Expected Commodity Futures Returns

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Abstract

In this article, we posit an empirical beta pricing model of expected commodity futures returns to explore predictable variation in their returns. Our model allows commodity futures returns to vary with the holdings of hedgers and allows these holdings to vary with business conditions. The model also allows for time variation in expected returns with relative scarcity of the commodity. Our evidence suggests that a large portion of the predictable variation in futures returns is explainable by these asset specific factors and that movements in these factors are related to macroeconomic variables. This evidence is consistent with rational return predictability.

I. Introduction

If return predictability is not spurious [Ferson, et al. (2003)], it can be interpreted as evidence of either market inefficiency or rational hedging responses to uncertain inter-temporal changes in business conditions. Hirshleifer (1988) models expected commodity futures returns that vary with the holdings of hedgers in that commodity; there is evidence in support of this prediction. Fama and French (1989) note that if variation in expected returns is common across securities then predictability is more likely to be rational. Cross-sectional studies using conditional versions of asset pricing models, like those of Ferson and Harvey (1991), confirm that predictable variation in expected equity returns. As suggested by Fama (1991), resolving the debate of whether return predictability is caused by rational or irrational behavior requires digging deeper to establish the links between expected returns and business conditions. In judging the nature of predictability, models of expected commodity futures returns that allow these holdings to be related to the macro-economy seem desirable.

Below we posit an empirical beta pricing model of expected commodity futures returns. In our model expected returns depend on a systematic factor, as well as two commodity specific risk factors, the hedging pressure and supply condition premiums for risk noted by Hirshleifer (1988) and Schwartz (1997), respectively.[1] In the conditional version of our model the risk factors vary with a set of information variables representing the state of the macro-economy. Sensitivity to the risk factors, captured by betas, is allowed to vary with market specific information.[2] Our goal in the conditional framework is to test for significant predictable time variation in risk premia, particularly relative to hedging pressure. Evidence of predictable variation in risk premia provides support for rational asset return predictability. We also decompose time varying expected returns into variation due to betas and varying expected factor values. This clarifies whether varying exposure to the risk factors or changing factor expectations produces predictability.

[1] We estimate supply conditions using inventory data and estimate hedging demands with data on the number of long and short hedge positions in each commodity market.

[2] Ferson and Harvey (1993) use a similar modeling technique to determine the amount of predictable variation of international equities explained by liner factor models. Their model allows conditional betas to depend on local information variables, while global risk premia depend on global market variables.

Estimating our model, we find that both hedging pressure and supply conditions are significantly related to returns. In the conditional versions of the model, we find significant time variation in risk premia. The evidence for variation in betas is also statistically significant, although predicted variation in expected returns can be traced for the most part to the risk factors. Our results further suggest that expected futures returns are impacted by relative scarcity of a commodity as reflected in inventories. An important insight from our evidence is that, consistent with theory, holdings of hedgers in the markets we study vary with commonly used macro-economic instruments. A reliable proxy for such holdings is, unfortunately, not available in most asset markets. Without such a measure the proposition that changes in the investment opportunity set produce predictable variation in expected returns is only indirectly testable.[3]

The remainder of this article is organized as follows. In the next section, we briefly review the literature and then describe our data and empirical methods in Section III. Section IV presents the evidence and the article ends with a brief conclusion in Section V.

II. Business Conditions and Expected Futures Returns

In general, risk premia in equilibrium models of asset prices depend only on the assets sensitivity to economic state variables. All claims can be marketed free of cost, and hence a hedge portfolio perfectly correlated with one state variable and uncorrelated with others earns the factor premium. In Merton's intertemporal capital asset pricing model (ICAPM), asset demands adjust as risk-averse investor's update their exposure to the hedge portfolio, which hedges inter-temporal stochastic shifts in investment opportunities that impact future consumption. In equilibrium, expected returns compensate investors for bearing systematic risk, as well as for bearing risk of unfavorable shifts in the investment opportunity set. Predictability of risk premia leads to predictable time variation in expected returns through changing hedging demands. Cox, Ingersoll, and Ross (1985)

[3] Fama and French (1989) note that if variation in expected returns is common across securities then it is more likely to be rational and cross-sectional studies using conditional versions of asset pricing models, like those of Ferson and Harvey (1991), confirm that variation in expected returns is consistent with the ICAPM.

generalize this intuition such that investors can invest in both financial and real assets.

