Risk Appetite and Commodity Returns

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Abstract

This paper shows that fluctuations in the risk appetite of leveraged financial institutions such as security broker-dealers forecast commodity returns at quarterly horizons. The result holds robustly both in-sample and out-of-sample and is particularly strong for energy commodities: the single variable is able to forecast up to 30% of the variation in quarterly crude oil returns. The pattern emerged shortly after the launch of commodity futures contracts and is consistent with a model in which the economic role of broker-dealers is to provide insurance to producers and end-users of commodities. I estimate cross-sectional prices of risk using an arbitrage-free asset pricing approach and show that innovations in broker-dealer risk appetite forecast commodity returns through their association with time-varying risk premia. Additional predictions of the model also receive support in the data.

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1. Introduction

The last three decades witnessed impressive growth of leveraged financial institutions. This trend is displayed in Figure 1.1, which also shows the stark divergence of the growth of U.S. broker-dealer financial assets from the growth of household financial assets in the late 1970s.

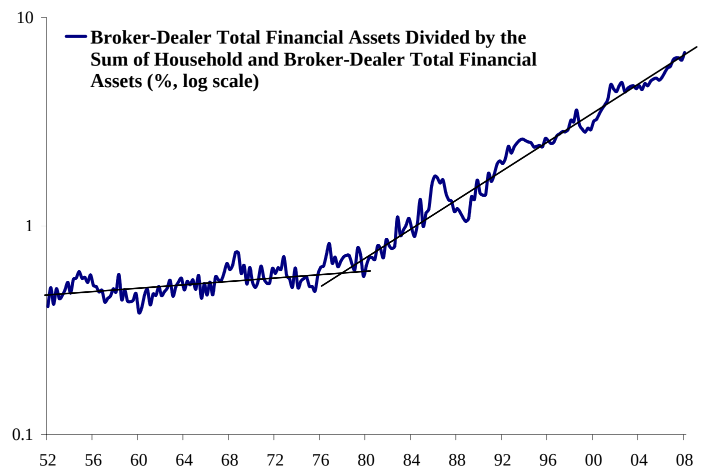

Figure 1.1: Broker-dealer asset share, Q1/1952-Q4/2007

While the plot is intriguing in its own right, the economic significance of the growth pattern is further amplified by the procyclicality of broker-dealer financial 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 balance sheets are accompanied by decreases in leverage as balance sheet constraints tighten. To an outside observed, it would be as if the preferences of broker-dealers were changing with market conditions. Combining this evidence of time-varying risk appetite with the substantial growth of the broker-dealer sector, it seems plausible to conjecture that fluctuations in broker-dealer balance sheets have also implications for asset prices.

This paper investigates the impact of broker-dealer risk appetite on commodity prices. I show that innovations in broker-dealer risk appetite, as proxied by innovations in broker-dealer aggregate balance sheets, have forecasting power for quarterly commodity returns across a cross-section of energy, metal, and agricultural commodities. The result holds robustly both in-sample and out-of-sample and is particularly strong for energy commodities: the single variable is able to forecast up to 30% of the variation in quarterly crude oil returns. The pattern emerged shortly after the launch of commodity futures contracts and is consistent with a model in which the economic role of broker-dealers is to provide insurance to producers and end-users of commodities in the futures market; fluctuations in broker-dealer risk appetite forecast commodity returns through their association with market-wide risk premia.

Figure 1.2 illustrates the emergence of return forecastability for crude oil by plotting the R^2 obtained from rolling regressions of crude oil returns on lagged innovations in broker-dealer asset share (that is, the ratio of broker-dealer assets to the sum of household and broker-dealer asset). The power of the forecasts jumps sharply approximately three years after the crude oil futures contract begins trading in the NYMEX and the CME in 1983. This change in the market structure (denoted by the red blot on the time axis) brought transparency into energy pricing and facilitated the matching of producers and end-users of commodities with speculators willing to supply insurance against commodity price risk.

To show how the power of the uncovered predictive relationship compares to the relative size of the broker-dealer sector, Figure 1.2 also reproduces the level of broker-dealer asset share from Figure 1.1. It may not be surprising that the predictive power of lagged broker-dealer asset growth has increased over time along with the relative size of the broker-dealer sector — but what is quite striking, the

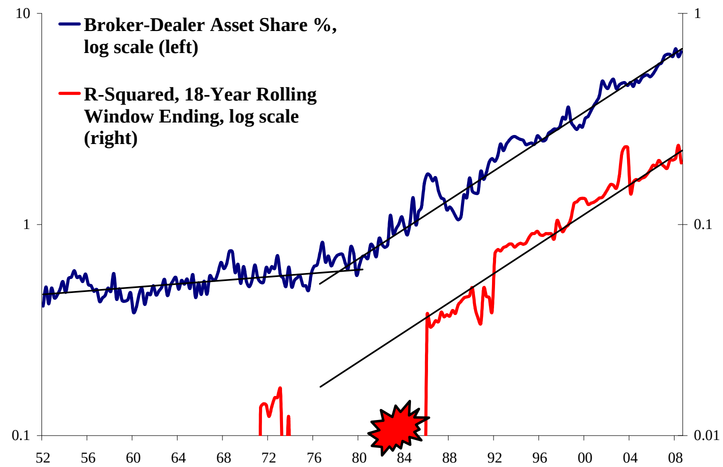

Figure 1.2: Predictive power of lagged innovations to broker-dealer asset share in rolling crude oil return regressions, Q1/1952-Q2/2008. Crude oil futures launched in March 1983.

two variables have also grown *at the same rate* as indicated by the parallel trend lines. This finding lends support to the stability of the forecasting relationship over time.

The theoretical section of the paper builds on existing literature on commodity pricing to argue that the impact of broker-dealer risk appetite on expected commodity returns stems from the importance of broker-dealers as "insurance brokers" (speculators) in commodity futures markets. Commodity futures are vital for producers and end-users of commodities (hedgers) because they are the principal means to unload spot commodity price risk. This risk is often termed "non-marketable" because the trading of many spot commodities involves significant transaction costs or informational asymmetries, which discourage speculators from engaging in spot commodity transactions in the marketplace. These transaction costs and informational asymmetries are alleviated in the futures market where the hedgers' demand for insurance is marketed through futures contracts that require no investment outlays. The insurance premia are determined by the risk appetite of speculators who offer to bear the price risk. To the extent that hedgers' demand for insurance is independent of the fluctuations in speculator risk appetite, innovations in speculator risk appetite should be reflected in equilibrium commodity returns.[1]

The link between broker-dealer risk appetite and expected commodity returns is rationalized in a simple pricing model where broker-dealers maximize expected return on equity subject to a value-at-risk constraint and have a role in providing insurance to producers and end-users of commodities. In equilibrium, expected commodity returns are determined by their loading on systematic marketable risk but also on systematic non-marketable risk whose price fluctuates with broker-dealer risk appetite.

The model predicts that broker-dealer risk appetite should be a significant determinant of expected returns for those commodities that load particularly heavily on systematic non-marketable (spot commodity) risk. The analysis shows that some energy commodities such as crude oil and its derivatives heating oil and unleaded gasoline have a large positive loading on systematic spot commodity risk, which makes them particularly sensitive to broker-dealer risk appetite: an increase in broker-dealer risk appetite forecasts low expected returns on energy commodities as speculators lower their required risk premia. The converse holds for some agricultural commodities such as wheat and cocoa, which have a significant *negative* loading on systematic spot commodity risk. For these commodities, an increase in broker-dealer risk appetite forecasts high expected returns as the risk premia required by speculators decrease. The model is also consistent with other quantitative and qualitative features of the data, including market risk premia, market volatility, and speculative activity in commodity futures markets.

[1] 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 speculator risk appetite.

The paper concludes with cross-sectional asset pricing tests, which confirm the significance of broker-dealer balance sheet innovations for the pricing of systematic spot commodity risk. Overall, the cross-sectional evidence lends strong support to the view that the uncovered forecastability of commodity returns is a reflection of changes in market-wide risk premia.

1.1. Related Literature

The risk appetite channel analyzed in this paper originates in Adrian and Shin (2008a,b,c) who demonstrate that the active management of financial intermediary balance sheets generates procyclical leverage, which has consequences for investor risk appetite. The authors exhibit evidence that the adjustment of balance sheets forecasts changes in aggregate market volatility, particularly the price of risk of volatility, at weekly horizons. The impact of procyclical leverage on asset prices is further explored in Adrian, Etula and Shin (2009) who show that the growth of U.S. financial intermediary balance sheets has systematic implications for the cross-section of currency returns. The view that balance sheet constraints influence risk premia is also supported by the 2007-2008 financial market turmoil, which shows how a sudden drying up of financial intermediary liquidity may have significant systematic consequences.

The literature on time-varying expected commodity returns can be divided roughly into two groups of theories. The first group uses the CAPM to argue that the expected return on commodity holdings reflects their value as a hedge against market fluctuations. 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 show 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) attribute a lesser role to the hedging value of commodities and argue that commodity futures as an asset class provide a return profile that is comparable to that of equities.

The second group of theories 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 risk premia and 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 spot. Models that allow both hedging pressure and systematic risk to affect futures prices include Stoll (1979) and Hirschleifer (1988, 1989). Empirical evidence for the combined role of commodity-specific hedging pressure and systematic market risk include Carter, Rausser and Schmidt (1992), Bessembinder (1992), and de Roon, Nijman and Veld (2000). In a recent paper, Gorton, Hayashi and Rouwenhorst (2007) 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.

The current paper contributes to the first group of theories 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 theories: broker-dealers have an important role in providing insurance to producers and end-users of commodities who wish to hedge their positions in spot commodities. This channel receives additional support from Erb and Harvey (2006) whose evidence indicates that futures strategies that engage in such insurance provision have earned positive excess returns. My findings are also nicely consistent with the work of Acharya, Lochstoer and Ramadorai (2008) who demonstrate that the default risk of oil and gas *producers* forecasts future returns on these commodities.

The theoretical framework builds on Danielsson, Shin and Zigrand (2008) where investor risk appetite 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. 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), limited arbitrage (e.g. Shleifer and Vishny, 1997), and market making (e.g. Grossman and Miller, 1988; Kyle, 1985). However, the distinguishing feature of the present framework is its ability to generate stochastic volatility even though the underlying fundamental risks remain constant. It is also free of restrictive assumptions on the behavior of noise traders.

