilon} \omega Q_1^{-1/\varepsilon - 1} (1 - \delta) E \left[ \Lambda e^{\frac{1}{\varepsilon} a_1} \right] - \frac{1}{\varepsilon} \omega e^{\frac{1}{\varepsilon} a_0} Q_0^{-1/\varepsilon - 1} / (1 - \delta). \quad (43)$$

and

$$E[\Lambda S_1] - S_0/(1 - \delta) = \omega Q_1^{-1/\varepsilon} E \left[ \Lambda e^{\frac{1}{\varepsilon} a_1} \right] - \omega Q_0^{-1/\varepsilon} e^{\frac{1}{\varepsilon} a_0} / (1 - \delta). \quad (44)$$

Focusing on the sign of the two last terms in the denominator on the left hand side of Equation (40), and substituting in the expressions from Equations (43) and (44), we have that:

$$\begin{aligned}
& -Q_1^{2/\varepsilon} \left( E \left[ \Lambda \frac{\partial S_1}{\partial I} \right] - \frac{\partial S_0}{\partial I} / (1 - \delta) \right) - \frac{2}{\varepsilon} Q_1^{2/\varepsilon-1} (1 - \delta) [E[\Lambda S_1] - S_0 / (1 - \delta)] = \dots \\
& \frac{1}{\varepsilon} \omega Q_1^{1/\varepsilon-1} (1 - \delta) E \left[ \Lambda e^{\frac{1}{\varepsilon} a_1} \right] + \frac{1}{\varepsilon} \omega e^{\frac{1}{\varepsilon} a_0} Q_1^{2/\varepsilon} Q_0^{-1/\varepsilon-1} / (1 - \delta) - \frac{2}{\varepsilon} Q_1^{1/\varepsilon-1} (1 - \delta) \omega E \left[ \Lambda e^{\frac{1}{\varepsilon} a_1} \right] + \frac{2}{\varepsilon} \omega Q_1^{2/\varepsilon-1} Q_0^{-1/\varepsilon} e^{\frac{1}{\varepsilon} a_0} \\
& = \frac{1}{\varepsilon} \omega e^{\frac{1}{\varepsilon} a_0} Q_1^{2/\varepsilon} Q_0^{-1/\varepsilon-1} \left( \frac{1}{1 - \delta} + 2Q_1^{-1} Q_0 \right) - \frac{1}{\varepsilon} \omega Q_1^{1/\varepsilon-1} (1 - \delta) E \left[ \Lambda e^{\frac{1}{\varepsilon} a_1} \right] \\
& = \frac{\omega}{\varepsilon} Q_1^{1/\varepsilon-1} \left( e^{\frac{1}{\varepsilon} a_0} (Q_1/Q_0)^{1/\varepsilon+1} \left( \frac{1}{1 - \delta} + 2Q_0/Q_1 \right) - (1 - \delta) E \left[ \Lambda e^{\frac{1}{\varepsilon} a_1} \right] \right). \tag{45}
\end{aligned}$$

We still cannot sign this term. However, we can use the following relations to get us the final step. Since  $(1 - \delta) E[\Lambda S_1] - S_0 > 0$ , using the inverse demand function, it follows that

$$\begin{aligned}
(1 - \delta) E \left[ \Lambda e^{\frac{1}{\varepsilon} a_1} \right] - (Q_1/Q_0)^{1/\varepsilon} e^{\frac{1}{\varepsilon} a_0} &> 0. \\
(1 - \delta) E \left[ \Lambda e^{\frac{1}{\varepsilon} a_1} \right] &> (Q_1/Q_0)^{1/\varepsilon} e^{\frac{1}{\varepsilon} a_0} > 0. \tag{46}
\end{aligned}$$

Using this inequality to sign Equation (45), we have that:

$$\frac{\omega}{\varepsilon} Q_1^{1/\varepsilon-1} \left( e^{\frac{1}{\varepsilon} a_0} (Q_1/Q_0)^{1/\varepsilon+1} \left( \frac{1}{1 - \delta} + 2Q_0/Q_1 \right) - (1 - \delta) E \left[ \Lambda e^{\frac{1}{\varepsilon} a_1} \right] \right) > \dots \tag{47}$$

$$\frac{\omega}{\varepsilon} Q_1^{1/\varepsilon-1} \left( e^{\frac{1}{\varepsilon} a_0} (Q_1/Q_0)^{1/\varepsilon+1} \left( \frac{1}{1 - \delta} + 2Q_0/Q_1 \right) - (Q_1/Q_0)^{1/\varepsilon} e^{\frac{1}{\varepsilon} a_0} \right) = \dots \tag{48}$$

$$\frac{\omega}{\varepsilon} Q_1^{1/\varepsilon-1} e^{\frac{1}{\varepsilon} a_0} (Q_1/Q_0)^{1/\varepsilon} \left( \frac{Q_1}{Q_0} \frac{1}{1 - \delta} + 1 \right) > 0. \tag{49}$$

Thus, referring now back to Equation (40),  $\frac{dI}{d\gamma_p} < 0$ . In the case of an inventory stock-out, we have trivially that  $\frac{dI}{d\gamma_p} = \frac{dI}{d\gamma_s} = 0$ .

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

$$\frac{d}{d\gamma_p} \frac{E[S_1] - S_0}{S_0} = \frac{\left( E \left[ \frac{dS_1}{dI} \frac{dI}{d\gamma_p} \right] - \frac{dS_0}{dI} \frac{dI}{d\gamma_p} \right) S_0 - (E[S_1] - S_0) \frac{dS_0}{dI} \frac{dI}{d\gamma_p}}{S_0^2} \tag{50}$$

$$= \frac{E \left[ \frac{dS_1}{dI} \right] S_0 - E[S_1] \frac{dS_0}{dI} \frac{dI}{d\gamma_p}}{S_0^2} > 0. \tag{51}$$

