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Broker-Dealer Risk Appetite and Commodity Returns

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Abstract

This paper shows that the risk-bearing capacity of U.S. securities brokers and dealers is a strong determinant of risk premia in commodity markets. Commodity derivatives are the principal instrument used by producers and consumers of commodities to hedge against commodity price risk. Broker-dealers play an important role in this hedging process because commodity derivatives are traded primarily over the counter. I capture the limits of arbitrage in this market in a simple asset-pricing model where producers and consumers of commodities share risk with broker-dealers who are subject to funding constraints. In equilibrium, the price of aggregate commodity risk decreases in the relative leverage of the broker-dealer sector. I estimate the model in the cross-section of commodities and find strong empirical support for its predictions. Fluctuations in risk-bearing capacity have particularly strong forecasting power for energy returns, both in sample and out of sample.

Key words: asset pricing, financial intermediaries, commodity prices, futures markets, risk appetite

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1. Introduction

This paper shows that the risk-bearing capacity of U.S. securities brokers and dealers is a strong determinant of risk premia in commodity markets. Commodity related derivatives are the principal means by which producers and consumers of commodities hedge the price risk of their physical positions. This risk is often termed "non-marketable" as transaction costs make the trading of physical commodities unattractive to financial investors. Since the majority of commodity derivatives are bilateral over-the-counter (OTC) contracts between a client and a financial intermediary, broker-dealers play a key role in the hedging process. I capture the limits of arbitrage (Shleifer and Vishny, 1997) in this market by deriving a simple asset pricing model where producers and consumers of commodities share risk with broker-dealers who are subject to funding constraints. In equilibrium, the price of aggregate commodity risk decreases in the relative leverage of the broker-dealer sector. I estimate the model in the cross-section of individual commodities and find strong empirical support for its predictions. Fluctuations in risk-bearing capacity have particularly strong forecasting power for energy returns, both in-sample and out-of-sample.

Broker-dealers are leveraged financial institutions, such as investment banks, who "buy and sell securities for a fee, hold an inventory of securities for resale, or do both."[1] They are distinguished from other investor classes by their active, pro-cyclical management of leverage: Adrian and Shin (2008a) document that expansions in broker-dealer assets are accompanied by increases in leverage as broker-dealers take advantage of greater balance sheet capacity. Conversely, contractions in broker-dealer assets are accompanied by decreases in leverage as risk constraints tighten. Consequently, to an outside observer, it would appear that the risk-bearing capacity, or *effective risk aversion*, of broker-dealers changes with market outcomes. The literature on limits of arbitrage and its applications to seg-

[1] *Guide to the Flow of Funds Accounts*, Board of Governors of the Federal Reserve (2000)

mented markets suggests that the pricing implications of time-varying effective risk aversion are largest when broker-dealers are predominantly on one side of the market.[2]

Following this literature, I argue that the effective risk aversion of broker-dealers determines risk premia in commodity derivatives because broker-dealers are, to a large extent, the marginal investor on the speculative side of the market. The importance of broker-dealers stems from the high degree of intermediation required to funnel financial investor capital into commodities. Unlike stocks, bonds and other securities, the trading of many physical commodities involves significant transportation and storage costs as well as possible informational asymmetries (such as quality concerns), which discourage financial investors from engaging in physical commodity transactions in the marketplace. To bypass these market imperfections, commodity price risk can be securitized and traded via derivatives that reference physical commodities. A brief overview of this market is provided below.

1.1. Market for Commodity Derivatives

There are two broad categories of commodity derivatives: exchange-traded derivatives and OTC derivatives. Exchange-traded derivatives include futures and options traded in exchanges such as the New York Mercantile Exchange and Chicago Mercantile Exchange. While in principle any investor can buy or sell these securities, the large notional sizes of futures contracts and the perceived riskiness of commodities have traditionally discouraged retail and institutional investors alike. Only recently have investable commodity indexes and exchange traded funds made the asset class more accessible to a broader class of investors.[3] Despite this de-

[2] Gromb and Vayanos (2010) provide an excellent survey of the theoretical literature on limits of arbitrage. An example of a situation where financial intermediaries are predominantly on one side of the market is provided by Froot (1999) who studies the pricing of catastrophe insurance.

[3] Tang and Xiong (2010) examine the financialization process of commodities precipitated by the rapid growth of index investment to the commodities markets since the early 2000s.

velopment, the exchange-traded market still represents *less than* 10% of the total market for commodity derivatives: At the peak of the June 2008 boom, the Commodity Futures Trading Commission (2008) estimated the total notional value of all commodity futures and options outstanding in U.S. exchanges to be $946 billion, which is approximately 85% of all exchange-traded commodity derivatives outstanding worldwide (Bank for International Settlements, 2008). At the same time, the Bank for International Settlements estimated the total notional value of all OTC commodity derivatives outstanding worldwide to be $13.2 trillion.

Unlike standardized contracts traded in exchanges, OTC derivatives (such as forwards, swaps, and options) are tailored to suit the needs of individual investors. In OTC transactions clients bargain *directly* with broker-dealers who are the market makers in these derivatives. Upon reaching an agreement, the broker-dealer may hold the commodity risk on its trading book until it receives an offsetting OTC position, or it may hedge its net exposure using an exchange-traded derivative or another OTC contract. In addition to the price risk associated with pure market making, most commodity traders take on commodity risk by choosing not to hedge their books or by holding entirely speculative positions. Some larger broker-dealers even speculate by holding outright positions in physical commodities.

The overwhelming size of the OTC market relative to the exchange-traded market highlights the importance of broker-dealer capital for the functioning of commodity derivatives markets. As such, the premium that hedgers are required to pay for insurance against commodity price risk is likely to be affected by the effective risk aversion of broker-dealers. To the extent that hedgers' demand for insurance is independent of broker-dealers' risk constraints, broker-dealers' effective risk aversion can be expected to impact the equilibrium returns on commodity derivatives.[4] Absence of arbitrage across derivatives markets implies that the risk

[4]Grossman and Miller (1988) emphasize that hedgers also have a strong preference for immediacy in hedging transactions. This further increases their vulnerability to shifts in broker-

premia of OTC transactions are also incorporated in the returns on exchange-traded derivatives.[5]

1.2. Theoretical and Empirical Strategy

I formalize the link between broker-dealer risk-bearing capacity and security risk premia by deriving a simple asset pricing model where risk-constrained broker-dealers provide insurance to households who wish to hedge their positions in physical commodities. Broker-dealer leverage is limited by a value-at-risk (VaR) constraint, which caps the probability of insolvency.[6] In equilibrium, the required return on a security depends on its comovement with the market portfolio, but also on its residual comovement with the aggregate portfolio of physical commodities. I refer to the latter as the aggregate non-marketable portfolio. Thus, there is an additional systematic risk factor—the return on the aggregate non-marketable portfolio—which determines security returns in addition to the market risk factor. The premium per unit of non-marketable risk is pinned down by the economy's effective risk aversion. I show that the effective risk aversion varies over time with the tightness of broker-dealers' risk constraints and it can be expressed as a function of aggregate balance sheet components of broker-dealers and households. This innovation allows me to estimate the model using aggregate balance sheet data from the Federal Reserve's Flow of Funds Accounts.

The model predicts that, controlling for market risk, the measure of effective risk aversion forecasts returns on securities that co-move with the aggregate non-marketable portfolio. Since the market risk adjusted returns of different securities load differently on the non-marketable risk factor, the model also delivers a cross-sectional prediction for the magnitude and direction of the forecasting

dealers' effective risk aversion.

[5] Due to poor availability of OTC forwards data, the empirical section uses data on futures contracts.

[6] Adrian and Shin (2008c) provide a micro foundation for this constraint from a moral hazard problem between borrowers and lenders.

relationship. The empirical section of the paper tests these predictions for 14 commodity futures, two investable commodity indexes, and other securities.

1.3. Related Literature

This paper builds on two broad strands of literature: the literature on financial market frictions and asset prices as well as the extensive literature on the determinants of commodity prices.

The idea that the risk-bearing capacity of arbitrageurs is limited and has consequences for asset prices originates in the work on limits of arbitrage pioneered by Shleifer and Vishny (1997). Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) are among the first to relate arbitrageurs' inability to exploit price differences to endogenous balance sheet constraints. The specific funding constraints analyzed in this paper build on the work of Adrian and Shin (2008a,b,c) who demonstrate that the active management of financial intermediary balance sheets generates procyclical leverage, which has consequences for asset prices. My finding that the risk-bearing capacity of broker-dealers determines risk premia in commodity markets is most similar in spirit to the finding of Adrian, Etula and Shin (2009) that fluctuations in short-term U.S. dollar funding liquidity determine risk premia in foreign exchange markets, and to the finding of Adrian and Shin (2008a) that fluctuations in short-term funding liquidity forecast changes in the VIX risk premium. The view that balance sheet constraints influence risk premia receives strong support in the events of the 2007-2009 financial market turmoil, which show how the tightening of financial intermediary funding constraints may lead to substantial systematic asset pricing consequences.