The outline of the paper is as follows. To fix ideas, Section 2 develops a simple framework, which introduces broker-dealer balance sheet constraints in an equilibrium pricing model for commodities. The model shows that if broker-dealers play an important role in providing insurance to producers and end-users of physical commodities, then fluctuations in broker-dealer risk appetite should be reflected in expected commodity returns through their association with risk premia. Section 3 confirms the predictions of the model in the data by showing that innovations in broker-dealer risk appetite, as proxied by innovations in broker-dealer balance sheets, forecast returns on commodities that have the heaviest loadings on systematic spot commodity risk. Section 4 tests additional predictions of the model. Section 5 implements a cross-sectional asset pricing framework with time-varying prices of risk and finds that balance sheet constraints matter for the pricing of the cross-section of commodity returns. Section 6 concludes.

2. Theoretical Framework

As discussed above, there is an extensive literature[2] that relates futures risk premia to two components: systematic marketable risk and commodity-specific hedging pressure. 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, futures F, and non-marketable securities N. Denote by r^i_{t+1} the excess return on security i. The non-marketable securities may serve as the underlying value of the futures contracts and can also coincide with some of the assets. While the returns on non-marketable securities r^N_{t+1} do not enter the market portfolio, they do influence portfolio choice.

Suppose there are two types of agents in the economy: risk-neutral broker-dealers and risk averse investors. The portfolio of agent j consists of positions in assets $\omega^j_{A,t}$, futures $\omega^j_{F,t}$, and non-marketable securities q^j_t:

$$r^j_{t+1} = \omega^{j\prime}_A r^A_{t+1} + \omega^{j\prime}_F r^F_{t+1} + q^{j\prime} r^F_{t+1}.$$

All positions are expressed as a fraction of the agent's financial wealth.

2.1. Risk-Neutral Broker-Dealers

Security brokers and dealers (bd) are leveraged financial institutions that finance long positions in risky securities (dollar value S_1) with short positions in other risky securities (dollar value $S_2 < 0$). Their cash holdings (c) earn the safe rate of return. A stylized broker-dealer balance sheet can be depicted as:

[2] For example, Stoll (1979), Hirshleifer (1988, 1989), Carter et al. (1983), Bessembinder (1992), and de Roon, Nijman and Veld (2000).

Assets	Liabilities
S_1	e^{bd}
c	$-S_2$

where $e^{bd} = S_1 + S_2 + c$ is the market value of broker-dealer equity.

Following Danielsson, Shin and Zigrand (2008), suppose broker-dealers maximize expected return on equity subject to a value-at-risk constraint:

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

That is, profit-maximizing broker-dealers leverage up to the maximum level permitted by their balance sheet constraints. Thus, under profit maximization, the value-at-risk constraint binds with equality. If VaR_t is some multiple κ of the forward-looking standard deviation of equity returns $e_t^{bd}\sqrt{Var_t\left(r_{t+1}^{bd}\right)}$, the constraint becomes $\sqrt{Var_t\left(r_{t+1}^{bd}\right)} \leq \frac{1}{\kappa}$.

Suppose for simplicity that broker-dealers do not have non-marketable securities. It follows that the return on broker-dealer equity is given by:

$$r_{t+1}^{bd} = \omega_{A,t}^{bd\prime} r_{t+1}^{A} + \omega_{F,t}^{bd\prime} r_{t+1}^{F}.$$

The Lagrangian is:

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

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

$$\omega_t^{bd} = \frac{1}{\kappa\mu_t}\left[Var_t\left(r_{t+1}\right)\right]^{-1} E_t\left(r_{t+1}\right). \tag{2.2}$$

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 $\kappa\mu_t$, the Lagrange multiplier associated with the balance sheet constraint scaled by the constant κ. In other words, broker-dealers are risk-neutral but behave as if they were risk-averse with the risk aversion fluctuating with market conditions. As the balance sheet constraint binds harder, the shadow price μ_t increases, and leverage must be reduced. The inverse of the scaled Lagrange multiplier, $\frac{1}{\kappa\mu_t}$, measures broker-dealer *risk appetite.*[3]

2.2. Risk-Averse Investors

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

$$r_{t+1}^{ra} = \omega_{A,t}^{ra\prime} r_{t+1}^{A} + \omega_{F,t}^{ra\prime} r_{t+1}^{F} + q_t^{ra\prime} r_{t+1}^{N}.$$

Agent ra chooses positions in the marketable securities to solve:

$$\max_{\omega_t^{ra}} E_t\left(r_{t+1}^{ra}\right) - \frac{\gamma}{2} Var_t\left(r_{t+1}^{ra}\right),$$

which yields the FOC:

$$\omega_t^{ra} = \frac{1}{\gamma}\left[Var_t\left(r_{t+1}\right)\right]^{-1}\left[E_t\left(r_{t+1}\right) - Cov_t\left(r_{t+1}, r_{t+1}^{N}\right) q_t^{ra}\right]. \tag{2.3}$$

Note that the optimal porfolio choices of broker-dealers and risk-averse investors are linked by:

$$\omega_t^{bd} = \frac{\gamma}{\kappa\mu_t}\left\{\omega_t^{ra} + \left[Var_t\left(r_{t+1}\right)\right]^{-1} Cov_t\left(r_{t+1}, r_{t+1}^{N}\right) q_t^{ra}\right\}.$$

[3] The Lagrange multiplier can be solved for from the balance sheet constraint and is given by:

$$\mu_t = \sqrt{E_t\left(r_{t+1}\right)' \left[Var_t\left(r_{t+1}\right)\right]^{-1} E_t\left(r_{t+1}\right)}.$$

That is, the Lagrange multiplier for the VaR constraint is proportional to the generalized sharpe ratio for the marketable securities in the economy.

2.3. Market Portfolio

Denote by s_t the share of broker-dealer equity (wealth) in the economy:

$$s_t = \frac{e_t^{bd}}{e_t^{ra} + e_t^{bd}}. \tag{2.4}$$

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

$$\omega_t^M = \begin{pmatrix} \omega_{A,t}^M \\ 0\iota \end{pmatrix} = \begin{pmatrix} (1 - s_t)\,\omega_{A,t}^{ra} + s_t \omega_{A,t}^{bd} \\ 0\iota \end{pmatrix}. \tag{2.5}$$

If the market portfolio is efficient in the sense that it satisfies the FOCs (2.2) and (2.3) for κ, μ_t, γ, q_t, and s_t, one obtains:

$$E_t\left(r_{t+1}\right) = \mu_t^M \left[Cov_t\left(r_{t+1}, r_{t+1}^M\right) + Cov_t\left(r_{t+1}, r_{t+1}^N\right) q_t^M\right], \tag{2.6}$$

where

$$\frac{1}{\mu_t^M} = \frac{1 - s_t}{\gamma} + \frac{s_t}{\kappa \mu_t} \tag{2.7}$$

is the aggregate risk appetite and

$$q_t^M = (1 - s_t)\, q_t^{ra} \tag{2.8}$$

is the vector of aggregate non-marketable positions in the economy. Note that the aggregates in (2.7) and (2.8) are linear combinations of the two investor groups' respective variables.

2.4. Equilibrium Returns

Let $\beta_t^i = \frac{Cov_t\left(r_{t+1}^i, r_{t+1}^M\right)}{Var_t\left(r_{t+1}^M\right)}$ denote security i's beta with the portfolio of marketable assets and rewrite the expression (2.6) for equilibrium returns as:

$$\begin{aligned} E_t\left(r_{t+1}\right) &= \beta_t E_t\left(r_{t+1}^M\right) + \left[Cov_t\left(r_{t+1}, r_{t+1}^N\right) q_t^M - \beta_t Cov_t\left(r_{t+1}^M, r_{t+1}^N\right) q_t^M\right] \mu_t^M \\ &= \beta_t E_t\left(r_{t+1}^M\right) + Cov_t\left(r_{t+1} - \beta_t r_{t+1}^M, r_{t+1}^{NM}\right) \mu_t^M. \end{aligned} \tag{2.9}$$

The second line defines:

$$r_{t+1}^{NM} \equiv r_{t+1}^{N\prime} q_t^M,$$

which is interpreted as the excess return on the aggregate production-weighted portfolio of Non-Marketable securities. If non-marketable securities are physical commodities, then r_{t+1}^{NM} is the excess return on the world production-weighted portfolio of spot commodities.

To further simplify the notation, denote the coefficient of μ_t^M in (2.9) by

$$\delta_t = Cov_t\left(r_{t+1} - \beta_t r_{t+1}^M, r_{t+1}^{NM}\right). \tag{2.10}$$

Note that δ_t contains the loadings of individual assets on aggregate non-marketable risk *in excess* of their loadings on aggregate marketable risk. It follows that (2.9) can be expressed concisely as:

$$\underbrace{E_t\left(r_{t+1}\right)}_{\substack{\text{Security} \\ \text{Risk Premium}}} = \underbrace{\beta_t E_t\left(r_{t+1}^M\right)}_{\substack{\text{Systematic} \\ \text{Marketable Risk}}} + \underbrace{\delta_t \mu_t^M}_{\substack{\text{Systematic} \\ \text{Non-Marketable Risk}}}. \tag{2.11}$$

The first component of the security risk premium captures the non-diversifiable risk that stems from the security's comovement with the value of aggregate marketable securities. The price of marketable risk is $E_t\left(r_{t+1}^M\right)$. The second component captures the non-diversifiable risk that stems from the security's comovement with the value of aggregate non-marketable securities and is not already captured by systematic marketable risk. The price of non-marketable risk is μ_t^M and it varies over time with the willingness of broker-dealers to provide insurance against non-marketable risks — i.e., it varies with broker-dealers' risk appetite as given by (2.7). Note that (2.11) prices both futures and assets.