Thus, the expected percentage spot price change is increasing in the producers' risk-aversion,  $\gamma_p$ , 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 (??) and (7)):

$$\frac{\partial}{\partial I} \left( \frac{E[S_1] - S_0 \frac{1+r}{1-\delta}}{S_0 \frac{1+r}{1-\delta}} \right) = \frac{\left( E \left[ \frac{\partial S_1}{\partial I} \right] - \frac{\partial S_0}{\partial I} \frac{1+r}{1-\delta} \right) S_0 - \left( E[S_1] - S_0 \frac{1+r}{1-\delta} \right) \frac{\partial S_0}{\partial I}}{S_0^2 \frac{1+r}{1-\delta}} \tag{52}$$

$$= \frac{S_0 E \left[ \frac{\partial S_1}{\partial I} \right] - E[S_1] \frac{\partial S_0}{\partial I}}{S_0^2 \frac{1+r}{1-\delta}} < 0, \tag{53}$$

since  $E \left[ \frac{\partial S_1}{\partial I} \right] < 0$ , and  $\frac{\partial S_0}{\partial I} > 0$ . Since  $\frac{dI}{d\gamma_p} < 0$ , the futures risk premium is increasing in producer risk-aversion ( $\gamma_p$ ) if there is no stock-out:  $\frac{d \frac{E(S_1) - F}{d\gamma_p}}{d\gamma_p} > 0$ .

Next, consider the case of a stock-out. Now, the spot price in period 0 and expected spot 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:

$$\frac{E[S_1] - F}{F} = \frac{E[S_1] - S_0 \frac{1+r}{1-\delta} + \lambda \frac{1+r}{1-\delta}}{S_0 \frac{1+r}{1-\delta} - \lambda \frac{1+r}{1-\delta}}. \quad (54)$$

From Equation (11), we have that:

$$(E[\Lambda S_1(I^*)] - (S_0(I^*) - \lambda(I^*)) / (1 - \delta)) = \frac{\gamma_p \gamma_s}{\gamma_s + \gamma_p} \sigma_s^2 Q_1 \quad (55)$$

$\Downarrow$

$$Q_1^{2/\varepsilon} (E[\Lambda S_1(I^*)] - (S_0(I^*) - \lambda(I^*)) / (1 - \delta)) = \frac{\gamma_p \gamma_s}{\gamma_s + \gamma_p} k Q_1. \quad (56)$$

First consider the derivative of  $\lambda$  with respect to  $\gamma_p$ :

$$\begin{aligned} & \frac{2}{\varepsilon} Q_1^{2/\varepsilon - 1} (1 - \delta) \frac{dI}{d\gamma_p} (E[\Lambda S_1(I^*)] - (S_0(I^*) - \lambda(I^*)) / (1 - \delta)) + \dots \\ Q_1^{2/\varepsilon} \left( \frac{\partial E[\Lambda S_1(I)]}{\partial I} \frac{dI}{d\gamma_p} - \frac{\partial S_0(I) / (1 - \delta)}{\partial I} \frac{dI}{d\gamma_p} + \frac{d\lambda}{d\gamma_p} / (1 - \delta) \right) &= \frac{\gamma_s^2}{(\gamma_s + \gamma_p)^2} k Q_1 + \frac{\gamma_p \gamma_s}{\gamma_s + \gamma_p} k \frac{dI}{d\gamma_p} (1 - \delta). \end{aligned} \quad (57)$$

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

$$\frac{d\lambda}{d\gamma_p} = \frac{(1 - \delta) \gamma_s^2}{(\gamma_s + \gamma_p)^2} k Q_1^{1 - 2/\varepsilon} > 0.$$

Given this, the derivative of the futures risk premium with respect to producers' risk-aversion in the case of a stock-out is:

$$\frac{d}{d\gamma_p} \frac{E[S_1] \frac{1-\delta}{1+r} - S_0 + \lambda}{S_0 - \lambda} = \frac{\frac{d\lambda}{d\gamma_p} (S_0 - \lambda) + (E[S_1] \frac{1-\delta}{1+r} - S_0 + \lambda) \frac{d\lambda}{d\gamma_p}}{(S_0 - \lambda)^2} = \frac{E[S_1] \frac{1-\delta}{1+r} \frac{d\lambda}{d\gamma_p}}{(S_0 - \lambda)^2} > 0, \quad (58)$$

since  $\frac{d\lambda}{d\gamma_p} > 0$ .

By the symmetry of the equilibrium condition (Equation (38)) it is clear that all the above statements regarding producer risk-aversion hold also for speculator risk-aversion. That is,  $\frac{dI}{d\gamma_s} < 0$ ,  $\frac{d \frac{E(S_1) - F}{d\gamma_s}}{d\gamma_s} > 0$ ,  $\frac{d}{d\gamma_s} \frac{E[S_1] - S_0}{S_0} > 0$ . Thus, equilibrium inventory holding is decreasing in producer and speculator risk-aversion, while expected spot and futures returns are increasing.

**Table 1 - Micro-level hedging**

Table 1: This table shows results using firm level hedging data collected from 10-Q reports for all firms with SIC code 1311 (Crude Oil and Natural Gas Extraction) in the period 2000Q1 to 2010Q4. For each firm-quarter, the fields given in Panel A was answered either 0 ("No"), 1 ("Yes") or missing if no information was given. Panel A gives the summary statistics for this data. Panel B shows regressions where the dependent variable is the firm-quarter data point corresponding to the question "Does the firm currently have significant short crude oil derivatives positions?" Panel B shows the results from both ols and dprobit regressions when measures of firm-quarter default risk are used as independent variables (the Zmijewski- and EDF-scores, respectively). Standard errors are robust and clustered by time.