The literature on the determinants of expected commodity returns can be roughly divided into two groups. The first group uses the CAPM to argue that the expected return on commodity holdings is compensation for systematic risk. Early studies include Black (1976) and Breeden (1980) who explain the variation in futures prices by systematic risk that stems from changes in economic state variables. Tests of these models find scant evidence in the data, as shown by Jagannathan (1985) and a number of other studies. More recently, Bessembinder and Chan (1992) find that the same variables that forecast market returns — e.g., dividend yield, interest rate, and yield spread — also forecast commodity returns. This suggests that time-varying risk premia in commodities could be driven by macro-economic forces that determine asset allocation. Gorton and Rouwenhorst (2006) argue that commodity futures, as an asset class, provide a risk-return profile that is comparable to that of equities.

The second group of studies argues that the expected return of holding commodities is driven largely by commodity-specific factors. Most relevant for the present paper are the studies that find additional forecastability of commodity futures returns using the net positions of hedgers in the futures market, which is known as hedging pressure. The idea of hedging pressure dates back to Keynes (1930) whose theory of normal backwardation argues that producers short futures to hedge their initially long positions in the underlying physical commodity. Gorton, Hayashi and Rouwenhorst (2007) provide a comprehensive review of the literature and show that while the direction of net hedging is consistent with Keynes' hedging pressure hypothesis, commodity-specific hedging pressures do not have significant forecasting ability for futures returns. Models that allow both systematic and commodity-specific predictors of futures prices include Stoll (1979) and Hirschleifer (1988, 1989). Empirical evidence for the combined role of commodity-specific hedging pressure and systematic risk include Carter, Rausser and Schmidt (1992), Bessembinder (1992), and de Roon, Nijman and Veld (2000). Hong and Yogo (2009) show that the aggregate futures basis explains as much of the variation in expected returns as systematic predictors.

The current paper contributes to the first group of commodity studies by demonstrating that, for a set of commodities, a significant portion of the time-variation in expected returns can be attributed to time-variation in U.S. broker-dealer risk appetite. The paper's argument for why broker-dealer risk appetite matters for expected commodity returns builds on the second group of studies: broker-dealers have an important role in providing insurance to producers and consumers of commodities who wish to hedge their positions in the underlying commodities. Anson (2002) and Erb and Harvey (2006) suggest that futures strategies that engage in such insurance provision have earned positive excess returns. The results in this paper are also nicely consistent with the recent finding of Acharya, Lochstoer and Ramadorai (2009) that the risk appetite of oil and gas *producers*, as proxied by their default risk, forecasts future returns on these commodities. The authors build on my results to show that both broker-dealer risk-bearing capacity and producer default risk forecast commodity returns.

My theoretical framework combines insights from the commodity pricing model of de Roon, Nijman and Veld (2000) and the asset pricing model of Danielsson, Shin and Zigrand (2008). In the latter model, the risk appetite of arbitrageurs shifts endogenously with balance sheet constraints that fluctuate with market outcomes, generating endogenous risk. The balance sheet constraints are imposed by a contracting setting of Adrian and Shin (2008c), which yields a value-at-risk rule. In addition to the literature on limits of arbitrage, the model has similarities with the large behavioral finance literature on noise trader risk (e.g. DeLong, Shleifer, Summers and Waldmann, 1990; Barberis, Shleifer and Vishny, 1998; Hong and Stein, 1999) , and market making (e.g. Grossman and Miller, 1988; Kyle, 1985). It is also consistent with Duffie and Strulovici's (2009) model of limited capital mobility where higher costs of intermediation increase return volatility and prolong temporary risk premia. Overall, the distinguishing feature of the current theoretical framework is its ability to generate time-varying effective risk aversion without restrictive assumptions on the behavior of passive traders. By focusing on the actions of risk-constrained financial institutions, the model is also distinctly different from the consumption-based models that generate time-varying risk aversion through, for instance, habit formation (Campbell and Cochrane, 1999; Chan and Kogan, 2002).

The outline of the paper is as follows. Section 2 develops a simple theoretical model, which introduces risk-constrained broker-dealers in an equilibrium pricing model for commodities. Section 3 estimates the model in the data and conducts robustness checks. Section 4 digs deeper into energy commodities and offers a discussion of the 2008 run-up in energy prices. Section 5 concludes.

2. Theoretical Framework

As discussed above, there is an extensive literature that relates commodity risk premia to two components: systematic marketable risk and commodity-specific hedging pressure.[7] The latter arises from risks that agents cannot, or do not want to, trade because of market frictions such as transaction costs or informational asymmetries. Following this literature, consider an economy with marketable assets A, forwards contracts F, and non-marketable assets N. Let the respective vectors of *excess* returns be denoted by $\mathbf{r}_{t+1}^{A}$, $\mathbf{r}_{t+1}^{F}$, and $\mathbf{r}_{t+1}^{N}$. The non-marketable assets may serve as the underlying value of the forwards contracts and can also coincide with some of the marketable assets. While the non-marketable assets by definition do not enter the market portfolio, they may influence portfolio choice.

Suppose there are two types of agents in the economy: funding constrained broker-dealers and risk averse households. The portfolio of agent j consists of positions in marketable assets $\boldsymbol{\omega}_{A,t}^{j}$, forwards $\boldsymbol{\omega}_{F,t}^{j}$, and non-marketable assets $\mathbf{q}_t^j$:

$$r_{t+1}^{j} = \boldsymbol{\omega}_{A}^{j\prime}\mathbf{r}_{t+1}^{A} + \boldsymbol{\omega}_{F}^{j\prime}\mathbf{r}_{t+1}^{F} + \mathbf{q}^{j\prime}\mathbf{r}_{t+1}^{N}.$$

Each position is expressed as a fraction of the agent's financial wealth, e_t^j.

[7] For instance, de Roon, Nijman and Veld (2000).

2.1. Funding Constrained Broker-Dealers

Suppose broker-dealers (bd) are risk neutral but subject to risk constraints, which ensure that each dealer's equity $\left(e_t^{bd}\right)$ is sufficiently large to cover their Value at Risk (VaR_t).[8] Broker-dealers trade only marketable securities. That is, they tend to shy away from direct purchases and sales of physical commodities because of aforementioned costs associated with such transactions. Thus, the return on broker-dealer equity derives from positions in marketable assets and forwards:

$$r_{t+1}^{bd} = \boldsymbol{\omega}_{A,t}^{bd\prime}\mathbf{r}_{t+1}^{A} + \boldsymbol{\omega}_{F,t}^{bd\prime}\mathbf{r}_{t+1}^{F}.$$

Each broker-dealer chooses its portfolio to maximize expected return on equity, subject to the VaR constraint,

$$\max_{\boldsymbol{\omega}_{A,t}^{bd},\boldsymbol{\omega}_{F,t}^{bd}} E_t\left(r_{t+1}^{bd}\right) \quad s.t.\ VaR_t \leq e_t^{bd}.$$

By risk neutrality, the risk constraint binds with equality, determining the leverage of the dealer's portfolio. If VaR_t is some multiple κ of equity volatility $e_t^{bd}\sqrt{Var_t\left(r_{t+1}^{bd}\right)}$, the constraint becomes $\sqrt{Var_t\left(r_{t+1}^{bd}\right)} \leq \frac{1}{\kappa}$. The Lagrangian is:

$$\mathcal{L}_t = E_t\left(r_{t+1}^{bd}\right) - \phi_t\left(\sqrt{Var_t\left(r_{t+1}^{bd}\right)} - \frac{1}{\kappa}\right). \tag{2.1}$$

Define $\mathbf{r}_{t+1} = \left(\mathbf{r}_{t+1}^{A}, \mathbf{r}_{t+1}^{F}\right)'$, $\boldsymbol{\omega}_t^{bd} = \left(\boldsymbol{\omega}_{A,t}^{bd}, \boldsymbol{\omega}_{F,t}^{bd}\right)'$, and use the binding VaR constraint $\sqrt{Var_t\left(r_{t+1}^{bd}\right)} = \frac{1}{\kappa}$ to obtain the FOC:

$$\boldsymbol{\omega}_t^{bd} = \frac{1}{\kappa\phi_t}\left[Var_t\left(\mathbf{r}_{t+1}\right)\right]^{-1} E_t\left(\mathbf{r}_{t+1}\right). \tag{2.2}$$

This characterizes the broker-dealer's optimal portfolio choice.