3. Empirical Implementation

The simple model outlined above implies that commodity 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. Assuming constant conditional variances and covariances, (2.11) becomes:

$$E_t\left(r_{t+1}^i\right) = \beta_i E_t r_{t+1}^M + \delta_i \mu_t^M, \quad i \in \{A, F\}. \tag{3.1}$$

In order to obtain a time-series estimate of δ_i, one needs a proxy for μ_t^M. Recall from equation (2.7) that $\frac{1}{\mu_t^M}$ is proportional to $s_t \frac{1}{\kappa \mu_t}$. That is, if broker-dealers manage some positive fraction s_t of the economy's wealth, then the aggregate risk appetite $\frac{1}{\mu_t^M}$ rises whenever the tightness of broker-dealer balance sheet constraints $\kappa\mu_t$ decreases, permitting an increase in leverage. Since leverage is the market value of assets $\left(a_t^{bd}\right)$ over the market value of equity $\left(e_t^{bd}\right)$, one obtains the proportionality:

$$\frac{1}{\mu_t^M} \sim s_t \frac{a_t^{bd}}{e_t^{bd}} = \frac{a_t^{bd}}{e_t^{bd} + e_t^{ra}},$$

where the equality follows from the definition of s_t in (2.4). If the aggregate leverage in the economy, $L_t \equiv \left(a_t^{bd} + a_t^{ra}\right) / \left(e_t^{bd} + e_t^{ra}\right)$, is constant over time the above proportionality can be rewritten as:

$$\frac{1}{\mu_t^M} \sim L \frac{a_t^{bd}}{a_t^{bd} + a_t^{ra}}, \tag{3.2}$$

where $a_t^{bd} + a_t^{ra}$ is the value of the economy's total asset supplies. Intuitively, the procyclicality of broker-dealer leverage implies that innovations in broker-dealer assets constitute a proxy for innovations in leverage, and hence for innovations in risk appetite, as long as one controls for any long-term trends in the economy's total asset supplies. It follows that the innovation in broker-dealer asset share is negatively related to the innovation in the aggregate risk premium μ_t^M

To formalize this intuition in the context of the pricing model (3.1), decompose the aggregate risk premium into a predictable part and an innovation:

$$\mu_t^M = \hat{\mu}_t^M + \tilde{\mu}_t^M,$$

where $\hat{\mu}_t^M \equiv E_{t-1}\left(\mu_t^M|1,\mu_{t-1}^M\right)$ is the fitted risk premium and $\tilde{\mu}_t^M \equiv \mu_t^M - E_{t-1}\left(\mu_t^M|1,\mu_{t-1}^M\right)$ is the innovation. Replacing expectations by realizations in equation (3.1) and adding a constant yields:

$$r_{t+1}^i = \alpha_i + \beta_i r_{t+1}^M + \delta_i^1 \hat{\mu}_t^M + \delta_i^2 \tilde{\mu}_t^M + \epsilon_{t+1}^i, \quad i \in \{A, F\}, \tag{3.3}$$

where $\epsilon_{t+1}^i \equiv r_{t+1}^i - E_t\left(r_{t+1}^i|1, r_{t+1}^M, \hat{\mu}_t^M, \tilde{\mu}_t^M\right)$ is the prediction error. This is the regression model that I will estimate below.

3.1. Data

The empirical exercises that follow investigate the impact of lagged broker-dealer asset growth on the excess returns of commodity futures and spot commodities. The analysis includes 14 individual commodities and two investable commodity indexes. The individual commodities are selected based on their respective world production quantities and the liquidity of futures contracts. The time-period under consideration is Q3/1990-Q4/2007.

The data on aggregate balance sheets is obtained from the Federal Reserve, which publishes the figures quarterly as part of the Flow of Funds Accounts. To construct broker-dealer asset shares, I divide broker-dealer total financial assets by the sum of broker-dealer and household total financial assets and remove a linear time trend. I then decompose this series into a predictable part and an innovation to obtain a proxy for the innovation in aggregate risk appetite. A plot of the asset share innovation is displayed in Figure 3.1. Note that most of the 17.7 basis point quarterly standard deviation is driven by the volatility of broker-dealer balance sheets.

Two features of the balance sheet variable deserve attention. First, due to the high persistence of broker-dealer asset share, the innovations in this series turn out to be nearly perfectly correlated with the changes in broker-dealer asset share ($\rho = 0.97$). Hence, all of the regression results that follow also obtain if one replaces the innovation in broker-dealer asset share with the change in the

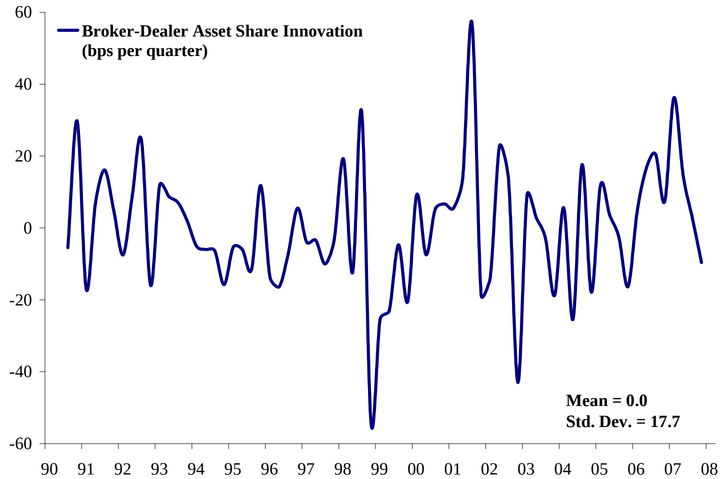

Figure 3.1: Quarterly innovations to the ratio of broker-dealer assets divided by the sum of broker-dealer assets and household assets. Quarterly basis points, Q3/1990-Q4/2007.

asset share. Second, the value of broker-dealer total financial assets is very small relative to the value of household total financial assets (only $1-7\%$). This implies that one can simply use the ratio of broker-dealer assets to household assets in lieu of the current definition of the asset share without affecting the qualitative results.

The price data on individual commodities and commodity indexes are obtained from Bloomberg and Datastream. Excess 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.[4]

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

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

The data on equity returns, bond returns, and technical indicators used as controls in the regressions are provided by Global Financial Data. The data on the S&P 500 implied volatility index (VIX) and the credit default swap index (CDX) are from Bloomberg.

The paper also employs quantity data on the positions of market participants in commodity futures exchanges. These variables are obtained from the Commitment of Traders reports, which are published weekly by the Commodity Futures Trading Commission. The CFTC requires that large traders in futures exchanges report whether they take a position for hedging ('commercial') or for speculative ('non-commercial') purposes. To register as a hedger, one must hold a cash position in the underlying. Thus, the hedgers in commodity futures markets consist primarily of producers and end-users of physical commodities: producers (such as farmers) have long positions in the underlying commodity and wish to short the futures contract in order to hedge against spot price fluctuations; conversely, end-users (such as flour mills) have a future need for the physical commodity and want to long the futures contract in order to lock in the purchase price today. Speculators consist of broker-dealers and other market participants who hold the futures for non-hedging purposes. See Bessembinder (1992) for further discussion of the distinction between commercial and non-commercial traders.

The baseline regressions cover the time period Q3/1990-Q4/2007, the beginning of which was selected based on data availability. Year 2008 is excluded because the key assumption of the model fails to hold in most quarters of the year: as discussed above, the use of broker-dealer asset share innovations as a proxy for the innovations broker-dealer risk appetite relies on the finding of Adrian and Shin (2008a) that broker-dealer leverage is procyclical; that is, increases in broker-dealer assets are matched by increases in leverage to keep VaR/equity constant. As

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.

the financial crisis expanded in 2008, a significant part of the expansions in broker-dealer balance sheets was instead financed by capital-raising.[5] For instance, the first quarter of 2008 witnessed substantial growth in broker-dealer assets while leverage decreased significantly, suggesting that the innovation in broker-dealer asset share was not a good proxy for the innovation in broker-dealer risk appetite. A decrease in risk appetite in Q1/2008 would correctly predict the run-up in oil prices in Q2/2008, which the asset share proxy fails to capture.[6]

However, even a breakdown of the relation between broker-dealer asset share and leverage cannot explain the downward spiral in oil prices in the second half of 2008. It is instead possible that the steep negative returns were driven by a sequence of unanticipated negative shocks to risk appetite, which contemporaneously depressed returns. I discuss contemporaneous return responses in Sections 3.3 and 4.3.

3.2. In-Sample Regressions

Table 1 implements the baseline OLS specification of equation (3.3) for the futures (panel A) and spot returns (panel B) of 14 individual energy, metal, and agricultural commodities. For each commodity, two specifications are considered: The first columns I regress the quarterly excess return on the S&P 500 excess return and the lagged asset share innovation only. The second columns follow (3.3) more closely by also including a lag of the fitted asset share.

Let us begin by looking at the first specification. The results in panel A show that the innovation in broker-dealer asset share is a significant predictor of expected futures returns for crude oil, its derivatives heating oil and unleaded

[5] As the liquidity of short-term debt markets decreased during the escalation of the financial crisis, it is conceivable that the relative cost of equity decreased not only in financial terms but also in terms of the usual stigma associated with equity financing. Thus, the financing decisions of 2008 find some support in the pecking order theory of Myers and Majluf (1984).

[6] Unfortunately, it is hard to find reliable aggregate data on broker-dealer leverage. This is a topic for future work.

gasoline, natural gas, silver, copper, wheat, and cocoa. Note, however, that the sign of the coefficient for most agricultural commodities is positive rather than negative — this finding is consistent with the theory and will be discussed below. The economic power of the regressions is the strongest for the three energy commodities crude oil, heating oil and unleaded gasoline, for which the adjusted R^2 ranges between 19% and 33%. For crude oil, a one standard deviation increase in the broker-dealer variable forecasts an 8 percentage point decrease in excess returns over the following quarter.

The results for the second specification show that including a lag of the fitted asset share adds little to the forecasting power of the regressions with the exception of gold, wheat, and cotton, which all have a significant positive loading on the asset share innovation. For the majority of commodities the observed forecastability of returns thereby seems to stem from the innovation in risk appetite rather than the level.

Table 1B conducts the same sets of regressions for excess spot returns. Consistent with the predictions of the model, the results are very similar albeit somewhat stronger for the futures. An additional set of regressions for the futures basis (price of future minus price of spot) as the dependent variable confirms that broker-dealer risk appetite has no predictive power for the front-month slope of the futures curve at this frequency. These supplementary results can be obtained from the author.

Finally, Table 1C runs these baseline regressions for the excess returns on the S&P Goldman Sachs Commodity Index (futures and spot) and the Dow Jones Commodity Index (futures), which are readily accessible to investors. The results show that the innovation in broker-dealer asset share is a highly significant predictor of excess returns on all indexes. Again, the fitted asset share is insignificant. The table also includes the regressions for the Dow Jones Corporate Bond index to show that neither of the broker-dealer balance sheet variables have predictive power for excess bond returns.

While the regressions of Table 1 include the contemporaneous market excess return as an additional predictor variable, one should note that this control has no material impact on the significance of the lagged innovations or fitted values of the asset share nor the power of the regressions. It is included merely to adhere to the theoretical specification in equation (3.3). The next subsection will investigate the contemporaneous responses to balance sheet innovations.

3.3. Contemporaneous Return Responses

The forecasting regressions of Tables 1A-1C were motivated by arguing that innovations in broker-dealer asset share proxy for innovations in risk appetite. A loosening of balance sheet constraints induces an increase in leverage and a higher level of broker-dealer assets. To an outside observer, it would be as if the preferences of broker-dealers were changing toward greater willingness to take on risk. The greater risk appetite associated with larger broker-dealer asset share drives down the equilibrium risk premium, which creates return forecastability for positions in risky securities, including those in commodity futures. This is what we observe in the data.