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**Panel A: Summary statistics on micro hedging**

For each quarter and firm:	# firm-quarter obs.	fraction "yes"
use derivatives?	2,400	88.0%
futures or forwards?	547	47.7%
swaps?	1,781	80.6%
options?	1,800	81.8%
significant short crude?	1,738	69.8%
significant long crude?	964	1.0%

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**Panel B: Crude oil hedging vs. firm level default risk measures**  
(dependent variable: "significant short crude?" (0 or 1 for each firm-quarter))

Indep.var:	Firm-quarter <i>Zm</i> -score					Firm-quarter log <i>EDF</i> -score				
	$\beta$	( <i>s.e.</i> )	fixed effect	$R^2_{adj}$	<i>N</i>	$\beta$	( <i>s.e.</i> )	fixed effect	$R^2_{adj}$	<i>N</i>
dprobit	0.053***	(0.014)	time <i>f.e.</i>	6.1%	926	0.057***	(0.009)	time <i>f.e.</i>	7.3%	1,100
	0.055***	(0.019)	firm <i>f.e.</i>	18.6%	548	0.022***	(0.008)	firm <i>f.e.</i>	20.6%	660
	0.058***	(0.020)	time & firm <i>f.e.</i>	25.2%	548	0.058***	(0.016)	time & firm <i>f.e.</i>	26.8%	660
ols	0.055***	(0.014)	time <i>f.e.</i>	5.0%	926	0.057***	(0.009)	time <i>f.e.</i>	6.0%	1,100
	0.034***	(0.011)	firm <i>f.e.</i>	29.8%	926	0.011**	(0.004)	firm <i>f.e.</i>	31.6%	1,100
	0.041***	(0.011)	time & firm <i>f.e.</i>	32.7%	926	0.036***	(0.009)	time & firm <i>f.e.</i>	34.7%	1,100

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**Table 2 - Summary statistics**

Table 2: Panel A shows summary statistics for the futures returns and the measures of commodity producer default risk, where producers are taken as firms with SIC code 1311 (Crude Oil and Natural Gas extraction). The longest sample (Heating Oil) is from 1979Q4 to 2010Q4. Crude Oil futures return data is from 1983Q3 to 2010Q4, Gasoline futures data is from 1985Q1 to 2010Q4, while Natural Gas futures data is from 1990Q3 to 2010Q4. The Expected Default Frequency (EDF) data is from 1979Q3 to 2009Q4, while the Zmijewski-score (Zm-score) data is from 1979Q3 to 2010Q3. Panel B shows summary statistics for the underlying set of firms in SIC code 1311 over the same sample period. Firms are required to have total assets larger than 10MM to be included in the sample. The observations the percentiles are based on are at the firm-year level. The aggregate leverage observations are annual. For the Zmijewski-score sample, there are 2971 firm-year observations, whereas for the EDF sample from KMV, which contains larger firms on average, there are 892 firm-year observations.

<b>Panel A:</b> Aggregate	Mean	St.dev.	AR(1)	N
<b>Quarterly futures return:</b>				
Crude Oil	3.75%	20.5%	-0.07	110
Heating Oil	4.16%	20.0%	-0.03	125
Gasoline	6.29%	21.4%	-0.11	104
Natural Gas	-0.28%	28.7%	0.08	82
<b>Aggregate producer default risk measures:</b>				
EDF	1.89%	1.70%	0.82	121
Zm	-2.60	0.334	0.76	125

<b>Panel B:</b> firm-level	5%-tile	25%-tile	50%-tile	75%-tile	95%-tile	Mean
<i>Zmijewski-score sample:</i>						
Firm size (\$M)	9	44	194	946	7247	1701
Leverage	0%	0%	14%	31%	67%	20%
VW aggregate leverage	15%	19%	22%	29%	38%	25%
Zmijewski-score	-4.5	-3.8	-2.7	-1.7	1.2	-1.2
<i>EDF-score sample:</i>						
Firm size	15	122	542	2079	13877	2841
Leverage	0%	14%	27%	42%	77%	30%
VW aggregate leverage	18%	23%	30%	38%	49%	31%
EDF	0.1%	0.2%	0.6%	2.2%	16%	2.6%

**Table 3 - Futures and spot return forecasting regressions**

Table 3: Panel A shows the results from regressions of Crude Oil, Heating Oil, Gasoline, and Natural Gas futures returns on lagged default risk of oil and gas producers, as measured by the Expected Default Frequency (*EDF*) and Zmijewski-score (*Zm*) of firms with SIC code 1311. The controls in the regressions are lagged futures basis, aggregate default risk, GDP growth forecast (from Survey of Professional Forecasters), the risk-free rate, as well as quarterly dummy variables as controls for seasonality. Panel B shows the same regressions, but for forecasting log spot price changes. Heteroskedasticity and autocorrelation adjusted standard errors are used (Newey-West; 3 lags). In the pooled regressions, in the two right-most columns, Rogers standard errors are used to control for heteroskedasticity and autocorrelation (3 lags). \* denotes significance at the 10% level, \*\* denotes significance at the 5% level, and \*\*\* denotes significance at the 1% level.

	Crude Oil		Heating Oil		Gasoline		Natural Gas		All	
	EDF	Zm	EDF	Zm	EDF	Zm	EDF	Zm	EDF	Zm
<b>Panel A:</b> Dependent variable: next quarter futures return ( $r_{t,t+1}^i$ )										
<i>DefRisk<sub>t</sub></i>	0.058*** (0.023)	0.045*** (0.017)	0.047*** (0.021)	0.035*** (0.017)	0.040* (0.026)	0.031 (0.024)	0.061* (0.035)	0.058 (0.039)	0.046*** (0.019)	0.038*** (0.016)
controls?	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
<i>R</i> <sup>2</sup>	10.6%	9.7%	9.6%	8.5%	15.2%	13.4%	10.0%	11.0%	7.6%	7.1%
<i>N</i>	107	110	122	125	100	103	79	82	408	420
<b>Panel B:</b> Dependent variable: next quarter log spot price change ( $\Delta s_{t,t+1}^i$ )										
<i>DefRisk<sub>t</sub></i>	0.056*** (0.023)	0.043*** (0.018)	0.038*** (0.019)	0.033*** (0.016)	0.051*** (0.023)	0.045*** (0.022)	0.063*** (0.027)	0.059* (0.034)	0.045*** (0.016)	0.038*** (0.016)
controls?	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
<i>R</i> <sup>2</sup>	18.0%	16.9%	19.2%	19.1%	17.7%	17.0%	14.4%	15.4%	10.4%	10.1%
<i>N</i>	107	110	122	125	100	103	79	82	408	420