Note that equation (2.2) is identical to the standard mean-variance choice but with the risk-aversion parameter replaced by $\kappa\phi_t$, the Lagrange multiplier

[8] My formulation follows Danielsson, Shin and Zigrand (2009) who study this optimization problem in another context.

associated with the risk constraint scaled by the constant κ. In other words, broker-dealers are risk-neutral but behave as if they were risk-averse. As the risk constraint binds harder, the shadow price ϕ_t increases, and leverage must be reduced. The scaled Lagrange multiplier $\kappa\phi_t$ measures the *effective risk aversion* of broker-dealers. Plugging the broker-dealers' portfolio choice (2.2) in the binding VaR constraint, one obtains:

$$\phi_t = \sqrt{E_t\left(\mathbf{r}_{t+1}\right)' \left[Var_t\left(\mathbf{r}_{t+1}\right)\right]^{-1} E_t\left(\mathbf{r}_{t+1}\right)}.$$

That is, the Lagrange multiplier associated with the risk constraint is proportional to the generalized Sharpe ratio for the set of risky securities traded in the market as a whole.

2.2. Risk Averse Households

Suppose the rest of the investors are risk averse households (hh). They trade off mean against variance in the portfolio return, which depends on the returns on marketable assets, forwards, and non-marketable assets:

$$r_{t+1}^{hh} = \boldsymbol{\omega}_{A,t}^{hh\prime}\mathbf{r}_{t+1}^{A} + \boldsymbol{\omega}_{F,t}^{hh\prime}\mathbf{r}_{t+1}^{F} + \mathbf{q}_t^{hh\prime}\mathbf{r}_{t+1}^{N}.$$

Households choose positions in marketable securities to solve:

$$\max_{\boldsymbol{\omega}_{A,t}^{hh},\boldsymbol{\omega}_{F,t}^{hh}} E_t\left(r_{t+1}^{hh}\right) - \frac{\gamma}{2} Var_t\left(r_{t+1}^{hh}\right).$$

Defining $\boldsymbol{\omega}_t^{hh} = \left(\boldsymbol{\omega}_{A,t}^{hh}, \boldsymbol{\omega}_{F,t}^{hh}\right)'$, one obtains the optimal portfolio choice:

$$\boldsymbol{\omega}_t^{hh} = \frac{1}{\gamma}\left[Var_t\left(\mathbf{r}_{t+1}\right)\right]^{-1}\left[E_t\left(\mathbf{r}_{t+1}\right) - \gamma Cov_t\left(\mathbf{r}_{t+1}, \mathbf{r}_{t+1}^{N}\right)\mathbf{q}_t^{hh}\right]. \tag{2.3}$$

2.3. Market Portfolio

Since forwards contracts are in zero net supply, market clearing implies:

$$\boldsymbol{\omega}_t^M = \begin{pmatrix} \boldsymbol{\omega}_{A,t}^M \\ 0 \\ \vdots \\ 0 \end{pmatrix} = \begin{pmatrix} \frac{e_t^{hh}}{e_t^{bd}+e_t^{hh}}\boldsymbol{\omega}_{A,t}^{hh} + \frac{e_t^{bd}}{e_t^{bd}+e_t^{hh}}\boldsymbol{\omega}_{A,t}^{bd} \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \tag{2.4}$$

If the market portfolio is efficient in the sense that it satisfies the FOCs (2.2) and (2.3) for κ, ϕ_t, γ, q_t^{hh}, e_t^{hh} and e_t^{bd}, one obtains:

$$E_t\left(\mathbf{r}_{t+1}\right) = \phi_t^M\left[Cov_t\left(\mathbf{r}_{t+1}, r_{t+1}^M\right) + Cov_t\left(\mathbf{r}_{t+1}, \mathbf{r}_{t+1}^N\right)\mathbf{q}_t^M\right], \tag{2.5}$$

where $r_{t+1}^M = \boldsymbol{\omega}_t^{M\prime}\mathbf{r}_{t+1}$ is the return on the market porfolio,

$$\frac{1}{\phi_t^M} = \frac{e_t^{hh}}{e_t^{bd}+e_t^{hh}}\frac{1}{\gamma} + \frac{e_t^{bd}}{e_t^{bd}+e_t^{hh}}\frac{1}{\kappa\phi_t} \tag{2.6}$$

is the inverse of the economy's effective risk aversion, and

$$\mathbf{q}_t^M = \frac{e_t^{hh}}{e_t^{bd}+e_t^{hh}}\mathbf{q}_t^{hh} \tag{2.7}$$

is the vector of aggregate non-marketable positions in the economy. Note that the aggregates in (2.6) and (2.7) are wealth-weighted combinations of the two investor groups' respective variables.

2.4. Equilibrium Returns

Letting $\beta_t^i = \frac{Cov_t\left(r_{t+1}^i, r_{t+1}^M\right)}{Var_t\left(r_{t+1}^M\right)}$ denote security i's beta with the portfolio of marketable assets, the expression (2.5) for equilibrium returns can be rewritten as:

$$\begin{aligned} E_t\left(r_{t+1}^i\right) &= \beta_t^i E_t\left(r_{t+1}^M\right) + \left[Cov_t\left(r_{t+1}^i, \mathbf{r}_{t+1}^N\right)\mathbf{q}_t^M - \beta_t^i Cov_t\left(r_{t+1}^M, \mathbf{r}_{t+1}^N\right)\mathbf{q}_t^M\right]\phi_t^M \\ &= \beta_t^i E_t\left(r_{t+1}^M\right) + Cov_t\left(r_{t+1}^i - \beta_t^i r_{t+1}^M, r_{t+1}^{NM}\right)\phi_t^M. \end{aligned} \tag{2.8}$$

The second line defines:

$$r_{t+1}^{NM} = \mathbf{r}_{t+1}^{N\prime}\mathbf{q}_t^M, \tag{2.9}$$

which is interpreted as the excess return on the aggregate production-weighted portfolio of Non-Marketable securities. Here non-marketable securities are physical commodities, and hence r_{t+1}^{NM} is the excess spot return on a portfolio of commodities weighted by world production values. The equilibrium of the model is summarized in:

Proposition 1 (Equilibrium Returns). *The risk premium of security i depends on its comovement with the aggregate portfolio of marketable assets and its comovement with the aggregate portfolio of non-marketable assets:*

$$\underbrace{E_t\left(r_{t+1}^i\right)}_{\substack{\text{Security}\\ \text{Risk Premium}}} = \underbrace{\beta_t^i E_t\left(r_{t+1}^M\right)}_{\substack{\text{Compensation for Systematic}\\ \text{Marketable Risk}}} + \underbrace{\delta_t^i \phi_t^M}_{\substack{\text{Compensation for Systematic}\\ \text{Non-Marketable Risk}}}, \tag{2.10}$$

where $\beta_t^i = Cov_t\left(r_{t+1}^i, r_{t+1}^M\right)/Var_t\left(r_{t+1}^M\right)$ is the security's market beta and $\delta_t^i = Cov_t\left(r_{t+1}^i - \beta_t r_{t+1}^M, r_{t+1}^{NM}\right)$ is the covariance of the security's risk-adjusted return with the aggregate non-marketable portfolio. The risk premium per a unit of β_t^i is the expected return on the portfolio of marketable assets, $E_t\left(r_{t+1}^M\right)$. The risk premium per a unit of δ_t^i is the economy's effective risk aversion, ϕ_t^M.

Importantly, the compensation for systematic non-marketable risk varies across securities, as summarised in the following corollary:

Corollary 1 (Cross-Sectional Prediction). *The risk premium of security i increases in effective risk aversion if its risk-adjusted return covaries positively with the portfolio of non-marketable assets, $\delta_t^i > 0$. Conversely, the risk premium of security i decreases in effective risk aversion if its risk-adjusted return covaries negatively with the portfolio of non-marketable assets, $\delta_t^i < 0$.*

Strictly speaking (2.10) prices only securities—marketable assets and forwards. However, it is possible that efficient inventory management (basis arbitrage) by holders of physical commodities keeps the excess returns on some cash commodities close to the returns on the corresponding nearby forwards contracts.[9] Hence, the equilibrium pricing predictions of the model may carry over to some spot returns.

2.5. Empirical Implementation

Proposition 1 states that security risk premia are determined by two systematic risk components: one that stems from aggregate marketable risk and another that stems from aggregate non-marketable risk. I can test the empirical validity of the proposition by estimating (2.10) for individual securities returns. To do this, I assume constant conditional variances and covariances, replace the expectations in by realizations, and add a constant to obtain:

$$r_{t+1}^{i} = \alpha_i + \beta_i r_{t+1}^{M} + \delta_i \phi_t^{M} + \epsilon_{t+1}^{i}, \tag{2.11}$$

where $\epsilon_{t+1}^{i} \equiv r_{t+1}^{i} - E\left(r_{t+1}^{i}|1, r_{t+1}^{M}, \phi_t^{M}\right)$ is the prediction error. Since the effective risk aversion ϕ_t^M is not directly observable in the data, the next step is to express it as a function of observable variables.