The theory in Section 2 also has implications for the contemporaneous relationship between innovations in broker-dealer asset share and commodity returns. A balance sheet expansion accompanied by an increase in risk appetite should move the prices of risky securities today so that they will in the future deliver the lower equilibrium risk premium that is implied by higher risk appetite Thus, the contemporaneous relationship between balance sheet innovations and commodity returns should be the opposite of the lagged relationship documented above.

To investigate the contemporaneous return responses, I include a contemporaneous asset share innovation as an additional regressor in (3.3). Table 1D displays these regressions for the sample of commodity futures, including the two futures indexes. The results show that the contemporaneous innovations are statistically insignificant for most commodities. The only exceptions are crude oil and sugar for which the contemporaneous effects are negative and marginally significant.

While the above evidence on contemporaneous returns is at best mixed, it may also point toward an important empirical limitation imposed by the low frequency of the available balance sheet data. Commodity markets are volatile and the instantaneous reactions may occur over weeks, days, or even intra-day. These movements are not captured by quarterly data, which are better suited for capturing slower-moving equilibrium responses. I will revisit the topic in Section 4 where an investigation of futures trading data uncovers some evidence in support of the theory's prediction for contemporaneous returns.

3.4. Estimated vs. Model-Predicted Loadings

To see how the coefficient estimates of Tables 1A-1C compare with the predictions of the pricing model (2.11), I compute the theoretical loadings on $\tilde{\mu}_t^M$ of individual commodity futures, spot returns, and indexes using:

$$\delta_i = Cov\left(r_{t+1}^i - \beta_i r_{t+1}^M, r_{t+1}^{NM}\right), \tag{3.4}$$

which is just a stationary version of (2.10). Recall that the weights of the non-marketable portfolio are given by the vector of aggregate non-marketable positions q_t^M in the economy. Thus, it seems natural to proxy the excess return r_{t+1}^{NM} on the non-marketable portfolio by the excess return on the GSCI Spot index, which weights commodities by their respective world production quantities.

Since $\tilde{\mu}_t^M$ is negatively related to the innovations in broker-dealer asset share, one must compare the estimated coefficients from Tables 1A-1C with $-\delta_i$'s computed by (3.4). Figure 3.2 displays the results for the futures contracts and Figure 3.3 draws the same comparison for the spot commodities. The scatter plots lend substantial support to the model: The empirical coefficient estimates line up cleanly with the model-predicted coefficients in both figures. For futures, the R^2

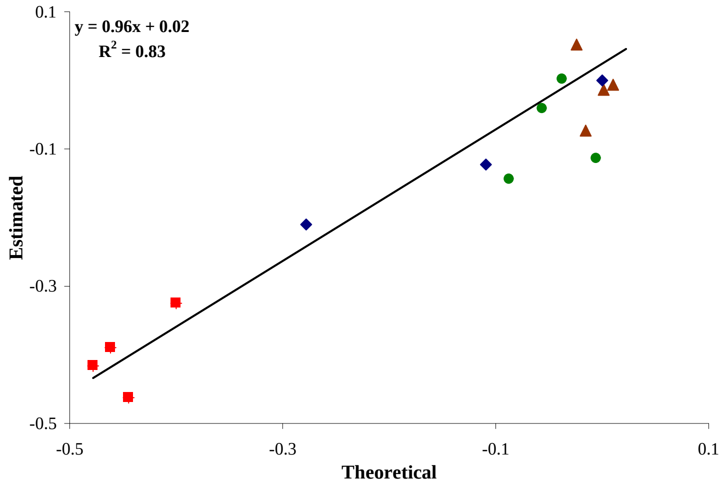

Figure 3.2: Commodity futures and futures indexes: Estimated vs. model-predicted coefficients of broker-dealer asset growth for energy (squares), metal (circles) and agricultural (triangles) commodities, plus three indexes (diamonds).

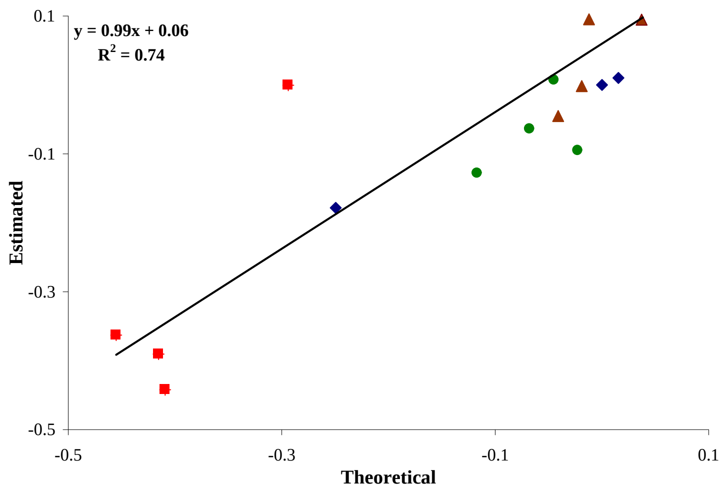

Figure 3.3: Spot commodities and indexes: Estimated vs. model-predicted coefficients of broker-dealer asset growth for energy (squares), metal (circles) and agricultural (triangles) commodities, plus three indexes (diamonds).

of the relationship is remarkable 83% and the slope of the line is approximately unity at 0.96. The results for the spot commodities are similar with R^2 of 74% and slope of 0.99. The only outlier is natural gas whose estimated coefficient in the spot regressions is greater than the model-predicted value.

The above results for the cross-section of commodities shed light to understanding why one observes such vast differences in the forecasting ability of broker-dealer asset growth across commodities — not only in terms of power but also in terms of the sign of the predictive relationship. They confirm the prediction of the model that fluctuations in broker-dealer risk appetite have the greatest impact on the risk premia of those commodities that covary the most with the aggregate non-marketable portfolio; that is, on the commodities that load heavily on the price of systematic non-marketable risk, which fluctuates strongly with broker-dealer risk appetite.

3.5. In-Sample Robustness Checks

The remainder of the section will investigate the robustness of the forecasting relationships uncovered in the panels of Table 1. In the interest of space, the analysis will be limited to crude oil futures and the GSCI futures index. The results for the spot counterparts are similar.

The panels of Table 2 display the quarterly in-sample regressions of crude oil excess return (panel A) and GSCI excess return (panel B) on the lagged innovation in broker-dealer asset share, lagged fitted asset share, and a set of controls. Column (i) reproduces the familiar baseline results from the panesl of Tables 1 and column (ii) demonstrates that the results are not affected by the inclusion of an autoregressive term. Columns (iii)-(viii) add a number of control variables from the literature,[7] which include lags of the VIX volatility index, interest rate, yield spread, dividend yield, inflation, and hedging pressure.[8] The coefficient of

[7] See, for instance, Bessembinder and Chan (1992).

[8] Hedging pressure measures commercial hedgers' net exposure to a particular futures market.

the broker-dealer asset share innovation variable remains significant at 1% level across all specifications. Its magnitude is also preserved in all regressions, for both crude oil and the GSCI. The converse holds for the fitted asset share, which is insignificant in all specifications.

Few controls help predict commodity prices in the same regression with broker-dealer balance sheet innovations. For crude oil, only lagged dividend yield and hedging pressure are significant.[9] The message is similar in the GSCI regressions where only lagged VIX is significant in the last specification. One might suspect that multicollinearity causes part of the observed insignificance of control variables. However, the stability of adjusted R^2 across the different specifications suggests that dividend yield and hedging pressure are the only controls that contribute materially to the power of the regression.

One can furthermore test the robustness of the above predictive relationships at different forecast horizons. Regressions with Newey-West standard errors for returns $2 - 8$ quarters ahead show that both the statistical significance as well as the economic magnitude of the relationships remain stable over longer horizons.[10] These results lend additional support to the strength and robustness of the dynamic connection between broker-dealer balance sheet innovations and commodity returns.

3.6. Out-of-Sample Regressions

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 misspecification problems. To show the extent to which the above in-sample results

It is defined as the net short open interest of hedgers divided by the total open interest of hedgers (e.g. de Roon, Nijman and Veld, 2000). I omit hedging pressure for the GSCI because the open interest figures required for the calculation are unavailable for a substantial part of the sample period.

[9] Note that the results are also robust to the inclusion of inventory figures or any additional proxies for the phase of the business cycle.

[10] These robustness checks can be obtained from the author.

survive this tougher test, the following investigates the forecastability of excess commodity returns out-of-sample. In order to avoid look-ahead bias in the construction of the regressor, I use quarterly changes in the broker-dealer asset share to proxy for innovations in broker-dealer risk appetite.[11] Again, the analysis will be limited to crude oil futures and the GSCI futures index. The results are produced using recursive regressions with the out-of-sample portion running from the second quarter of 1996 until the end of 2007.

Table 3 compares the predictive power of the proposed broker-dealer model to three benchmarks (restricted models) that are standard in the literature of out-of-sample forecasting: (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: $\Delta MSE\text{-}adj. = MSE_r - (MSE_u - adj.)$. 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 (2008) show, a significant Clark-West adjusted statistic implies that there exists an optimal combination between the 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 the broker-dealer variable (x_t) outperform all three benchmarks at 1% significance level for both crude oil (panel A) and the GSCI (panel B). The time-series of forecasted and realized returns in Figure 3.4 provide an illustration of the out-of-sample performance for crude oil.

[11] As mentioned above, the correlation between the change in the asset share and the innovation in the asset share is 97% over the sample period.

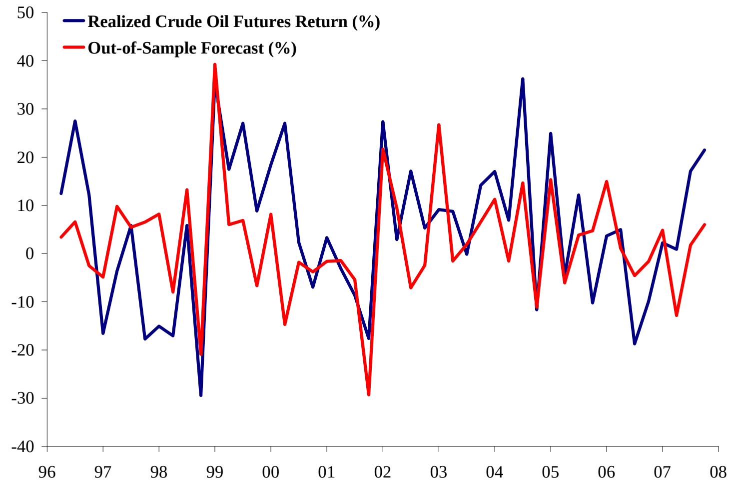

Figure 3.4: Forecasting crude oil futures returns out of sample, Q2/1996-Q4/2007

4. Additional Predictions

In addition to the relationships investigated above, the theoretical framework of Section 2 also yields a number of other predictions. This section provides a brief investigation of the extent to which these additional predictions might hold in the data. It is by no means exhaustive and only aims to serve as a small step toward understanding the links between broker-dealer balance sheets and the rest of the economy.