**Table 4 - Sample partitions: Hedgers vs. non-hedgers and out-of-sample analysis**

Table 4: Panel A shows the results from joint regressions of Crude Oil, Heating Oil, Gasoline, and Natural Gas futures returns on the aggregate Zmijewski- and EDF-scores of oil producers that hedge and oil producers that do not hedge. The classification of hedgers versus non-hedgers is based on the quarterly reports of firms with SIC code 1311 over the period 2000Q4 to 2010Q4, as explained in the main text. The default-scores of hedgers are orthogonalized with respect to the non-hedger scores, and all default risk measures are normalized to have unit variance.  $\beta_H$  is the regression coefficient on the measures of hedger default risk, while  $\beta_{NH}$  is the default risk of the producers that do not hedge. Panel B shows out-of-sample  $R^2$ 's for futures return forecasting regressions using the default risk measures as the predictive variable for each commodity. The in-sample estimation period uses data up until 2005Q4, while the out-of-sample results are for the period 2006Q1 to 2010Q4 (2010Q1 in the case of the EDF-score given its data availability). The out-of-sample  $R^2$ 's are calculated with respect to the respective commodity's sample mean up until 2005Q4, as explained in the main text. Heteroskedasticity and autocorrelation adjusted (Newey-West; 3 lags) standard errors are used. \* denotes significance at the 10% level, \*\* denotes significance at the 5% level, and \*\*\* denotes significance at the 1% level.

<b>Panel A: Hedgers vs. non-hedgers</b>	<b>Zm - score</b>		<b>EDF - score</b>	
Hedger default risk ( $\beta_H$ )	0.052** (0.022)	0.096*** (0.028)	0.069*** (0.024)	0.081*** (0.023)
Non-hedger default risk ( $\beta_{NH}$ )	-0.017 (0.013)	-0.004 (0.020)	-0.032 (0.029)	-0.021 (0.037)
controls?	no	yes	no	yes
$R^2$	5.6%	11.9%	10.3%	13.9%
$N$	172	172	160	160

<b>Panel B: Out-of-sample results</b> ( $r_{t,t+1}^i = \alpha^i + \beta^i DefRisk_t + \varepsilon_{t,t+1}^i$ )	<b>Crude Oil</b>		<b>Heating Oil</b>		<b>Gasoline</b>		<b>Natural Gas</b>	
	EDF	Zm	EDF	Zm	EDF	Zm	EDF	Zm
In-sample: until 2005Q4								
$R_{in-sample}^2$	1.3%	2.6%	1.5%	2.5%	0.9%	0.8%	2.4%	2.1%
$N_{in-sample}$	90	90	105	105	83	83	62	62
Out-of-sample: 2006Q1 - 2009Q4/2010Q4								
$R_{out-of-sample}^2$	3.5%	6.8%	1.0%	6.2%	7.8%	5.1%	-28.7%	3.9%
$N_{out-of-sample}$	16	20	16	20	16	20	16	20

**Table 5 - Interaction between hedging desire and speculator risk tolerance**

Table 5: The two first columns of Panel A show the results from pooled regressions of Crude Oil, Heating Oil, Gasoline, and Natural Gas futures returns on lagged default risk of oil and gas producers, as measured by the Expected Default Frequency (*EDF*) and Zmijewski-score (*Zm*), respectively, as well as realized variance (*RV*) for each of the futures returns and their interaction. The two last columns of Panel A show the change in the log spot prices regressed on the same regressors. The controls in the regressions are lagged futures basis, aggregate default risk, forecasted GDP growth, the risk-free rate, as well as quarterly dummy variables (seasonality), Panel B uses growth in Broker-Dealer assets relative to household assets (*BD*) as the regressor instead of the realized variance used in Panel A. Panel C has both lagged *BD* and *RV* as regressors, as well as the interaction of both of these variables with the default risk measures. Rogers standard errors are used to control for heteroskedasticity, cross-correlation, and autocorrelation (3 lags). \* denotes significance at the 10% level, \*\* denotes significance at the 5% level, and \*\*\* denotes significance at the 1% level.

	Joint tests across all commodities								
	Futures return		Spot change		Futures return		Spot change		
	EDF	Zm	EDF	Zm	EDF	Zm	EDF	Zm	
<b>Panel A:</b>					<b>Panel B:</b>				
<i>RV<sub>t</sub></i>	-0.002 (0.013)	-0.007 (0.012)	0.000 (0.015)	-0.006 (0.012)	<i>BD<sub>t</sub></i>	-0.046*** (0.011)	-0.041** (0.015)	-0.048*** (0.010)	-0.043*** (0.015)
<i>DefRisk<sub>t</sub></i>	0.036** (0.016)	0.033* (0.018)	0.036** (0.016)	0.034* (0.018)	<i>DefRisk<sub>t</sub></i>	0.032** (0.015)	0.024 (0.020)	0.031* (0.015)	0.027 (0.020)
<i>RV × DefRisk</i>	0.022** (0.010)	0.015** (0.07)	0.026** (0.010)	0.021*** (0.006)	<i>BD<sub>t</sub> × DefRisk<sub>t</sub></i>	-0.028*** (0.007)	-0.015** (0.006)	-0.026*** (0.008)	-0.013 (0.011)
controls?	yes	yes	yes	yes	controls?	yes	yes	yes	yes
<i>R</i> <sup>2</sup>	8.6%	7.7%	11.8%	11.5%	<i>R</i> <sup>2</sup>	13.7%	10.9%	17.5%	15.0%
<i>N</i>	404	416	404	416	<i>N</i>	408	420	408	420
<b>Panel C:</b>									
<i>RV<sub>t</sub></i>	-0.004 (0.013)	-0.006 (0.012)	-0.003 (0.013)	-0.006 (0.012)					
<i>BD<sub>t</sub></i>	-0.045*** (0.011)	-0.042** (0.016)	-0.049*** (0.010)	-0.045*** (0.016)					
<i>DefRisk<sub>t</sub></i>	0.029* (0.017)	0.018 (0.023)	0.029 (0.018)	0.020 (0.024)					
<i>RV × DefRisk</i>	0.017* (0.010)	0.017** (0.007)	0.020** (0.010)	0.021*** (0.007)					
<i>BD × DefRisk</i>	-0.026*** (0.006)	-0.014** (0.007)	-0.024*** (0.008)	-0.012 (0.011)					
controls?	yes	yes	yes	yes					
<i>R</i> <sup>2</sup>	13.8%	11.3%	18.1%	16.1%					
<i>N</i>	404	416	404	416					

**Table 6 - CFTC positions, Inventory, and the Basis Spread**

Table 6: This table shows the results from pooled regressions of net short hedger positions relative to total hedger positions as recorded by the CFTC, inventory, and the spot-futures basis for Crude Oil, Heating Oil, Gasoline, and Natural Gas on contemporaneous default risk of oil and gas producers. The default risk measures are the Expected Default Frequency (*EDF*) and Zmijewski-score (*Zm*). The inventory and basis regressions apply an instrumental variable approach described in the main text. The controls in the regressions are the futures basis, aggregate default risk, forecasted GDP growth, the risk-free rate, the lagged dependent variable, as well as quarterly dummy variables (seasonality). Rogers standard errors are used to control for heteroskedasticity, cross-correlation, and autocorrelation (3 lags). \* denotes significance at the 10% level, \*\* denotes significance at the 5% level, and \*\*\* denotes significance at the 1% level.