Start by rewriting (2.6) as

$$\phi_t^M = \gamma \left[1 + \frac{e_t^{bd}}{e_t^{hh}}\left(1 - \frac{\phi_t^M}{\kappa\phi_t}\right)\right]. \tag{2.12}$$

In order to obtain an expression for $\frac{\phi_t^M}{\kappa\phi_t}$, plug the equilibrium expressions (2.5) and (2.9) in the broker-dealer's FOC (2.2):

$$\boldsymbol{\omega}_t^{bd} = \frac{\phi_t^M}{\kappa\phi_t}\left[Var_t\left(\mathbf{r}_{t+1}\right)\right]^{-1}\left[Cov_t\left(\mathbf{r}_{t+1}, r_{t+1}^{M}\right) + Cov_t\left(\mathbf{r}_{t+1}, r_{t+1}^{NM}\right)\right].$$

Using the definition of the market portfolio and defining $\mathbf{h}_t \equiv \left[Var_t\left(\mathbf{r}_{t+1}\right)\right]^{-1} Cov_t\left(\mathbf{r}_{t+1}, r_{t+1}^{NM}\right)$, the above simplifies to:

$$\boldsymbol{\omega}_t^{bd} = \frac{\phi_t^M}{\kappa\phi_t}\left(\boldsymbol{\omega}_t^{M} + \mathbf{h}_t\right), \tag{2.13}$$

[9] See, for instance, Acharya, Lochstoer and Ramadorai (2009).

where vector $\mathbf{h}_t$ captures the net short open interest of households. To see this, note that households collectively wish to short $h_t^i \left(e_t^{bd} + e_t^{hh}\right)$ dollars worth of marketable security i to hedge the price risk that stems from their aggregate holdings of non-marketable securities.[10] Equation (2.13) states that broker-dealers fulfill a fraction $\frac{\phi_t^M}{\kappa \phi_t}$ of this open interest. Note that h_t^i is loosely related to the notion of hedging pressure, which is commonly defined as the net short open interest of hedgers divided by the total open interest of hedgers. Summing (2.13) over individual securities positions, one obtains:

$$\frac{\phi_t^M}{\kappa \phi_t} = \frac{\sum_i \omega_{i,t}^{bd}}{\sum_i \omega_{i,t}^M + \sum_i h_{i,t}}. \tag{2.14}$$

By balance sheet identity, the value of risky securities holdings of investor j must equal the value of equity plus the value of debt:

$$e_t^j \sum_i \omega_{i,t}^j = e_t^j + debt_t^j,$$

which implies that one can define the financial leverage of broker-dealers and households as:

$$lev_t^j \equiv 1 + \frac{debt_t^j}{e_t^j} = \sum_i \omega_{i,t}^j, \quad j \in \{bd, hh\},$$

and the aggregate financial leverage is given by:

$$lev_t^M \equiv 1 + \frac{debt_t^{bd} + debt_t^{hh}}{e_t^{bd} + e_t^{hh}} = \sum_i \omega_{i,t}^M.$$

Using this notation, substitute (2.14) into (2.12) to obtain:

$$\phi_t^M = \gamma \left[1 + \frac{e_t^{bd}}{e_t^{hh}} \left(1 - \frac{lev_t^{bd}}{lev_t^M + \sum_i h_{i,t}}\right)\right]. \tag{2.15}$$

Since the focus of this paper is the broker-dealer sector, not the hedging decisions of producers and consumers of commodities, I will assume that the aggregate

[10] Since the net supply of hedging positions is zero, these positions are not part of the market portfolio.

net open interest of hedgers is constant over time, $\sum_i h_{i,t} \stackrel{t}{=} H$, such that:

$$\phi_t^M = \gamma \left[1 + \frac{e_t^{bd}}{e_t^{hh}} \left(1 - \frac{lev_t^{bd}}{lev_t^M + H} \right) \right]. \tag{2.16}$$

Equation (2.16) states that the time-variation in effective risk aversion can be explained by the product of two terms: the first term is the fraction of broker-dealer equity relative to household equity; the second term is the fraction of broker-dealer financial leverage relative to the financial leverage of the market plus a constant. In the absence of broker-dealers $\left(e_t^{bd} = 0\right)$, the effective risk aversion is constant and given by γ. Normalizing the constants $\gamma = 1$ and $H = 0$, equation (2.16) motivates the following empirical proxy for effective risk aversion:

$$\hat{\phi}_t^M = 1 + \frac{\text{Broker-Dealer Equity}_t}{\text{Household Equity}_t} \left(1 - \frac{\text{Broker-Dealer Leverage}_t}{\text{Market Leverage}_t} \right). \tag{2.17}$$

2.5.1. Time-Series

I employ (2.17)'s measure of effective risk aversion in (2.11) to obtain the time-series regression:

$$r_{t+1}^i = \alpha_i + \beta_i r_{t+1}^M + \delta_i \hat{\phi}_t^M + \epsilon_{t+1}^i, \tag{2.18}$$

where r_{t+1}^i is the excess return on security i, and r_{t+1}^M is the excess return on the market. This is the main regression specification to be estimated in Section 3.2.

A potential caveat of the measure of effective risk aversion in (2.17) is the implicit assumption that one can always infer broker-dealers' risk-bearing capacity from their *level* of leverage. In reality, however, this assumption may not hold. For instance, it is conceivable that there are frictions in the market that do not allow broker-dealers to adjust leverage instantaneously in response to changes in risk constraints. One such potential friction is market illiquidity, which limits the broker-dealer's ability to rapidly buy and sell large quantities of securities in the marketplace. In the presence of such frictions, tighter risk constraints may coincide with high but decreasing leverage as broker-dealers strive to decrease the size of their balance sheets. Similarly, more permissive funding conditions may coincide with low but increasing leverage as broker-dealers look for ways to put their increased balance sheet capacity to work.

Thus, it is possible that one may not be able to accurately infer the level of effective risk aversion from the levels of balance sheet variables. Yet, one might be able to capture changes in effective risk aversion, or at least the direction of these changes, from observable balance sheet dynamics. To investigate this possibility, Section 3.2 also implements the following specification:

$$r_{t+1}^{i} = \alpha_i + \beta_i r_{t+1}^{M} + \delta_i \Delta \hat{\phi}_t^{M} + \epsilon_{t+1}^{i}, \tag{2.19}$$

where $\Delta \hat{\phi}_t^{M} = \hat{\phi}_t^{M} - \hat{\phi}_{t-1}^{M}$ is the first difference in (2.17).

2.5.2. Cross-Section

In order to test the cross-sectional prediction of the model (Corollary 1), I compute the model-predicted loadings on ϕ_t^M for individual commodity derivatives and indexes by:

$$\delta_i^{Model} = Cov\left(r_{t+1}^{i} - \beta_i r_{t+1}^{M}, r_{t+1}^{NM}\right), \tag{2.20}$$

where β_i is the OLS estimate of security i's market beta, r_{t+1}^{M} is the market excess return, and r_{t+1}^{NM} is the excess return on the GSCI Spot index, which weights commodities by their respective world production quantities.[11] I then compare these model-predicted loadings δ_i^{Model} to the OLS estimates of δ_i obtained from (2.18) . The results are analyzed in Section 3.3.

3. Empirical Results

The previous section provided a simple theoretical justification for the link between the tightness of broker-dealer risk constraints and the economy's effective

[11] Recall that the weights of the non-marketable portfolio r_{t+1}^{NM} are given by the vector of aggregate non-marketable positions q_t^M in the economy.

risk aversion, ϕ_t^M. The analysis also demonstrated how to construct an empirical proxy for effective risk aversion using data on the aggregate balance sheet components of broker-dealers and households. In this section, I follow these instructions to investigate the extent to which the theoretical predictions of the model hold in the data. The baseline regressions cover the time period Q3/1990-Q4/2007, the beginning of which was selected based on data availability. The time period Q1/2008-Q3/2009, which includes the 2008 run-up and crash in crude oil prices as well as the dramatic contraction in broker-dealer balance sheets, is studied separately at the end of the section.

3.1. Data

The empirical analysis focuses on the futures and spot returns of four energy commodities (crude oil, heating oil, gasoline and natural gas), four metals (copper, silver, platinum, gold), and six agricultural commodities (sugar, cotton, corn, soybeans, cocoa, and wheat).[12] The individual commodities were selected based on their respective world production quantities and the liquidity of futures contracts. I also use data on two investable commodity futures indexes (S&P Goldman Sachs Commodity Index and Dow Jones-UBS Commodity Index). The price data on individual commodities and commodity indexes are obtained from Bloomberg and Datastream. Excess spot returns are generated by subtracting the 3-Month Treasury Bill rate from the total quarterly returns. Since positions in futures contracts are "pure bets" in the sense that they require no investment outlays, excess futures returns are given simply by percentage price changes. To ensure liquidity, I compute quarterly returns from rolling front-month contracts.[13]

[12] Due to poor availability of data on OTC forwards, I use data on futures contracts instead. By absence of arbitrage, futures returns can be expected to reflect the risk premia of OTC contracts.