4.1. Market Risk Premia

Consider first the association of broker-dealer balance sheet fluctuations with common gauges of investor risk appetite. Rearranging (2.7), one obtains:

$$\frac{1}{\mu_t^M} = \frac{1}{\gamma} + s_t \left(\frac{1}{\kappa \mu_t} - \frac{1}{\gamma} \right), \tag{4.1}$$

which implies that aggregate risk appetite increases in broker-dealer risk appetite. Thus, innovations in broker-dealer risk appetite, as proxied by innovations in broker-dealer asset share should be negatively associated with innovations in proxies of market risk premia. I begin by investigating this prediction for the VIX risk premium, which is defined as the option-implied S&P 500 volatility minus the realized S&P 500 volatility. I also test the prediction for the Investment Grade CDX index even though the data is available only since Q4/2003.

Table 4 first considers the association with the level of VIX risk premium. Column (i) demonstrates that the innovations in broker-dealers asset share are associated with low VIX risk premia; that is, times of high market risk appetite tend to coincide with growing broker-dealer balance sheets. The relationship is significant at 1% level and the single variable explains 23% of the variation in the VIX risk premium. Column (ii) shows that including the fitted asset share in the regression does not improve the power of the specification. Columns (iii) and (iv) run the same regressions for the change in the VIX risk premium and find a similar pattern: The innovation in broker-dealer asset share is again highly significant and the single variable is capable of explaining as much as 22% of the variation in quarterly changes in the VIX risk premium. The fitted asset share is statistically insignificant.

Finally, columns (v) and (vi) investigate the association of broker-dealer balance sheets with the CDX. While the sample size is very small, bootstrapped standard errors show that the innovation in broker-dealer asset share has a significant negative associated with the CDX index while the fitted asset share is again insignificant. That is, broker-dealer balance sheet expansions coincide with periods of low risk premia also in the market for corporate default risk.

In sum, these results lend substantial support to the view that fluctuations in broker-dealer balance sheets reflect not only changes in broker-dealer risk appetite but they also convey information about market-wide risk premia. This association is central in the cross-sectional analysis of Section 5.

4.2. Market Volatility

Consider next the effect of broker-dealer balance sheet growth on market volatility. Using equation (2.5) and the FOCs, one obtains:

$$\begin{aligned} Var_t\left(r_{t+1}^{M}\right) &= Var_t\left(r_{t+1}^{M,\gamma}\right) + 2s_t\left(\frac{\gamma}{\kappa\mu_t} - 1\right) Cov_t\left(r_{t+1}^{M,0}, r_{t+1}^{M,\gamma}\right) \\ &\quad + s_t^2\left(\frac{\gamma}{\kappa\mu_t} - 1\right)^2 Var_t\left(r_{t+1}^{M,0}\right), \end{aligned} \tag{4.2}$$

where $r_{t+1}^{M,0}$ denotes the market return in a world without broker-dealers and non-marketable assets, and $r_{t+1}^{M,\gamma}$ is the market return in a world where $\mu_t = \gamma$ for all t. Mathematically:

$$\begin{aligned} r_{t+1}^{M,0} &= \left\{\frac{1}{2\gamma}\left[Var\left(r_{t+1}\right)\right]^{-1} E_t\left(r_{t+1}\right)\right\}' r_{t+1}, \\ r_{t+1}^{M,\gamma} &= r_{t+1}^{M,0} - \left\{\left[Var\left(r_{t+1}\right)\right]^{-1} Cov\left(r_{t+1}, r_{t+1}^{NM}\right)\right\}' r_{t+1}. \end{aligned}$$

The predictions of (4.2) are investigated in Table 5.

Column (i) mimics a contemporaneous version of (4.2) by running the realized S&P 500 variance on the innovation in broker-dealer asset share, the fitted asset share plus the squares of these two variables. All regressors are significant at 5% level. The innovation in asset share is positively associated with market volatility while the fitted asset share has a negative coefficient. That is, market volatility increases as broker-dealer balance sheets expand but large balance sheets are associated with low volatility — this is consistent with the familiar notion of counter-cyclical market volatility. The coefficients of the squared regressors are positive as predicted by the last term in (4.2); the positive squared innovation suggests that high volatility of broker-dealer risk appetite is associated with high market volatility. Overall, the regressors explain 22% of the variation in market variance on an adjusted R^2 basis. Running the regression with lagged right-hand-side variables yields no significance at this horizon.

Columns (ii) and (iii) assess the link of broker-dealer balance sheets with changes in S&P 500 volatility. The results show that innovations in broker-dealer asset share are positively associated with changes in market volatility. The regressor is significant at 1% level and explains a remarkable 26% of the variation in volatility growth. The explanatory power of the regression is unaffected by the inclusion of the fitted asset share. To connect these results with the performance of the market, column (iv) includes the S&P 500 excess return in column (iii)'s specification. While the coefficient of balance sheet innovations remains positive and significant, the negative and significant coefficient of the market return suggests that the counter-cyclicality of market volatility may be separate from the uncovered positive link between innovations in broker-dealer asset share and market volatility at this frequency. In light of the results from the previous subsection, one may conjecture that the amplification of volatility during balance sheet expansions may simply be due to the increasing risk appetite that drives up leverage in the market portfolio, independently of the direction of the market.[12]

4.3. Speculative Demand in the Futures Market

Finally, consider the impact of broker-dealer risk appetite on speculative activity in commodity futures. If innovations in broker-dealer risk appetite drive expected commodity returns via the proposed mechanism, one should expect to see contemporaneous changes in speculators' open interest as broker-dealer risk appetite fluctuates. In particular, an increase (decrease) in broker-dealer risk appetite that lowers futures risk premia should be associated with an increase (decrease) in speculators' share of futures demand.[13]

[12] When thinking about the dynamics of broker-dealer balance sheet fluctuations and market volatility, it is also useful to note that periods of high broker-dealer asset growth tend to be preceeded by low market volatility (results available upon request). This suggests that past market conditions also influence the tightness of broker-dealer balance sheet constraints; low realized portfolio volatility permits an increase in leverage.

[13] It should, however, be noted that the CFTC classification of traders into hedgers and speculators is quite noisy and hence the results in this subsection should be taken with a grain a salt

The interaction term in column (i) of Table 6 demonstrates this effect for crude oil: a positive innovation in broker-dealer balance sheets that bids up current crude oil prices (compresses risk premia) is associated with an increase in the speculator share of open interest. The result is significant at 1% level.

Using the trading data as an additional piece of identification, one can also sharpen the image for the contemporaneous link between balance sheet innovations and crude oil returns. The specification in column (ii) shows that an expansion in broker-dealer balance sheets that increases the share of speculative demand in the futures market is associated with a contemporaneous increase in crude oil prices (compression of risk premia).[14]

Taken together, the evidence from the futures market lends additional support to the prediction of the model that broker-dealer risk appetite determines expected commodity returns through its association with systematic risk premia.

5. Cross-Sectional Prices of Risk

In order to investigate the significance of broker-dealer risk appetite for the pricing of the cross-section of commodity returns, this section constructs and implements a cross-sectional asset pricing model with time-varying prices of risk.

(e.g. Gorton, Hayashi and Rouwenhorst, 2007).

[14]Note the similarity of these results to Campbell, Grossman and Wang (1993) where risk-averse market makers accommodate selling pressure from liquidity traders. Their model predicts that an asset price decline on a high-volume day is more likely to be associated with an increase in the expected asset return than an asset price decline on a low-volume day. In the present framework, liquidity traders (hedgers) have to accommodate changes in broker-dealer (speculator) risk appetite by accepting a higher/lower futures price. A futures price increase is more likely to be associate with an increase in broker-dealer risk appetite when speculative activity is increasing than when speculative activity is decreasing.

5.1. Cross-Sectional Asset Pricing Approach

Let r^i_{t+1} be the excess return on a position in commodity i. Denoting the pricing kernel by M_{t+1}/M_t, the expected excess return is:

$$E_t\left(\frac{M_{t+1}}{M_t}r^i_{t+1}\right)=0.$$

Define the commodity risk premium,

$$\eta_t=-Cov_t\left[\frac{M_{t+1}/M_t}{E_t\left(M_{t+1}/M_t\right)},r^i_{t+1}\right], \tag{5.1}$$

and express the excess return in terms of two components:

$$\underbrace{r^i_{t+1}}_{\substack{\text{Excess}\\ \text{Return}}} = \underbrace{\eta_t}_{\substack{\text{Commodity}\\ \text{Risk Premium}}} + \underbrace{u^i_{t+1}}_{\substack{\text{Commodity}\\ \text{Risk}}}, \tag{5.2}$$

where $E_t\left(u^i_{t+1}\right)=0$.

In order to estimate the prices of risk λ_t, assume the pricing kernel is exponentially affine in a set of state variables X_t:

$$\begin{aligned}\frac{M_{t+1}}{M_t} &= \exp\left(-\ln\left(r_t\right)-\frac{1}{2}\lambda_t'\lambda_t-\lambda_t'v_{t+1}\right),\\ \Sigma_t\lambda_t &= \lambda_0+\lambda_1X_t,\end{aligned}$$

where

$$\begin{aligned}X_{t+1} &= \mu+\phi X_t+\Sigma_tv_{t+1},\\ vec\left(\Sigma_t\Sigma_t'\right) &= S_0+S_1X_t,\end{aligned}$$

and $v_{t+1}\sim N\left(0,I_k\right)$. Using Stein's lemma for the commodity risk premium (5.1) and defining $\beta^{i\prime}_t=Cov_t\left(r^i_{t+1},X_{t+1}\right)\Sigma_t^{-1}$, the pricing equation (5.2) becomes:

$$r^i_{t+1}=\beta^{i\prime}_t\left(\lambda_0+\lambda_1X_t\right)+u^i_{t+1}.$$

Following Adrian and Moench (2008), one can further decompose the commodity-specific risk into a systematic and idiosyncratic component to obtain:

$$\underbrace{r^i_{t+1}}_{\substack{\text{Excess}\\ \text{Return}}} = \underbrace{\beta^{i\prime}_t \left(\lambda_0 + \lambda_1 X_t\right)}_{\substack{\text{Commodity}\\ \text{Risk Premia}}} + \underbrace{\beta^{i\prime}_t v_{t+1}}_{\substack{\text{Systematic}\\ \text{Commodity Risk}}} + \underbrace{\epsilon^i_{t+1}}_{\substack{\text{Idiosyncratic}\\ \text{Commodity Risk}}} , \quad (5.3)$$

where $\epsilon^i_{t+1} \sim N\left(0,1\right)$ for all i.