	<b>CFTC positions</b>		<b>Inventory</b>		<b>Basis Spread</b>	
	EDF	Zm	EDF	Zm	EDF	Zm
<i>DefRisk</i>	0.097** (0.048)	0.152*** (0.044)	-0.096** (0.047)	-0.067** (0.038)	0.138** (0.069)	0.151 (0.093)
controls?	yes	yes	yes	yes	yes	yes
$R^2$	16.3%	20.1%	43.0%	44.8%	9.1%	10.1%
$N$	354	370	408	420	408	420

**Table 7 - Sample partitions: The Role of Managerial Risk Aversion**

Table 7: The table shows results relating firm level hedging data collected from 10-Q reports for all firms with SIC code 1311 (Crude Oil and Natural Gas Extraction) in the period 2000Q1 to 2010Q4, to data on executive compensation from ExecuComp from 1992 to 2010. Based on the CEO company stock holdings and option positions relative to the base salary, firms are classified as in a yearly cross-sectional sort as having a 'risk averse' or 'risk tolerant' manager, coded with value of '1' and '0', respectively. High stock holdings and low option holdings leads to a classification as a risk averse manager, while low stock holdings and high option holdings lead to classification as a risk tolerant manager. The ExecuComp data is annual and Panel A show panel regressions where the dependent variable is the average firm-year data point corresponding to the question "Does the firm currently have significant short crude oil derivatives positions?" and where the binary variable giving the risk aversion of the manager is on variable is on the right hand side ( $\beta_{execu}$ ). Firm size is used as a control in the regressions ( $\beta_{size}$ ), as well as time fixed effects. The standard errors are robust and clustered at the CEO level. Panel B shows the results from pooled regressions of Crude Oil, Heating Oil, Gasoline, and Natural Gas futures returns on lagged measures of aggregate default risk of oil and gas producers that have risk averse managers ( $\beta_{RA}$ ) versus the default risk of oil producers that have risk tolerant managers ( $\beta_{RT}$ ). The median Zmijewski- and EDF-scores for each set of firms are used as the forecasting variables. Rogers standard errors are used to control for heteroskedasticity, cross-correlation, and autocorrelation (3 lags). \* denotes significance at the 10% level, \*\* denotes significance at the 5% level, and \*\*\* denotes significance at the 1% level.

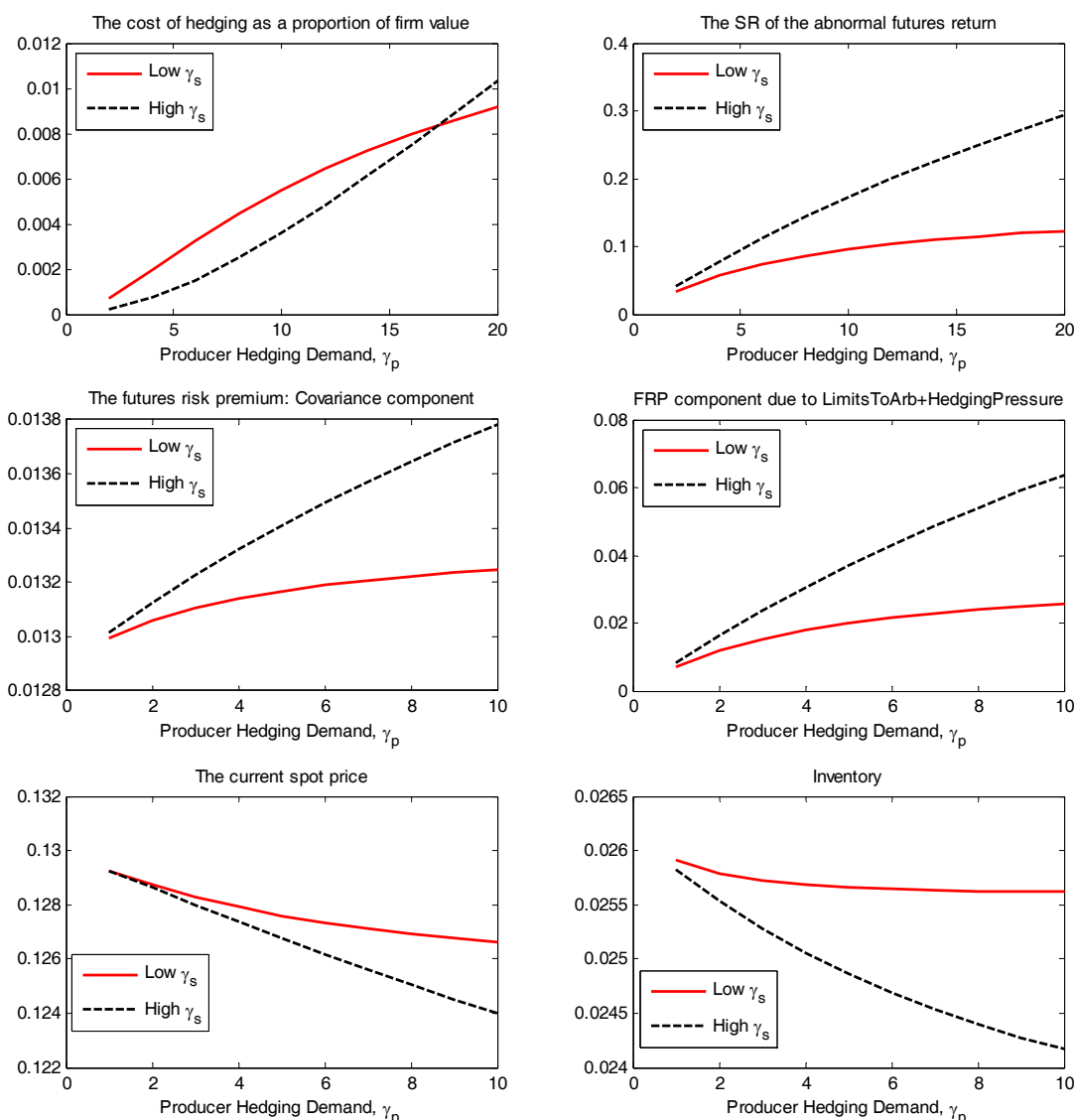
<b>Panel A: Crude oil hedging vs. managerial risk aversion</b>							
Indep.var:	Indicator for top half firm equity and bottom half options / salary						
Specification	$\beta_{execu}$	(s.e.)	$\beta_{size}$	(s.e.)	time fixed effect?	$R^2_{adj}$	$N$
1	0.172	(0.106)			no	6.3%	291
2	0.191*	(0.116)			yes	17.4%	291
3	0.187**	(0.092)	-0.086**	(0.038)	no	23.1%	291
4	0.206**	(0.104)	-0.084**	(0.042)	yes	29.2%	291