[13] The one-month excess return at the end of month t is given by

$$\frac{F_{t,T}}{F_{t-1,T}} - 1,$$

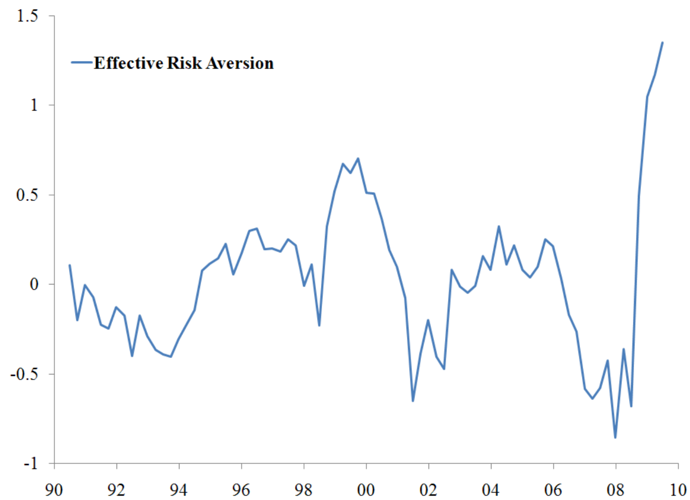

Figure 3.1: Effective risk aversion, linearly detrended, Q3/1990 - Q3/2009.

The balance sheet data are obtained from the Federal Reserve's Flow of Funds database, which reports quarterly aggregate values of financial assets and liabilities for U.S. securities broker-dealers and households. These data and the precise instructions in (2.17) allow me to construct an empirical measure of effective risk aversion.[14] I remove a secular downward trend by orthogonalizing the variable relative to a linear time trend. A plot of the resulting series is displayed in Figure 3.1. Note the sharp increases in effective risk aversion following the U.S. bond market blow-up and the Latin American crisis of 1994-95, the LTCM crisis of 1998, the corporate scandals that preceded the Sarbanes-Oxley act of 2002, and the deepening of the subprime crisis in 2008.

I also use supplementary data on equity returns, bond returns, bond yields and

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

[14] Since the leverage (assets/equity) of the broker-dealer sector exceeds the leverage of households, the measure of $\hat{\phi}_t^M$ in (2.17) is less than unity for all t.

technical indicators, which are provided by Bloomberg. The data on the positions of hedgers (commercials) and speculators (non-commercials) in commodity futures exchanges are obtained from the Commitment of Traders reports published weekly by the Commodity Futures Trading Commission.[15]

3.2. Time-Series Analysis

Table 1 displays the results from the estimation of section 2's model for futures returns (panel A) and spot returns (panel B) of individual energy, metal, and agricultural commodities. For each commodity, two specifications are considered: the first estimates (2.18) by regressing the quarterly excess return on the S&P 500 excess return and lagged effective risk aversion; the second estimates (2.19) by regressing the quarterly excess return on the S&P 500 excess return and lagged change in effective risk aversion. Note that all independent variables have been standardized to zero mean and unit variance to facilitate the interpretation of regression results.

Beginning with the first specification, the results in panel A show that effective risk aversion is a statistically significant predictor of expected futures returns for crude oil, its derivatives heating oil and unleaded gasoline, natural gas, soybeans, cocoa, and wheat. The coefficients of effective risk aversion also reveal an interesting sign pattern: they are positive for energy commodities but negative for most agricultural commodities. For instance, if the level of effective risk aversion is one standard deviation above average, investors require 4 percentage points higher returns on their long positions in crude oil futures but 5 percentage points lower returns on their long positions in wheat futures over the following quarter. This cross-sectional finding is consistent with the theoretical model and will be discussed in detail in the next subsection.

The results from the second specification are very similar. The only qualitative

[15] See Bessembinder (1992) for a discussion of the CFTC's distinction between hedgers and speculators.

difference is that the change in effective risk aversion seems to beat the level as a predictor of returns on energy commodities while the level seems to beat the change as a predictor of returns on agricultural commodities. For instance, if the increase in effective risk aversion is one standard deviation greater than the average quarterly change, investors require as much as 8 percentage points higher returns on long crude oil futures positions but only about 3 percent lower returns on long wheat positions over the following quarter. The finding that the change in risk appetite also forecasts excess returns lends support to the conjecture that there may be frictions in the marketplace that prevent broker-dealers from adjusting leverage instantaneously in response to changes in risk constraints; thus, the change in this balance sheet based measure of effective risk aversion may be a better proxy for higher-frequency fluctuations in risk constraints.

While my asset pricing theory does not directly apply to prices of physical commodities, efficient inventory management may generate comovement between the expected spot and futures return for some commodities. Panel B investigates this possibility by conducting the above set of regressions for excess spot returns. The table shows that the level of effective risk aversion is not a statistically significant predictor of excess returns for most spot commodities. The change in effective risk aversion offers more explanatory power but overall the results for spot returns are substantially weaker than the results for futures returns.[16]

Finally, Table 1C estimates the model for index returns. The first columns consider the S&P Goldman Sachs Commodity Index (GSCI) and the Dow Jones-UBS Commodity Index (DJCI), which are tradeable futures indexes with different underlying compositions. The GSCI is weighted by world production values and is thereby biased toward energy commodities.[17] In light of Table 1A's results, it is

[16] An additional set of regressions for the futures basis (futures price relative to the spot price) as the dependent variable shows that my measure of effective risk aversion is not related to the basis. These supplementary results can be obtained from the author.

[17] Over the sample period, energy commodities have constituted approximately 50-60% of the GSCI portfolio in dollar terms.

then not surprising that higher effective risk aversion forecasts higher returns on the GSCI. The construction methodology of the DJCI, on the other hand, relies primarily on liquidity data of futures contracts and U.S. dollar-adjusted production data and is thereby substantially more diversified across different classes of commodities.[18] The results show that only the change in effective risk aversion is a statistically significant predictor of DJCI returns. As a check, the last columns of the table estimate the model for the Dow Jones Corporate Bond index. The results show that my measures of effective risk aversion have no predictive power for excess bond returns.

3.3. Cross-Sectional Analysis

The time-series results in Table 1 uncovered an interesting cross-sectional pattern: an increase in effective risk aversion forecasts higher returns on energy futures but lower returns on most agricultural futures. In this subsection, I will investigate how this pattern squares with the cross-sectional prediction of the model (Corollary 1). First, I follow the instructions in (2.20) to construct model-predicted coefficients δ_i^{Model} of individual security returns on the lag of effective risk aversion. I then plot the OLS-estimated coefficients from Tables 1A and 1C against the model-predicted coefficients. The results are displayed in Figure 3.2. The scatter plot lends substantial support to the model: the empirical coefficient estimates line up with the model-predicted coefficients; the R^2 of a linear fit is 81%.

This cross-sectional result provides an asset-pricing explanation for the diverse impact of effective risk aversion on risk premia across commodities. As predicted by the model, time-variation in effective risk aversion has the greatest impact on securities whose risk-adjusted returns covary the most (positively or negatively) with the aggregate non-marketable portfolio, which constitutes an additional source of systematic risk. Intuitively, some securities are riskier than what

[18] See http://www.djindexes.com/ubs/.

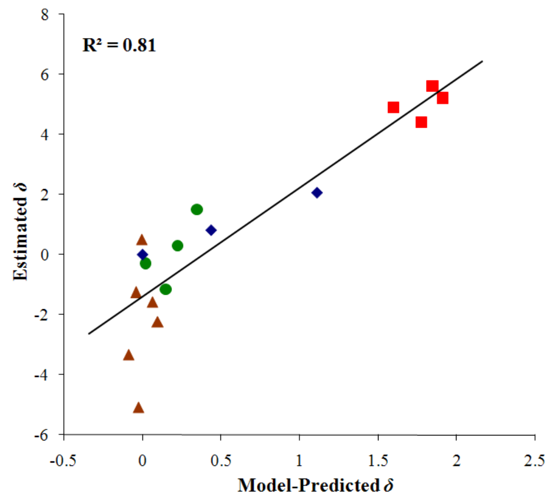

Figure 3.2: Commodity futures and futures indexes: Estimated vs. model-predicted coefficients of effective risk aversion for energy (squares), metal (circles) and agricultural (triangles) commodities, plus three indexes (diamonds).

is predicted by their loading on the market risk factor since they comove positively with the aggregate non-marketable portfolio. Investors demand higher risk premia for holding these securities and the risk premia grow as effective risk aversion increases. Conversely, other securities may be hedges against non-marketable risks and command a lower risk premium than what would be predicted by their loading on the market risk factor. When effective risk aversion increases, the hedging value of these securities increase and their risk premia compress.

One can go further by computing the average compensation that investors require for a unit exposure of non-marketable risk. Using the coefficient estimates from Tables 1A and 1C, a straightforward application of the Fama and MacBeth (1973) two-step approach delivers an average risk premium per a unit of δ of 0.46% per quarter. The average risk premium per a unit of β (market risk) is statistically insignificant.[19]

[19] These supplementary results can be obtained from the author.