5.2. Estimating Prices of Risk

The cross-sectional model in (5.3) is estimated by way of three-stage OLS regressions applied to the cross-section of 14 commodity futures discussed above. For simplicity, it is assumed that the commodity-specific betas β^i are constant over time. The steps of the estimation procedure are outlined in Adrian and Moench (2008).

Building on the reduced-form factor model (2.11) sketched in Section 2, let the vector of state variables be given by:

$$X_t = \left(\begin{array}{c} \text{S\&P 500 Excess Return} \\ \text{GSCI Spot Excess Return} \\ \text{Broker-Dealer Asset Share Innovation} \end{array} \right),$$

where the S&P 500 is a proxy for the returns on marketable assets (r^M_t), the GSCI Spot is a proxy for the returns on non-marketable securities (r^{NM}_t), and the innovation in broker-dealer asset share is a state variable that proxies for the innovations in the aggregate risk appetite.

Before proceeding to the results, note what to expect based on Section 2's theoretical outline. First, the main prediction of the model concerns the association of the asset share innovation with the price of non-marketable risk, which I denote by λ^{GSCI}_t. In particular, λ^{GSCI}_t ought to have a significant negative load on the lagged innovation in broker-dealer asset share. Since the cross-sectional specification in (5.3) links the dynamics of prices of risk λ_t to the state variables

X_t, one can use it to quantify this relationship. Second, note that the model in its current static form remains silent about whether the asset share innovation should also be a priced risk factor. For an intertemporal asset pricing model with broker-dealer balance sheet constraints, see Adrian, Etula and Shin (2009).

The estimates for the cross-sectional prices of risk are displayed in Table 7. The first four columns give the loadings of the prices of risk λ_t^k on a constant (λ_0) and on the lags of the three state variables $\left(\lambda_1^l\right)$. The associated t-statistics are based on a bootstrap with 1000 iterations. Note that the price of non-marketable risk (on the second row) has a significant negative loading on the innovation in broker-dealer asset share. This lends support to the prediction of the model that the price of non-marketable risk is inversely linked to broker-dealer risk appetite.

The significance of the prices of risk is tested in Column (v). The p-values in brackets show that out of the three state variables only the price of non-marketable (GSCI) risk is statistically significant. The finding that the S&P 500 risk is not priced is consistent with numerous previous studies, which have demonstrated that systematic market risk is not significant for the pricing of commodity returns.

Figure 5.1 plots the estimated price of non-marketable risk λ_t^{GSCI} over the estimation period. The series is highly volatile, which reflects the same time-variation in commodity risk premia that was found to generate forecastability of returns in Section 2. Three of the most extreme peaks easily map to large events that shook the broker-dealer industry: the LTCM crisis in late 1998, the Enron collapse in late 2001, and the Sarbanes-Oxley Securities Act in 2002. The figure also features the beginning of the recent subprime meltdown. It is instructive to map these peaks to the corresponding (subsequent) fluctuations in the crude oil market, as illustrated in Fig. 3.4. The average risk premium for non-marketable risk is 1.68% per quarter, which is comparable to the estimates of equity premium.

One may also assess the significance of individual commodities' loadings on the risk premia, the first column of Table 8 tests the joint significance of betas

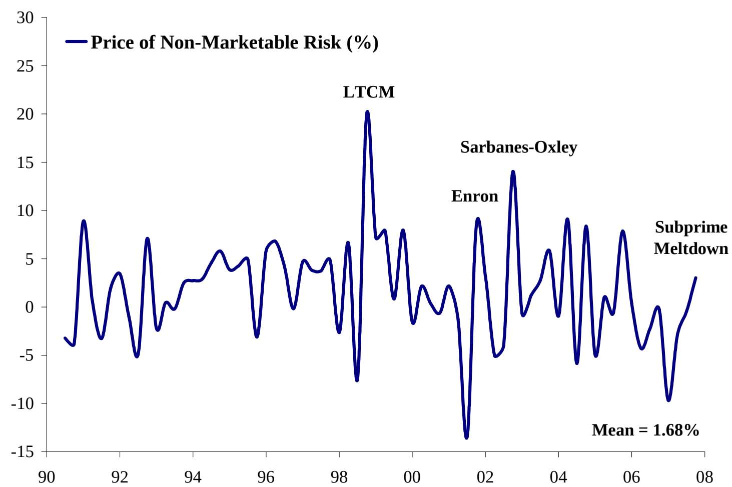

Figure 5.1: Price of GSCI spot commodity risk (Q3/1990-Q4/2007)

for each commodity. The bootstrapped p-values in brackets indicate that 8 out of 14 commodity futures have statistically significant loadings on the innovations of state variables. The second column conducts similar tests for the commodity risk premia, which correspond to the currency-specific betas multiplied by the prices of risk. The risk premium is significant at 1% level for crude oil, heating oil and unleaded gasoline; any differences relative to Table 1A stem from the cross-sectional restrictions imposed by the model.

Finally, column (iii) investigates the quality of the pricing model by testing the predictability of forecast residuals by lagged state variables. The test of excess forecastability is significant only for soybeans, which indicates that the model does a good job in pricing rest of the cross-section. That is, the observed predictability of commodity returns is explained by market-wide risks, which cannot be diversified away in the cross-section of commodities.

In sum, the cross-sectional evidence supports the paper's view that the forecastability of commodity returns uncovered in Table 1 is in fact a reflection of systematic changes in risk premia. As broker-dealer balance sheets expand, speculators' risk appetite increases. This decreases the risk premia that speculators demand for insuring producers and end-users of commodities against spot commodity risk in the futures market; i.e., it decreases the price of non-marketable risk. Conversely, as balance sheets contract, investor risk appetite decreases. This increases the risk premia that speculators demand for taking on spot commodity risk, raising the price of non-marketable risk.

6. Conclusion

This paper shows that fluctuations in broker-dealer balance sheets forecast commodity returns at quarterly horizons, both in-sample and out-of-sample. The pattern emerged following the establishment of futures markets and strengthened as the share of broker-dealer assets increased in the U.S. economy. I rationalize the results in a simple pricing model where broker-dealers provide insurance to producers and end-users of commodities in the futures market. To the extent that hedgers' demand for insurance is independent of the fluctuations in broker-dealer risk appetite, innovations in broker-dealer risk appetite are reflected in expected commodity returns through their association with risk premia. The model is also consistent with other quantitative and qualitative features of the data.

Cross-sectional evidence further suggests that the observed forecastability is largely a reflection of changes in market-wide risk premia: excess commodity returns are compensation for systematic non-marketable risk whose price fluctuates with broker-dealer risk appetite. The cross-sectional findings lend additional support to the view that broker-dealer balance sheet constraints operate through shifts in risk appetite.

In sum, the empirical and theoretical contributions of the paper may be regarded as the first steps toward understanding the impact of broker-dealer risk appetite on commodity prices. Fluctuations in broker-dealer risk appetite seem to be the common thread that ties together commodity price movements with changes in risk premia. Thus, the documented forecastability of commodity returns may be accompanied by shifting risk premia that are consistent with forward-looking portfolio decisions of investors.

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TABLE 1A: Forecasting Quarterly Excess Returns on Commodity Futures (Q3/1990 - Q4/2007)

	Energy							
	Crude Oil		Heating Oil		U. Gasoline		Natural Gas	
S&P 500 Excess Return	−0.398*	−0.392*	−0.382*	−0.411*	−0.369	−0.380	−0.248	−0.280
	(−1.869)	(−1.809)	(−1.647)	(−1.670)	(−1.452)	(−1.433)	(−0.482)	(−0.507)
Asset Share Innov. (Lag 1)	−0.462***	−0.463***	−0.390***	−0.386***	−0.416***	−0.415***	−0.325**	−0.321**
	(−5.683)	(−5.620)	(−4.054)	(−4.072)	(−4.446)	(−4.382)	(−2.100)	(−2.000)
Fitted Asset Share (Lag 1)		0.015		−0.071		−0.026		−0.078
		(0.234)		(−0.870)		(−0.350)		(−0.561)
Constant	4.125***	4.127**	4.275**	4.264**	4.367**	4.363**	2.006	1.994
	(2.584)	(2.567)	(2.208)	(2.197)	(2.288)	(2.273)	(0.527)	(0.524)
# Observations	69	69	69	69	69	69	69	69
Adjusted R^2	33.11%	32.16%	18.51%	18.59%	22.00%	20.98%	1.83%	0.89%
	Metals							
	Gold		Silver		Platinum		Copper	
S&P 500 Excess Return	−0.155*	−0.132	−0.004	0.025	0.140	0.141	0.159	0.164
	(−1.817)	(−1.544)	(−0.028)	(0.204)	(0.841)	(0.815)	(0.895)	(0.911)
Asset Share Innov. (Lag 1)	0.001	−0.002	−0.114*	−0.118*	−0.042	−0.042	−0.144*	−0.145*
	(0.040)	(−0.043)	(−1.704)	(−1.662)	(−0.647)	(−0.643)	(−1.730)	(−1.710)
Fitted Asset Share (Lag 1)		0.058**		0.071**		0.002		0.013
		(2.115)		(2.051)		(0.057)		(0.252)
Constant	0.480	0.489	1.094	1.105	2.034*	2.035*	2.329	2.330
	(0.651)	(0.683)	(0.843)	(0.862)	(1.921)	(1.911)	(1.407)	(1.398)
# Observations	69	69	69	69	69	69	69	69
Adjusted R^2	0.53%	6.39%	0.69%	2.59%	−0.98%	−2.53%	0.89%	−0.56%
	Agriculture							
	Wheat		Corn		Soybeans		Cocoa	
S&P 500 Excess Return	−0.107	−0.051	0.084	0.111	−0.034	−0.002	−0.595**	−0.579**
	(−0.516)	(−0.268)	(0.443)	(0.606)	(−0.196)	(−0.015)	(−2.365)	(−2.228)
Asset Share Innov. (Lag 1)	0.218***	0.210***	−0.006	−0.010	0.052	0.048	0.203***	0.201***
	(2.577)	(2.752)	(−0.078)	(−0.123)	(0.682)	(0.621)	(2.700)	(2.656)
Fitted Asset Share (Lag 1)		0.139**		0.068		0.077*		0.039
		(2.056)		(1.299)		(1.709)		(0.800)
Constant	−0.140	−0.119	−1.365	−1.355	1.117	1.129	0.350	0.355
	(−0.088)	(−0.077)	(−0.847)	(−0.845)	(0.811)	(0.840)	(0.235)	(0.238)
# Observations	69	69	69	69	69	69	69	69
Adjusted R^2	5.45%	12.51%	−2.82%	−2.24%	−2.28%	0.16%	15.23%	14.73%
	Agriculture							
	Cotton		Sugar					
S&P 500 Excess Return	0.222	0.262	−0.369	−0.379				
	(0.976)	(1.267)	(−0.867)	(−0.853)				
Asset Share Innov. (Lag 1)	−0.073	−0.078	−0.014	−0.012				
	(−1.050)	(−1.146)	(−0.110)	(−0.098)				
Fitted Asset Share (Lag 1)		0.099**		−0.025				
		(2.197)		(−0.320)				
Constant	−1.704	−1.689	1.788	1.784				
	(−1.138)	(−1.165)	(0.782)	(0.773)				
# Observations	69	69	69	69				
Adjusted R^2	−0.43%	3.64%	−0.79%	−2.19%				