<b>Panel B: Managerial Risk Aversion and Default Risk</b>				
	<b>Zm - score</b>		<b>EDF - score</b>	
Risk averse managers' default risk ( $\beta_{RA}$ )	0.048*	0.044*	0.016	0.032**
	(0.026)	(0.026)	(0.022)	(0.014)
Risk tolerant managers' default risk ( $\beta_{RT}$ )	-0.007	0.009	0.004	0.027
	(0.038)	(0.040)	(0.039)	(0.034)
controls?	no	yes	no	yes
$R^2$	7.7%	11.0%	6.0%	11.6%
$N$	272	272	272	272

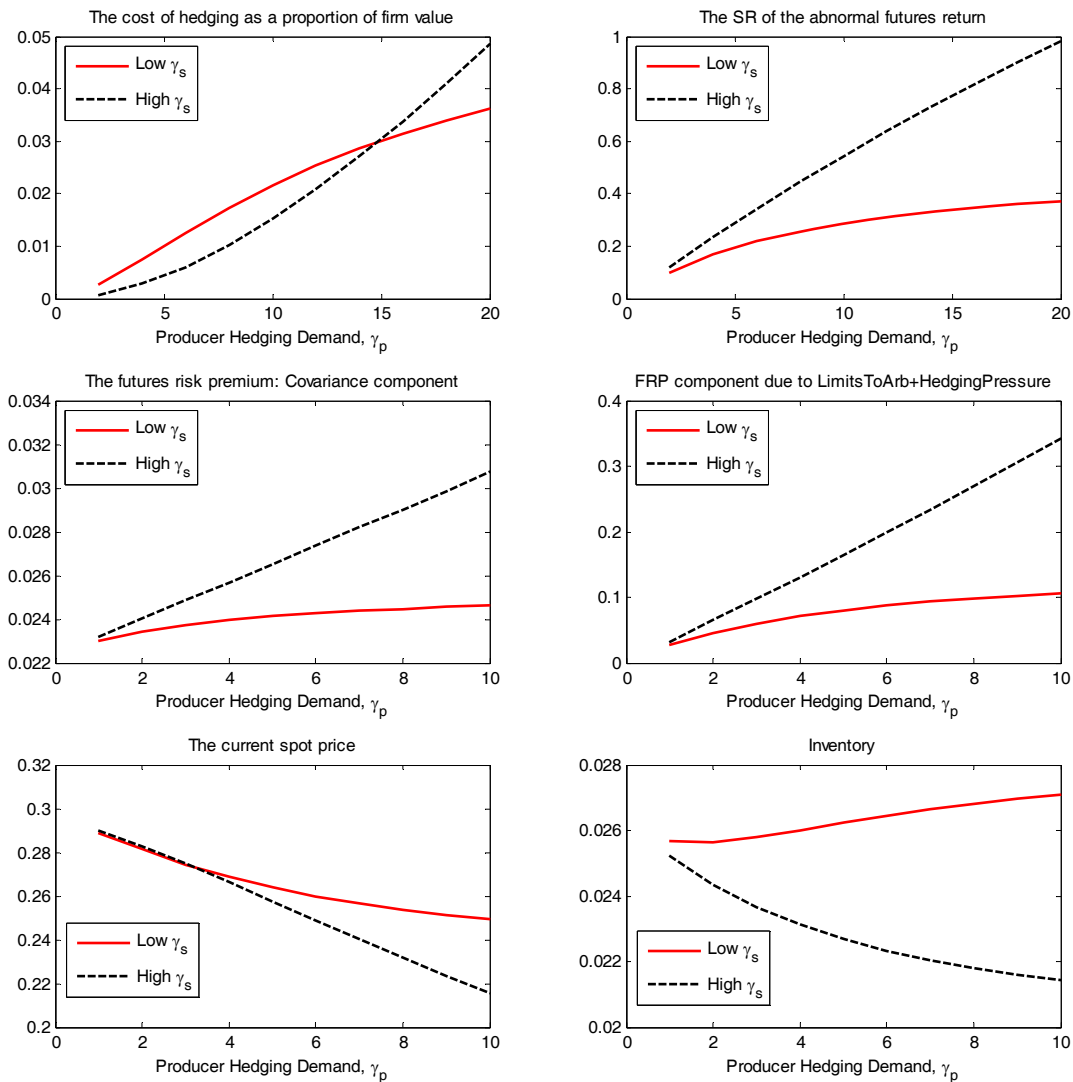
**Figure 1a – General Equilibrium Model Predictions**

All plots have producer fundamental hedging demand ( $\gamma_p \in \{2, 4, \dots, 20\}$ ) on the horizontal axis. The dashed line corresponds to high speculator capital constraints ( $\gamma_s=40$ ), while the solid line is the case of low speculator capital constraints ( $\gamma_s=8$ ). The two top plots show the cost of hedging as a proportion of firm value (left) and the quarterly Sharpe ratio of the abnormal returns earned by speculators. The two middle plots show (on the left) the component of the futures risk premium due to the covariance with the equity market pricing kernel and (on the right) the component due to the combination of hedging pressure and limits to arbitrage. The two lowest graphs show the current spot price and the optimal inventory. Here the elasticity of intratemporal substitution ( $\varepsilon$ ) equals 0.1 and the weight of the commodity in the utility function ( $\omega$ ) equals 0.01. The other numbers used in the calibration of the model are given in the main text.