3.4. Robustness

The estimation results in Tables 1A and 1C demonstrated that effective risk aversion is a statistically and economically significant predictor of many commodity futures returns, controlling for market risk. In this subsection, I will take a step away from the theoretical specification to investigate the extent to which the predictive information contained in my measure of effective risk aversion is new to the literature. Specifically, I will compare the forecasting ability of effective risk aversion to the forecasting ability of other variables that previous literature has identified as significant predictors of commodity returns. In the interest of space, I will focus the analysis on two commodity futures, crude oil and wheat, which represent the two extremes in terms of the direction of the predictive relationship.

The results are displayed in the panels of Table 2. Panel A regresses the crude oil futures return on lagged effective risk aversion, lagged change in effective risk aversion and a set of lagged controls. Panel B conducts the same regressions for wheat futures. Column (i) shows that effective risk aversion alone explains approximately 18% of the returns on crude oil futures over the next quarter; and approximately 12% of the returns on wheat futures. Column (ii) includes an autoregressive term and columns (iii)-(viii) add a number of lagged control variables from the literature:[20] The common predictors include the VIX volatility index, interest rate, yield spread, dividend yield, and inflation rate. The commodity specific predictors include the futures basis and hedging pressure.[21] For wheat, the coefficient of effective risk aversion is significant across all specifications and its magnitude increases from -4.6 to -7.2 as one adds the full set of controls. For crude oil, the level of effective risk aversion seems to be dominated by the change in risk aversion, which is highly significant across all specifications. The magnitude of the coefficient is also robust to the addition of controls; it stays above 8.2

[20] See, for instance, Bessembinder and Chan (1992) and Hong and Yogo (2009).

[21] Hedging pressure measures commercial hedgers' net exposure to a particular futures market. It is defined as the net short open interest of hedgers divided by the total open interest of hedgers.

in all specifications. These results suggest that the information contained in the measure of effective risk aversion is quite different from the information content of existing predictors.[22]

The results also demonstrate that few controls help predict commodity returns beyond the measure of effective risk aversion: For crude oil, only lagged hedging pressure is statistically significant; and for wheat, only lagged VIX and lagged hedging pressure are significant. One might suspect that multicollinearity causes part of the observed insignificance of control variables. However, comparing the adjusted R^2 across different specifications suggests that only the statistically significant controls contribute materially to the power of the regressions.[23]

3.5. Focus on Energy

In order to dig deeper in the link between effective risk aversion and risk premia, this subsection narrows the scope of investigation by focusing on energy returns. I will first investigate the emergence of return forecastability. I will then study the robustness of the forecasting relationship out-of-sample. Finally, I will examine the extent to which my measure of effective risk aversion can explain the large fluctuations of energy prices in 2008-2009. While the primary focus is on crude oil, the qualitative results obtain also for heating oil, gasoline, and the GSCI, which has a high weight on energy.

3.5.1. Emergence of Return Forecastability

I use rolling regressions to investigate the predictive power of effective risk aversion over time. Since the trading of crude oil futures began only in 1983, I can

[22] The results are also robust to the inclusion of seasonal dummies, inventory figures and additional proxies for the phase of the business cycle.

[23] As an additional test, one can investigate the robustness of the above predictive relationships at different forecast horizons. Regressions for returns $2-8$ quarters ahead show that both the statistical significance and the economic magnitude of the relationships remain stable over longer horizons. These results lend additional support to the strength and robustness of the dynamic connection between effective risk aversion and commodity returns.

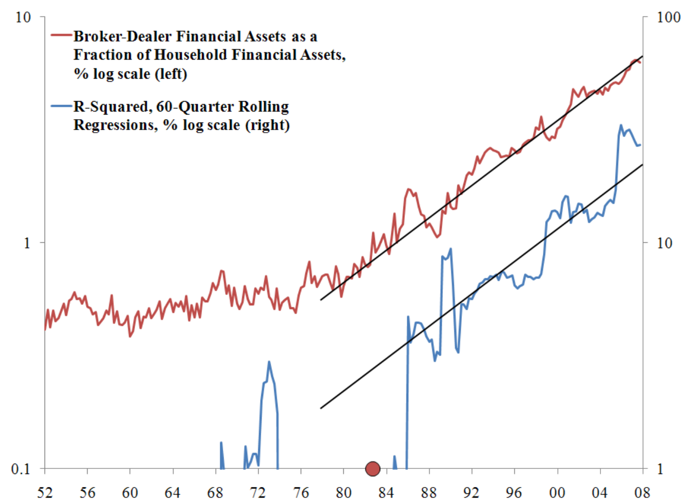

Figure 3.3: Forecasting crude oil excess returns over time. The figure plots the R-squared from rolling forecasting regressions (blue line) and the fraction of broker-dealer financial assets relative to household financial assets (red line), Q1/1952-Q4/2007. The red dot marks the March 1983 launch of crude oil futures.

extend the sample by using the excess return on spot crude oil as a dependent variable instead. Building on the result of Tables 1A-B that the change in effective risk aversion predicts both futures and spot returns, I use the lagged change in effective risk aversion as the explanatory variable. Figure 3.3 plots the R^2 from the resulting univariate regression using a 60-quarter rolling window (note the log scale). Two things are worth noting. First, the power of forecasts jumps sharply approximately three years after the crude oil futures contract begins trading in the NYMEX and the CME. This sudden increase in forecasting power suggests that the change in market structure (denoted by the red circle on the time axis) triggered a considerable improvement in price transparency in the market for crude oil.

Second, the forecasting ability of effective risk aversion has increased steadily over time. To put the growth into perspective, the figure also plots the fraction of broker-dealer assets relative to the sum of broker-dealer and household assets over time. It may not be surprising that the forecasting ability of broker-dealer risk appetite has increased along with the relative value of assets managed by the broker-dealer sector — but what is quite striking, the two variables have also grown *at the same rate* as indicated by the parallel trend lines. Taken together, these two finding lend support to the stability of the forecasting relationship over time.

3.5.2. Out-of-Sample Forecasts

As is well known, the high in-sample forecasting power of a regressor does not guarantee robust out-of sample performance, which is more sensitive to mis-specification problems. To investigate the extent to which my measure of effective risk aversion survives this tougher test, the following tests the forecastability of energy returns out of sample. In order to avoid look-ahead bias in constructing the regressor, I proxy effective risk aversion by the quarterly changes in (2.17), without detrending the series. I use recursive regressions with the out-of-sample portion starting in the third quarter of 1995.

Table 3 compares the predictive power of effective risk aversion to three benchmarks (restricted models) that are standard in the literature of out-of-sample forecasting:[24] (1) random walk, (2) random walk with drift, and (3) first-order autoregression. These benchmarks are nested in the "unrestricted" specifications, which allows one to evaluate their performance using the Clark and West (2006) adjusted difference in mean squared errors, $MSE_r - (MSE_u - adj.)$. The Clark-West test accounts for the small-sample forecast bias (*adj.*), which works in favor of the simpler restricted models and is present in the unadjusted Diebold-Mariano/West (DMW) tests. As Rogoff and Stavrakeva (2009) show, a significant Clark-West adjusted statistic implies that there exists an optimal combination between the

[24] See for instance Chen, Rogoff and Rossi (2009) who study the forecastability of commodity returns by the exchange rates of commodity currencies.

unrestricted model and the restricted model, which will produce a combined forecast that outperforms the restricted model in terms of mean squared forecast error; i.e., the forecast will have a DMW statistic that is significantly greater than zero.

The results in Table 3 show that the models with effective risk aversion outperform all three benchmarks at 1% significance level. The strength of these out-of-sample results lends additional support to the robustness of the forecasting relationship over time.

3.5.3. Effective Risk Aversion and the Energy Boom of 2008

My baseline analysis deliberately excludes the recent time period 2008-2009, which features large fluctuations in both broker-dealer leverage and energy prices. To put this period of volatility in a historical perspective, Figure 3.4 plots quarterly crude oil excess returns over the past two decades. The figure also plots the change in effective risk aversion, lagged by one quarter. The time-series of crude oil returns demonstrates that the sequence of strong positive returns from Q1/2007 to Q2/2008 has few rivals in the recent history. Similarly, the dramatic decline in the price of crude oil in the second half of 2008 from $140 per barrell to less than $40 per barrell exceeds previous price drops by a factor of two. The rate of recovery in the first half of 2009 is also record-breaking within the sample.

Inspection of the two time-series confirms the regression result that the change in effective risk aversion has a strong track record in predicting quarterly crude oil returns. In the commodity boom of early 2008, however, there seems to be a temporary break in this risk-based predictive relationship: my measure of effective risk aversion cannot explain the rise and fall in oil prices in the second and third quarters of 2008. The predictive relationship revives in Q4/2008 and holds through Q4/2009.