Note: robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 1B: Forecasting Quarterly Excess Returns on Spot Commodities (Q3/1990 - Q4/2007)

	Energy							
	Crude Oil		Heating Oil		U. Gasoline		Natural Gas	
S&P 500 Excess Return	-0.437^{**}	-0.411^{**}	-0.490^{**}	-0.478^{*}	-0.513^{**}	-0.484^{**}	0.464	0.407
	(−2.191)	(−2.038)	(−1.967)	(−1.891)	(−2.490)	(−2.345)	(0.707)	(0.598)
Asset Share Innov. (Lag 1)	-0.390^{***}	-0.394^{***}	-0.363^{***}	-0.364^{***}	-0.442^{***}	-0.446^{***}	−0.000	0.007
	(−4.114)	(−4.117)	(−3.206)	(−3.170)	(−3.273)	(−3.317)	(−0.001)	(0.035)
Fitted Asset Share (Lag 1)		0.064		0.028		0.071		−0.139
		(1.014)		(0.447)		(1.015)		(−0.824)
Constant	2.107	2.117	2.671	2.676	3.002	3.013	5.234	5.213
	(1.328)	(1.342)	(1.329)	(1.325)	(1.361)	(1.360)	(1.206)	(1.205)
# Observations	69	69	69	69	69	69	69	69
Adjusted R^2	28.26%	28.65%	17.72%	16.66%	18.74%	18.46%	−2.11%	−2.44%
	Metals							
	Gold		Silver		Platinum		Copper	
S&P 500 Excess Return	-0.179^{**}	-0.154^{*}	−0.015	0.015	0.163	0.173	0.131	0.141
	(−1.996)	(−1.723)	(−0.124)	(0.126)	(0.960)	(0.997)	(0.782)	(0.825)
Asset Share Innov. (Lag 1)	0.007	0.004	−0.095	−0.099	−0.064	−0.065	-0.128^{*}	-0.130^{*}
	(0.183)	(0.092)	(−1.488)	(−1.463)	(−1.132)	(−1.145)	(−1.683)	(−1.670)
Fitted Asset Share (Lag 1)		0.060^{**}		0.073^{**}		0.024		0.024
		(2.181)		(2.157)		(0.661)		(0.494)
Constant	0.443	0.452	1.221	1.233	0.926	0.930	0.657	0.661
	(0.584)	(0.615)	(0.961)	(0.984)	(0.899)	(0.905)	(0.431)	(0.431)
# Observations	69	69	69	69	69	69	69	69
Adjusted R^2	1.29%	7.26%	−0.23%	2.08%	0.58%	−0.19%	0.52%	−0.73%
	Agriculture							
	Wheat		Corn		Soybeans		Cocoa	
S&P 500 Excess Return	0.043	0.083	0.030	0.058	0.046	0.085	-0.534^{**}	-0.523^{**}
	(0.190)	(0.373)	(0.125)	(0.240)	(0.227)	(0.455)	(−2.312)	(−2.183)
Asset Share Innov. (Lag 1)	0.311^{***}	0.306^{***}	0.095	0.091	0.095	0.090	0.189^{***}	0.187^{***}
	(3.355)	(3.558)	(1.052)	(1.016)	(1.096)	(1.034)	(3.090)	(3.011)
Fitted Asset Share (Lag 1)		0.099		0.070		0.095^{*}		0.028
		(1.201)		(1.072)		(1.835)		(0.655)
Constant	1.687	1.702	1.085	1.096	0.743	0.757	1.105	1.109
	(0.896)	(0.902)	(0.576)	(0.585)	(0.445)	(0.465)	(0.829)	(0.827)
# Observations	69	69	69	69	69	69	69	69
Adjusted R^2	9.98%	11.66%	−1.61%	−1.44%	−1.08%	1.58%	15.67%	14.91%
	Agriculture							
	Cotton		Sugar					
S&P 500 Excess Return	0.017	0.054	−0.221	−0.220				
	(0.079)	(0.269)	(−0.860)	(−0.809)				
Asset Share Innov. (Lag 1)	−0.002	−0.006	−0.045	−0.045				
	(−0.023)	(−0.096)	(−0.404)	(−0.395)				
Fitted Asset Share (Lag 1)		0.091^{*}		0.002				
		(1.667)		(0.023)				
Constant	−0.315	−0.301	0.641	0.641				
	(−0.219)	(−0.215)	(0.356)	(0.354)				
# Observations	69	69	69	69				
Adjusted R^2	−3.02%	0.62%	−1.12%	−2.67%				

Note: robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 1C: Forecasting Quarterly Excess Returns on Indexes (Q3/1990 - Q4/2007)

	GSCI (Futures)		GSCI (Spot)		DJCI (Futures)		DJ Corp. Bond Index	
S&P 500 Excess Return	−0.201	−0.197	−0.203	−0.188	−0.115	−0.107	0.012	0.014
	(−1.222)	(−1.165)	(−1.230)	(−1.123)	(−0.965)	(−0.884)	(0.296)	(0.351)
Asset Share Innov. (Lag 1)	−0.210***	−0.210***	−0.178***	−0.180***	−0.123***	−0.124***	0.010	0.010
	(−4.370)	(−4.316)	(−3.234)	(−3.227)	(−3.697)	(−3.625)	(0.619)	(0.593)
Fitted Asset Share (Lag 1)		0.009		0.037		0.020		0.006
		(0.224)		(0.948)		(0.849)		(0.654)
Constant	1.207	1.209	0.959	0.965	0.245	0.248	−0.710**	−0.709**
	(1.092)	(1.088)	(0.850)	(0.858)	(0.337)	(0.340)	(−2.458)	(−2.425)
# Observations	69	69	69	69	69	69	69	69
Adjusted R^2	18.01%	16.82%	13.68%	13.61%	13.76%	13.23%	−2.21%	−3.27%

Note: robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 1D: Futures Returns and Contemporaneous Asset Share Innovations (Q3/1990 - Q4/2007)

	Energy				Metals			
	Crude Oil	Heating Oil	U. Gasoline	Natural Gas	Gold	Silver	Platinum	Copper
S&P 500 Excess Return	−0.617**	−0.563*	−0.477	−0.343	−0.101	0.077	0.087	0.175
	(−2.394)	(−1.814)	(−1.557)	(−0.552)	(−0.968)	(0.454)	(0.519)	(0.904)
Asset Share Innov. (Lag 1)	−0.461***	−0.384***	−0.414***	−0.320**	−0.002	−0.118*	−0.041	−0.145*
	(−5.737)	(−4.011)	(−4.355)	(−1.978)	(−0.051)	(−1.681)	(−0.632)	(−1.712)
Fitted Asset Share (Lag 1)	0.016	−0.071	−0.025	−0.078	0.058**	0.071**	0.002	0.013
	(0.251)	(−0.878)	(−0.354)	(−0.558)	(2.063)	(2.021)	(0.058)	(0.250)
Asset Share Innov.	−0.183*	−0.124	−0.080	−0.051	0.025	0.042	−0.044	0.009
	(−1.868)	(−1.011)	(−0.700)	(−0.233)	(0.617)	(0.513)	(−0.593)	(0.098)
Constant	4.482***	4.504**	4.517**	2.093	0.441	1.024	2.120**	2.313
	(2.842)	(2.339)	(2.301)	(0.552)	(0.592)	(0.788)	(2.034)	(1.349)
# Observations	69	69	69	69	69	69	69	69
Adjusted R^2	34.71%	18.65%	20.33%	−0.58%	5.39%	1.46%	−3.36%	−2.12%

	Agriculture						Indexes	
	Wheat	Corn	Soybeans	Cocoa	Cotton	Sugar	GSCI	DJCI
S&P 500 Excess Return	0.109	0.112	−0.050	−0.469	0.217	−0.678	−0.307*	−0.156
	(0.449)	(0.498)	(−0.266)	(−1.448)	(0.986)	(−1.585)	(−1.660)	(−1.291)
Asset Share Innov. (Lag 1)	0.209***	−0.010	0.049	0.200**	−0.078	−0.010	−0.210***	−0.123***
	(2.720)	(−0.122)	(0.611)	(2.574)	(−1.125)	(−0.076)	(−4.197)	(−3.493)
Fitted Asset Share (Lag 1)	0.139**	0.068	0.077*	0.038	0.099**	−0.025	0.009	0.020
	(2.101)	(1.290)	(1.693)	(0.796)	(2.169)	(−0.317)	(0.235)	(0.874)
Asset Share Innov.	0.130	0.000	−0.039	0.090	−0.036	−0.244*	−0.089	−0.040
	(1.291)	(0.002)	(−0.546)	(1.074)	(−0.387)	(−1.809)	(−1.334)	(−0.968)
Constant	−0.370	−1.355	1.203	0.182	−1.619	2.256	1.381	0.326
	(−0.239)	(−0.841)	(0.905)	(0.118)	(−1.067)	(1.022)	(1.262)	(0.443)
# Observations	69	69	69	69	69	69	69	69
Adjusted R^2	13.60%	−3.84%	−1.06%	14.85%	2.38%	0.87%	17.87%	12.99%

Note: robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 2A: Quarterly In-Sample Regressions (Q3/1990 - Q4/2007)