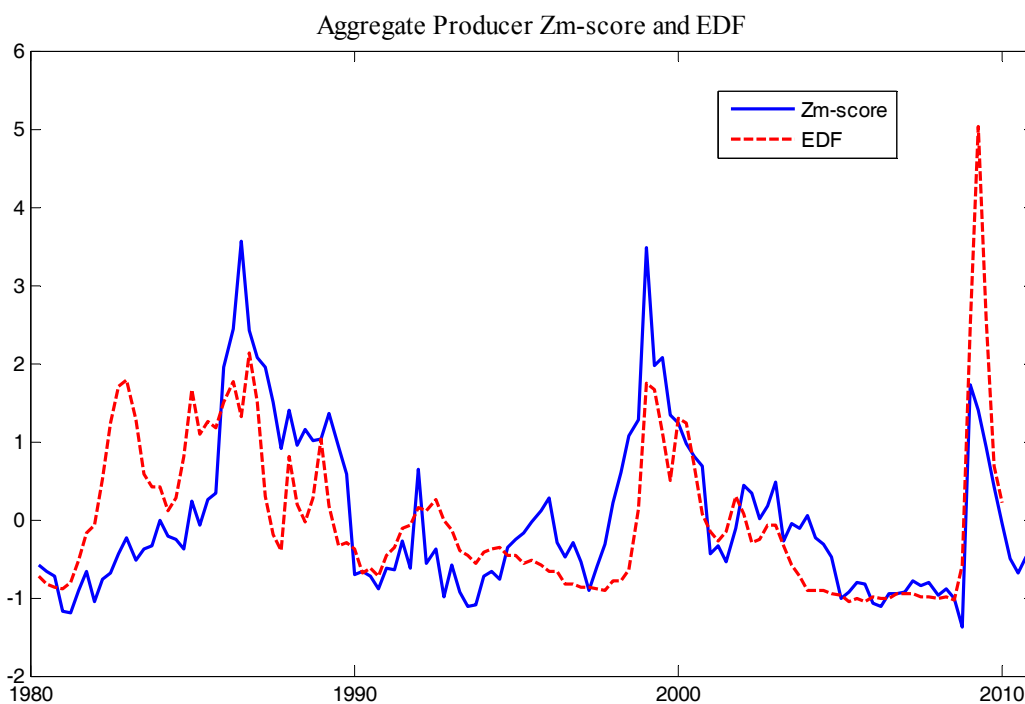
**Figure 1b – General Equilibrium Model Predictions**

All plots have producer fundamental hedging demand ( $\gamma_p \in \{2, 4, \dots, 20\}$ ) on the horizontal axis. The dashed line corresponds to high speculator capital constraints ( $\gamma_s=40$ ), while the solid line is the case of low speculator capital constraints ( $\gamma_s=8$ ). The two top plots show the cost of hedging as a proportion of firm value (left) and the quarterly Sharpe ratio of the abnormal returns earned by speculators. The two middle plots show (on the left) the component of the futures risk premium due to the covariance with the equity market pricing kernel and (on the right) the component due to the combination of hedging pressure and limits to arbitrage. The two lowest graphs show the current spot price and the optimal inventory. In this case, the elasticity of intratemporal substitution ( $\epsilon$ ) equals 0.08 and the weight of the commodity in the utility function ( $\omega$ ) equals 0.012 – slightly different from the case shown in Figure 1a. The other numbers used in the calibration of the model are given in the main text.



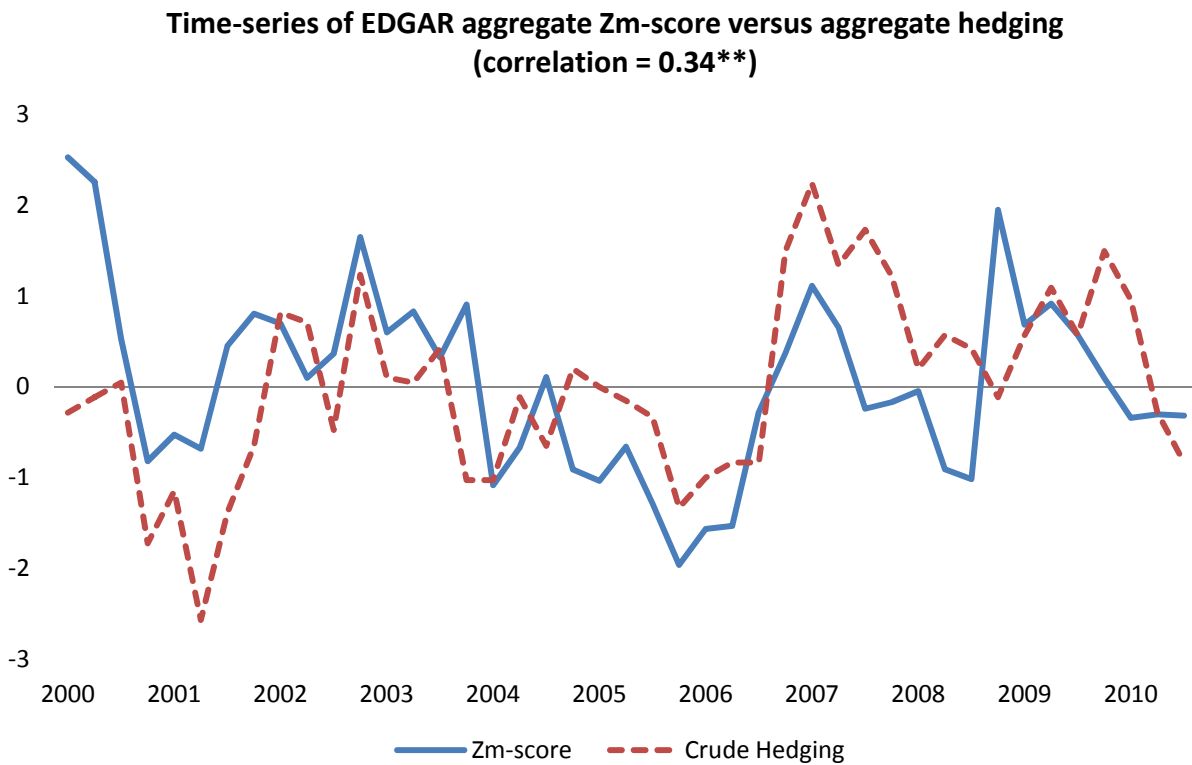
**Figure 2 – Aggregate Default Risk Measures**