A possible explanation for the temporary breakdown of the relationship is

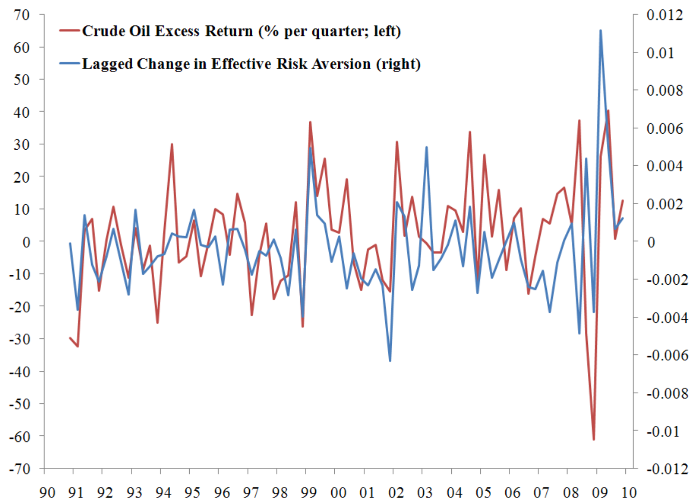

Figure 3.4: Crude oil excess returns and lagged changes in effective risk aversion

that my measure of effective risk aversion was for some time unreflective of *broader* appetite for commodity risk. Recall that this measure of effective risk aversion only reflects broker-dealers' capacity to bear risk and hence it does not capture changes in the risk preferences of other investor classes. For instance, in spring 2008 hedge funds were actively involved in a "long oil/short financials" trade, which unraveled in July 2008 as the SEC announced a ban on naked short sales. Some have also argued that increasing demand for long commodity futures positions by non-traditional investor classes such as index and pension funds were driving a bubble in energy prices that burst in the summer of 2008.[25]

[25] These commentators include George Soros who argued on April 17, 2008, that there is "a generalized commodity bubble due to commodities having become an asset class that institutions use to an increasing extent." Masters and White (2008) estimate that over the period from 2003 to mid-2008 investments in commodity indexes increased from $13 billion to $317 billion.

4. Conclusion

This paper shows how limits of arbitrage in the U.S. broker-dealer sector drive risk premia in the market for commodity derivatives. I derive a simple pricing model with non-marketable assets where time-variation in broker-dealer risk constraints generates time-variation in the economy's effective risk aversion. In equilibrium, risky securities compensate investors not only for systematic market risk but also for systematic non-marketable risk, which stems from fluctuations in the aggregate value of physical commodities. The price of non-marketable risk increases in the economy's effective risk aversion, which can be expressed as a function of aggregate balance sheet components of broker-dealers and households.

The estimation of the model in the data lends strong support to its theoretical predictions, both in the time-series and in the cross-section of commodity futures. My finding that risk constraints of broker-dealers are hardwired to risk premia in commodity derivatives has also implications for policy makers. Specifically, the paper shows how restrictions on broker-dealer trading activities can be expected to increase the costs of hedging for producers and consumers of commodities. This result will be central to understanding why restrictions on speculation by market makers may adversely impact the functioning of many derivatives markets.

In sum, the empirical and theoretical contributions of this paper may be regarded as first steps toward quantifying the asset pricing implications of limits of arbitrage in the broker-dealer sector. A plenty of research beckons in exploring this hypothesis in other derivatives markets and asset classes.

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Table 1A: Estimating the Model for Commodity Futures

The table displays the results from the estimation of (2.18) and (2.19) for returns on commodity futures. The dependent variable is the per-quarter excess futures return. Independent variables are the lagged effective risk aversion, the lagged change in effective risk aversion, and the excess return on S&P 500. All independent variables have zero mean and unit variance. The table reports point estimates with heteroskedasticity-robust t-statistics in parentheses (omitted for S&P 500 and the constant); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample period is Q3/1990- Q4/2007.

	Independent Variables						
	Effective Risk Aversion		Δ Effective Risk Aversion		S&P 500		
Excess Futures Return	(Lag 1)		(Lag 1)		Excess Return	Constant	Adj-R^2
Crude Oil	4.398**	(2.530)			-8.130**	4.971**	17.5%
			7.985***	(4.638)	-6.548*	5.162**	27.7%
Heating Oil	5.607***	(2.609)			-7.464**	4.990**	16.7%
			5.851***	(3.321)	-6.276*	5.177**	17.1%
Gasoline	5.209***	(2.819)			-8.233*	5.426**	15.9%
			6.826***	(3.623)	-6.864	5.617**	19.6%
Natural Gas	4.891*	(1.783)			-2.559	1.406	0.7%
			5.027	(1.594)	-1.538	1.568	0.8%
Copper	1.501	(1.094)			0.291	2.663*	-1.6%
			2.827*	(1.879)	0.850	2.729*	1.5%
Silver	-0.295	(-0.272)			-0.161	0.994	-2.9%
			2.284*	(1.850)	0.272	1.018	1.6%
Platinum	0.300	(0.277)			1.313	2.041**	-0.1%
			0.830	(0.744)	1.475	2.058**	0.8%
Gold	-1.164	(-1.429)			-1.377**	0.398	6.4%
			0.474	(0.748)	-1.301**	0.382	3.2%
Sugar	0.518	(0.306)			-1.669	0.836	-2.0%
			0.499	(0.210)	-1.567	0.853	-2.0%
Cotton	-1.572	(-1.304)			1.468	-1.404	0.5%
			1.857	(1.500)	1.804	-1.411	1.2%
Corn	-1.254	(-0.850)			1.133	-1.443	-1.2%
			0.458	(0.343)	1.205	-1.461	-2.1%
Soybeans	-2.228*	(-1.682)			0.160	1.031	1.5%
			-0.415	(-0.310)	0.054	0.982	-2.8%
Cocoa	-3.322***	(-2.697)			-3.333*	-0.511	13.4%
			-3.317**	(-2.248)	-4.008**	-0.620	13.2%
Wheat	-5.072**	(-2.493)			0.702	-0.468	11.8%
			-2.812**	(-2.204)	0.102	-0.604	1.6%

Table 1B: Estimating the Model for Spot Commodities

The table displays the results from the estimation of (2.18) and (2.19) for returns on spot commodities. The dependent variable is the per-quarter excess spot return. Independent variables are the lagged effective risk aversion, the lagged change in effective risk aversion, and the excess return on S&P 500. All independent variables have zero mean and unit variance. The table reports point estimates with heteroskedasticity-robust t-statistics in parentheses (omitted for S&P 500 and the constant); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample period is Q3/1990- Q4/2007.

	Independent Variables						
	Effective Risk Aversion		Δ Effective Risk Aversion		S&P 500		
Excess Spot Return	(Lag 1)		(Lag 1)		Excess Return	Constant	Adj-R^2
Crude Oil	2.665	(1.530)			-8.588**	3.113	15.6%
			7.122***	(3.495)	-7.193*	3.259	25.2%
Heating Oil	3.202*	(1.846)			-8.450**	3.417	14.0%
			6.199***	(2.600)	-7.225*	3.561	19.6%
Gasoline	2.715	(1.394)			-7.086***	2.993	9.9%
			7.564***	(3.013)	-5.605**	3.145	20.6%
Natural Gas	2.918	(0.698)			3.158	5.887	-1.4%
			-1.099	(-0.301)	2.984	5.930	-2.0%
Copper	0.933	(0.716)			0.210	0.939	-2.4%
			2.588*	(1.905)	0.716	0.992	1.4%
Silver	-0.532	(-0.512)			-0.196	1.116	-2.7%
			1.993*	(1.693)	0.179	1.132	0.7%
Platinum	0.068	(0.070)			1.378	0.979	0.1%
			1.342	(1.364)	1.636	0.998	3.0%
Gold	-1.264	(-1.525)			-1.500**	0.320	7.5%
			0.410	(0.647)	-1.437**	0.301	3.7%
Sugar	0.474	(0.317)			-0.832	-0.052	-2.5%
			1.008	(0.465)	-0.634	-0.029	-2.1%
Cotton	-2.184	(-1.440)			0.688	-0.472	1.3%
			0.646	(0.559)	0.785	-0.506	-2.3%
Corn	-2.267	(-1.340)			1.459	0.803	0.3%
			-1.119	(-0.729)	1.218	0.744	-1.5%
Soybeans	-2.953*	(-1.912)			0.819	0.811	2.7%
			-0.984	(-0.659)	0.595	0.740	-2.0%
Cocoa	-2.801***	(-2.629)			-3.078**	0.371	12.7%
			-3.208***	(-2.667)	-3.726**	0.274	14.7%
Wheat	-5.171**	(-2.144)			2.079	1.579	9.5%
			-4.427***	(-3.045)	1.169	1.420	6.4%

Table 1C: Estimating the Model for Indexes

The table displays the results from the estimation of (2.18) and (2.19) for indexes. The dependent variable is the per-quarter excess return. Independent variables are the lagged effective risk aversion, the lagged change in effective risk aversion, and the excess return on S&P 500. All independent variables have zero mean and unit variance. The table reports point estimates with heteroskedasticity-robust t-statistics in parentheses (omitted for S&P 500 and the constant); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample period is Q3/1990- Q4/2007.