	Crude Oil Futures Excess Return							
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Asset Share Innov. (Lag 1)	-0.492^{***}	-0.495^{***}	-0.491^{***}	-0.484^{***}	-0.484^{***}	-0.434^{***}	-0.432^{***}	-0.432^{***}
	(−5.959)	(−5.993)	(−5.975)	(−5.823)	(−5.798)	(−5.522)	(−5.473)	(−5.357)
Fitted Asset Share (Lag 1)	0.026	0.014	0.011	−0.036	−0.037	0.069	0.069	0.094
	(0.387)	(0.193)	(0.148)	(−0.446)	(−0.403)	(0.854)	(0.848)	(1.143)
VIX (Lag 1)			−0.075	−0.133	−0.134	−0.396	−0.394	−0.198
			(−0.309)	(−0.570)	(−0.561)	(−1.567)	(−1.536)	(−0.691)
Interest Rate (Lag 1)				-8.816^{**}	-8.722^{*}	5.905	6.024	4.341
				(−2.255)	(−1.716)	(0.803)	(0.836)	(0.595)
Yield Spread (Lag 1)					0.185	14.433	14.448	11.638
					(0.025)	(1.617)	(1.613)	(1.328)
Dividend Yield (Lag 1)						-9.604^{**}	-9.514^{**}	-7.983^{*}
						(−2.518)	(−2.360)	(−1.958)
Inflation (Lag 1)							−0.562	−0.655
							(−0.152)	(−0.170)
Hedging Pressure (Lag 1)								0.172^{**}
								(2.332)
Dependent Variable (Lag 1)		−0.069	−0.066	−0.068	−0.068	−0.025	−0.023	-0.115^{**}
		(−0.581)	(−0.572)	(−0.782)	(−0.752)	(−0.352)	(−0.324)	(−2.084)
Constant	3.521^{**}	3.845^{**}	5.260	14.874^{**}	14.671	14.404	14.407	11.341
	(2.255)	(2.480)	(1.128)	(2.374)	(1.454)	(1.593)	(1.576)	(1.318)
# Observations	69	69	69	69	69	69	69	69
Adjusted R^2	30.0%	29.7%	28.8%	32.0%	30.9%	36.4%	35.4%	40.8%

Note: robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 2B: Quarterly In-Sample Regressions (Q3/1990 - Q4/2007)

	GSCI Futures Excess Return						
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Asset Share Innov. (Lag 1)	-0.225^{***}	-0.227^{***}	-0.220^{***}	-0.215^{***}	-0.215^{***}	-0.194^{***}	-0.191^{***}
	(−4.583)	(−4.441)	(−4.572)	(−4.475)	(−4.459)	(−3.870)	(−3.756)
Fitted Asset Share (Lag 1)	0.014	0.006	−0.001	−0.034	−0.037	0.007	0.007
	(0.354)	(0.141)	(−0.022)	(−0.685)	(−0.663)	(0.129)	(0.129)
VIX (Lag 1)			−0.156	−0.195	−0.201	-0.307^{*}	-0.303^{*}
			(−0.941)	(−1.250)	(−1.304)	(−1.907)	(−1.859)
Interest Rate (Lag 1)				-6.015^{**}	−5.583	0.716	0.926
				(−2.385)	(−1.507)	(0.115)	(0.153)
Yield Spread (Lag 1)					0.856	7.022	7.059
					(0.160)	(0.974)	(0.981)
Dividend Yield (Lag 1)						−4.074	−3.923
						(−1.490)	(−1.377)
Inflation (Lag 1)							−0.943
							(−0.372)
Dependent Variable (Lag 1)		−0.104	−0.103	−0.112	−0.114	−0.084	−0.078
		(−0.946)	(−0.993)	(−1.324)	(−1.305)	(−0.962)	(−0.890)
Constant	0.903	1.051	3.996	10.566^{**}	9.635	9.299	9.274
	(0.878)	(1.022)	(1.212)	(2.378)	(1.203)	(1.152)	(1.144)
# Observations	69	69	69	69	69	69	69
Adjusted R^2	15.9%	16.2%	16.1%	20.3%	19.1%	21.0%	19.9%

Note: robust t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 3A: Quarterly Out-of-Sample Regressions (Q2/1995 - Q4/2007)

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

	Restricted Model (r)	Unrestricted Model (u)	DMW $MSE_r - MSE_u$	Clark-West Adjusted $MSE_r - (MSE_u - adj.)$
(1)	$E_t r_{t+1} = 0$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} x_t$	108.114***	216.945***
			[0.010]	[0.001]
(2)	$E_t r_{t+1} = \alpha_{0t}$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} x_t$	89.366**	195.332***
			[0.020]	[0.001]
(3)	$E_t r_{t+1} = \alpha_{0t} + \alpha_{1t} r_t$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} r_t + \beta_{2t} x_t$	89.150**	207.359***
			[0.020]	[0.001]
Number of Observations			47	47

Note: x_t = Change in Asset Share; p-values in brackets: *** p < 0.01, ** p < 0.05, * p < 0.1.

TABLE 3B: Quarterly Out-of-Sample Regressions (Q2/1995 - Q4/2007)

GSCI Futures Excess Return (r_{t+1})

	Restricted Model (r)	Unrestricted Model (u)	DMW $MSE_r - MSE_u$	Clark-West Adjusted $MSE_r - (MSE_u - adj.)$
(1)	$E_t r_{t+1} = 0$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} x_t$	21.044**	37.692***
			[0.025]	[0.002]
(2)	$E_t r_{t+1} = \alpha_{0t}$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} x_t$	20.989**	38.405***
			[0.028]	[0.002]
(3)	$E_t r_{t+1} = \alpha_{0t} + \alpha_{1t} r_t$	$E_t r_{t+1} = \beta_{0t} + \beta_{1t} r_t + \beta_{2t} x_t$	21.607**	39.190***
			[0.026]	[0.002]
Number of Observations			47	47

Note: x_t = Change in Asset Share; p-values in brackets: *** p < 0.01, ** p < 0.05, * p < 0.1.

TABLE 4: Risk Appetite and Market Risk Premia

	VIX Premium		ΔVIX Premium		CDX	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Asset Share Innovation	−0.101***	−0.101***	−0.146***	−0.146***	−0.292**	−0.302**
	(−3.338)	(−3.282)	(−4.370)	(−4.305)	(−2.020)	(−2.020)
Fitted Asset Share		0.007		0.035		0.073
		(0.466)		(1.263)		(0.520)
Constant	4.937***	4.937***	0.001	0.001	49.825***	49.324***
	(13.051)	(12.981)	(0.001)	(0.001)	(18.250)	(18.650)
# Observations	70	70	70	70	17	17
Adjusted R^2	23.2%	22.4%	21.8%	24.1%	13.0%	10.4%

Note: robust t-statistics (bootstrapped for CDX) in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

TABLE 5: Risk Appetite and Market Volatility

	S&P 500 Variance	Δ S&P 500 Volatility		
	(i)	(ii)	(iii)	(iv)
Asset Share Innovation	4.152^{**}	0.204^{***}	0.204^{***}	0.127^{***}
	(1.962)	(4.056)	(4.108)	(3.073)
Fitted Asset Share	-1.742^{**}		-0.028	-0.027
	(-2.002)		(-1.108)	(-1.080)
[Asset Share Innovation]^2	0.180^{***}			
	(3.931)			
[Fitted Asset Share]^2	0.050^{**}			
	(2.525)			
S&P 500 Excess Return				-0.406^{***}
				(-4.077)
Constant	145.258^{***}	0.095	0.095	0.631
	(4.847)	(0.132)	(0.132)	(0.985)
Number of Observations	70	70	70	70
Adjusted R^2	21.8%	26.0%	26.2%	40.4%

Note: robust t-statistics in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

TABLE 6: Risk Appetite and Speculative Activity in the Futures Market

	Δ Speculators' Share of OI	Crude Oil Excess Return
	(i)	(ii)
Asset Share Innovation	0.098^{*}	-0.012
	(1.756)	(-0.086)
Fitted Asset Share	0.035	-0.160^{**}
	(0.859)	(-2.505)
Crude Oil Excess Return	0.183^{***}	
	(2.798)	
[Asset Share Innov.] × [Crude Oil Excess Ret.]	0.009^{***}	
	(3.359)	
Δ Speculators' Share of OI		0.555^{***}
		(2.967)
[Asset Share Innov.] × [Δ Spec. Share of OI]		0.024^{**}
		(2.213)
Constant	-0.550	2.930^{*}
	(-0.656)	(1.659)
# Observations	69	69
Adjusted R^2	18.5%	15.4%

Note: robust t-statistics in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

TABLE 7: Cross-Sectional Prices of Risk

Residual	λ_0	$\lambda_1^{S\&P500}$	λ_1^{GSCI}	λ_1^{B-D}	$\lambda_0 = \lambda_1^{S\&P500} = ... = \lambda_1^{B-D} = 0$
S&P 500 Excess Return	−1.083	0.324*	0.153*	−0.063	[0.299]
	(−0.76)	(1.79)	(1.72)	(−1.00)	
GSCI Spot Excess Return	2.408***	0.176**	−0.069	0.179***	[0.000]***
	(3.28)	(2.12)	(−1.24)	(4.68)	
Asset Share Innovation	21.713**	−1.032	0.194	0.818**	[0.115]
	(2.50)	(−0.82)	(0.27)	(2.15)	

Note: Bootstrapped t-statistics in parentheses, p-values in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 8: Significance of β's, $\beta'\lambda$'s and Excess Predictability

Test Asset	$\beta^{S\&P500} = ... = \beta^{B-D} = 0$	$\beta'\lambda_0 = \beta'\lambda_1^{S\&P500} = ... = \beta'\lambda_1^{B-D} = 0$	Predictability of Forecast Residuals
Crude Oil	[0.000]***	[0.000]***	[0.777]
Heating Oil	[0.000]***	[0.000]***	[0.956]
U. Gasoline	[0.000]***	[0.000]***	[0.887]
Natural Gas	[0.053]*	[0.116]	[0.984]
Gold	[0.000]***	[0.319]	[0.747]
Silver	[0.889]	[0.888]	[0.236]
Platinum	[0.037]**	[0.342]	[0.194]
Copper	[0.006]***	[0.121]	[0.232]
Wheat	[0.330]	[0.499]	[0.504]
Corn	[0.813]	[0.951]	[0.268]
Soybeans	[0.851]	[0.933]	[0.054]*
Cocoa	[0.013]**	[0.745]	[0.270]
Cotton	[0.757]	[0.937]	[0.619]
Sugar	[0.525]	[0.414]	[0.899]

Note: Bootstrapped p-values in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.