The graph shows the aggregate commodity default risk measures (the Zm-score and EDF) for Crude Oil and Natural Gas producers (SIC code 1311), measured quarterly. The Zm-score data is from 1979Q3 to 2010Q4. The EDF data is from 1980Q1 to 2009Q4. Both series are normalized to have zero mean and unit variance for ease of comparison.



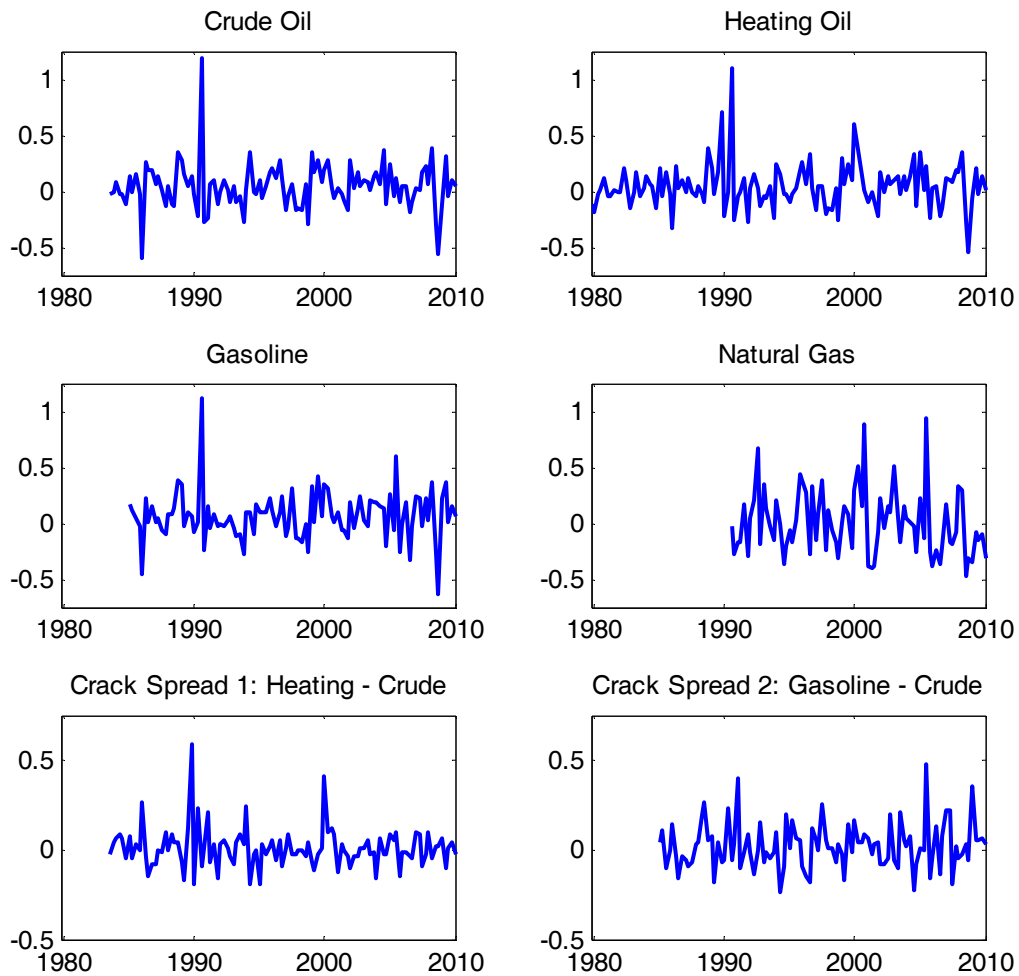
**Figure 3 – Firm Crude Oil Hedging and Default Risk**

The top plot shows the average “Significant short crude derivatives positions” (see main text for definition) across firms in a given quarter for which 10-Q data on Crude Oil hedging is available versus the median Zmijewski-score across the same firms in the same quarter. The data period is 2000Q1 to 2010Q4. In order to facilitate easy comparison between these aggregate data series, both series have been normalized to have zero mean and unit variance.



**Figure 4 – Futures returns**

The figure shows the quarterly futures returns used in the paper for the sample that is available for each commodity. The futures return is for the second to closest to maturity contract. The position is assumed to be rolled over if the next-nearest to maturity changes within the quarter. The vertical axis is the log return (1 corresponds to a 100% log return). The horizontal axis gives the year. The sample length varies as different contracts were introduced at different times.



**Figure 5 – Hedging versus Arbitrage Activity**

The top plot shows the product of Crude Oil quarterly futures return and lagged demeaned EDF (solid line) versus the lagged growth in Broker-Dealer assets relative to households assets (dotted line). The former is a measure of the realized covariance of the futures risk premium and hedging demand, whereas the latter is a measure of arbitrage risk tolerance. The bottom plot shows the same for the Zmijewski-score. The two measures are plotted as annual moving averages. The graphs show that if speculators have high risk tolerance (i.e., B-D growth is high), changes in hedging demand has a small effect on the risk premium as demand is met elastically. If, however, speculators have low risk capacity (B-D growth is low), small changes in hedging demand has a large impact on the futures risk premium as these investors now need more incentive (in the case of increased hedging demand) to take the opposing positions.