	Dependent Variable: Excess Return					
	GSCI (Futures)		DJCI (Futures)		DJ Corp. Bond Index	
Effective Risk Aversion. (Lag 1)	2.060**		0.812		-0.194	
	(2.260)		(1.378)		(-0.698)	
Δ Effective Risk Aversion (Lag 1)		3.577***		2.179***		-0.083
		(3.764)		(3.466)		(-0.275)
S&P 500 Excess Return	-3.819*	-3.109	-1.051	-0.624	0.230	0.211
	(-1.950)	(-1.633)	(-1.212)	(-0.773)	(0.790)	(0.690)
Constant	1.554	1.641	-0.014	0.030	-0.776**	-0.738**
	(1.245)	(1.366)	(0.020)	(0.045)	(-2.533)	(-2.541)
# Observations	70	70	70	70	70	70
Adj-R^2	12.4%	19.1%	1.9%	12.9%	-1.4%	-1.9%

Table 2A: Robustness Checks (Crude Oil)

The dependent variable is the per-quarter excess return on crude oil futures. Forecasting variables are the lagged level and the lagged change in effective risk aversion. Control variables (each lagged by one quarter) are: the VIX implied volatility of the S&P 500, the 3-month U.S. treasury bill rate, the yield spread (difference between Moody's Aaa corporate yield and the treasury rate), the S&P 500 dividend yield, the U.S. inflation, the basis (future price over spot price), and the hedging pressure (net short open interest of hedgers relative to the total open interest of hedgers, as reported by the CFTC). A lag of the dependent variable is included in (ii)-(viii). All independent variables have zero mean and unit variance. The table reports point estimates with heteroskedasticity-robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample period is Q3/1990- Q4/2007.

	Crude Oil Futures Excess Return							
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Effective Risk Aversion. (Lag 1)	1.267	2.239	2.289	1.841	2.408	0.662	0.615	0.342
	(0.686)	(1.057)	(1.057)	(0.752)	(0.925)	(0.271)	(0.247)	(0.130)
Δ Effective Risk Aversion (Lag 1)	8.822***	8.466***	8.312***	8.576***	8.210***	8.655***	8.501***	8.500***
	(4.288)	(4.149)	(4.163)	(3.548)	(3.524)	(4.207)	(4.137)	(3.493)
Dependent Variable (Lag 1)		-0.180	-0.174	-0.171	-0.182	-0.158	-0.146	-0.260*
		(-1.373)	(-1.357)	(-1.370)	(-1.343)	(-1.136)	(-1.097)	(-1.672)
VIX (Lag 1)			-0.955	-0.860	-1.048	-2.262	-2.163	-0.577
			(-0.556)	(-0.502)	(-0.607)	(-1.151)	(-1.070)	(-0.218)
Interest Rate (Lag 1)				1.077	2.165	5.782	6.008	5.238
				(0.248)	(0.397)	(1.360)	(1.377)	(1.201)
Yield Spread (Lag 1)					1.803	4.676	4.679	3.405
					(0.601)	(1.609)	(1.589)	(1.120)
Dividend Yield (Lag 1)						-4.027	-3.652	-1.960
						(-1.161)	(-0.982)	(-0.451)
Inflation (Lag 1)							-1.358	-1.821
							(-0.743)	(-0.936)
Basis (Lag 1)								1.174
								(0.718)
Hedging Pressure (Lag 1)								5.571**
								(2.238)
Constant	5.174**	5.953**	5.916**	5.906**	5.917**	5.809**	5.764**	6.344**
	(2.299)	(2.307)	(2.287)	(2.302)	(2.290)	(2.196)	(2.188)	(2.321)
# Observations	70	70	70	70	70	70	70	70
Adj-R^2	18.0%	20.0%	19.0%	18.0%	17.0%	17.2%	16.2%	20.6%

Table 2B: Robustness Checks (Wheat)

The dependent variable is the per-quarter excess return on wheat futures. Forecasting variables are the lagged level and the lagged change in effective risk aversion. Control variables (each lagged by one quarter) are: the VIX implied volatility of the S&P 500, the 3-month U.S. treasury bill rate, the yield spread (difference between Moody's Aaa corporate yield and the treasury rate), the S&P 500 dividend yield, the U.S. inflation, the basis (future price over spot price), and the hedging pressure (net short open interest of hedgers relative to the total open interest of hedgers, as reported by the CFTC). A lag of the dependent variable is included in (ii)-(viii). All independent variables have zero mean and unit variance. The table reports point estimates with heteroskedasticity-robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample period is Q3/1990- Q4/2007.

	Wheat Futures Excess Return							
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Effective Risk Aversion. (Lag 1)	-4.628**	-5.106***	-5.145***	-5.402**	-4.966**	-7.027**	-6.962**	-7.125**
	(-2.185)	(-2.833)	(-3.043)	(-2.567)	(-2.268)	(-2.245)	(-2.204)	(-2.260)
Δ Effective Risk Aversion (Lag 1)	-1.268	-1.156	-1.682	-1.532	-1.806	-1.319	-1.491	-1.067
	(-1.092)	(-0.994)	(-1.588)	(-1.226)	(-1.379)	(-0.897)	(-1.026)	(-0.753)
Dependent Variable (Lag 1)		-0.078	-0.133	-0.135	-0.127	-0.168	-0.168	-0.181
		(-0.518)	(-0.949)	(-0.976)	(-0.892)	(-1.357)	(-1.326)	(-1.446)
VIX (Lag 1)			-3.485***	-3.430***	-3.577***	-4.997***	-4.872***	-5.124***
			(-2.748)	(-2.781)	(-2.847)	(-3.246)	(-3.118)	(-3.159)
Interest Rate (Lag 1)				0.613	1.457	5.608	5.767	5.983
				(0.320)	(0.578)	(1.232)	(1.263)	(1.294)
Yield Spread (Lag 1)					1.384	4.738	4.754	4.768
					(0.588)	(1.308)	(1.300)	(1.305)
Dividend Yield (Lag 1)						-4.589	-4.198	-3.393
						(-1.303)	(-1.220)	(-1.002)
Inflation (Lag 1)							-1.180	-1.416
							(-0.727)	(-0.879)
Basis (Lag 1)								1.322
								(0.907)
Hedging Pressure (Lag 1)								2.719***
								(4.754)
Constant	-0.495	-0.520	-0.578	-0.575	-0.601	-0.621	-0.616	-0.600
	(-0.324)	(-0.335)	(-0.386)	(-0.381)	(-0.398)	(-0.424)	(-0.419)	(-0.415)
# Observations	70	70	70	70	70	70	70	70
Adj-R^2	12.3%	11.5%	16.9%	15.8%	14.9%	18.3%	17.7%	20.4%

Table 3: Out-of-Sample Regressions

This table investigates the ability of effective risk aversion to forecast commodity returns out-of-sample. The analysis focuses on crude oil futures (Panel A) and the S&P GSCI (Panel B). Three benchmarks are considered: (1) random walk, (2) random walk with a drift, and (3) first-order autoregression. x_t is the change in effective risk aversion and r_{t+1} is the excess return. The table reports the Diebold-Mariano/West difference in mean-squared errors and the Clark-West adjusted difference in mean-squared errors. The associated p-values are in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The out-of-sample period is Q3/1995- Q4/2007.

Panel A: Crude Oil Futures Excess Return (r_{t+1})

			DMW	Clark-West Adjusted
	Restricted Model (r)	Unrestricted Model (u)	$MSE_r - MSE_u$	$MSE_r - (MSE_u - adj.)$
(1)	$E_t r_{t+1} = 0$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} x_t$	105.204**	217.227***
			[0.011]	[0.001]
(2)	$E_t r_{t+1} = \alpha_{0t}$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} x_t$	84.920**	191.628***
			[0.025]	[0.002]
(3)	$E_t r_{t+1} = \alpha_{0t} + \alpha_{1t} r_t$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} r_t + \beta_{2t} x_t$	83.467**	204.563***
			[0.025]	[0.001]

Panel B: S&P GSCI Excess Return (r_{t+1})

			DMW	Clark-West Adjusted
	Restricted Model (r)	Unrestricted Model (u)	$MSE_r - MSE_u$	$MSE_r - (MSE_u - adj.)$
(1)	$E_t r_{t+1} = 0$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} x_t$	19.721**	37.189***
			[0.024]	[0.002]
(2)	$E_t r_{t+1} = \alpha_{0t}$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} x_t$	19.433**	37.440***
			[0.029]	[0.002]
(3)	$E_t r_{t+1} = \alpha_{0t} + \alpha_{1t} r_t$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} r_t + \beta_{2t} x_t$	19.412**	38.080***
			[0.029]	[0.002]