In the theoretic work on commodity futures pricing the impact of changing hedging pressure on asset prices is clearly defined. Keynes (1930) posits that futures prices are downward biased estimates of the expected spot price. This bias produces positive futures risk premia that compensate speculators for the insurance they provide to hedgers. Brennan (1958) suggests that the "marginal risk aversion may be assumed to be constant or, more likely, an increasing function of stocks held", leaving open the role commodity inventories might play in determining futures prices. Schwartz (1997) conjectures covariance between the market price of risk and inventory, but to our knowledge there is no conclusive study in the commodities literature relating the physical inventory to futures returns.

In a series of papers, Hirshleifer (1988, 1989, and 1990) clarifies these insights in the context of equilibrium asset pricing theory showing that both systematic and commodity specific factors impact futures prices. De Roon, Nijman, and Veld (2000) present a model of futures markets which places limits on direct market participation. Similar to the work by Hirshleifer their model allows both hedging pressures and systematic risk to affect futures prices. In light of Merton as well as Cox, Ingersoll and Ross, hedging pressures may also vary with macro-economic conditions. Along with these theoretic reasons to model asset returns as a time-varying function of both hedging pressure and supply conditions, there is empirical evidence that motivates our model specification.

Brennan (1958) calculates spreads between contemporaneous prices along the futures term structure and reports spreads that persist at high inventory levels. He interprets these findings as indicative of an additional variable necessary to explain futures prices which may be related to a risk premium term. Evidence on hedging pressure effects upon futures prices remained scarce until Bessembinder (1992). De Roon, Nijman, and Veld (2000), extend the results of Bessembinder (1992) by documenting that cross-market hedging pressures are also important in determining commodity futures returns. Bessembinder and Chan (1992) document that instrumental variables from the equity and bond markets forecast futures returns. Fama and French (1988) describe how commodity convenience yields and inventories vary with business cycles.

In this paper we propose a simple model for commodity futures returns in the spirit of Hirshleifer (1988, 1989, and 1990). We model the expected futures return as a linear function of systematic risk and two commodity specific factors, hedging pressure and a proxy for the scarcity of the commodity. Because we are interested in understanding if changes in the investment environment impact expected futures returns through hedging pressures and supply conditions we turn to a conditional version of our three factor model. The model of time-varying expected futures returns is similar in structure to models used in the equities pricing literature by Ferson and Harvey (1991, 1993) and in the bond pricing literature by Ilmanen (1995).

The model of expected futures returns $R_{i,t}$ conditional on the information set available at time $t-1$, Ω_{t-1} is

$$E(R_{i,t} \mid \Omega_{t-1}) = \sum_{j=1}^{k} \beta_{i,j}(\Omega_{t-1})\lambda_j(\Omega_{t-1}). \tag{1}$$

Here $\beta_{i,j}(\Omega_{t-1})$ are the time varying conditional exposures to the k factors and the $\lambda_j(\Omega_{t-1})$ are the time varying conditional expectations of the factors. We partition the information set Ω_{t-1} into two subsets, Z_{t-1} which contains informational variables pertaining to the macro-economy and Z^i_{t-1} which contains informational variables specific to the i commodities. The unconditional version of the model simply assumes that Ω_{t-1} equals the null set. We assume that time variation in the expectations of the factors is driven by the information set related to the macro-economy or business conditions. In the interest of parsimony, we assume that the time variation in the factor exposures is driven by the information which is specific to the commodity.

III. Data and Methods

Our data is from the Crude Oil (CL), Copper (CO), Gold (GC) and Natural Gas (NG) markets, a composition similar to that used by Schwartz (1997). The data span January of 1987 through December of 2005 for Crude Oil, but start in January of 1995 for the remaining markets.

A. *Futures Returns*

We obtain daily settlement prices for the nearest to maturity New York Mercantile Exchange (NYMEX) futures contracts. Bloomberg reports continuous futures price series that quantify the experience of an investor who roll over maturing contracts to always hold the nearest to maturity contract. Following Bessembinder we construct continuous futures return series from the corresponding price series. Although the term "futures return" is a misnomer, it is standard in the futures literature. Continuously compounded daily returns on futures prices linked to yield returns over the monthly holding period (beginning to end) are henceforth referred to as futures returns.

B. The Factors

Our model has three factors. We use the returns on the Standard and Poor 500 index in excess of the 1-month treasury bill return from Ibbotson and Associates to proxy for the systematic factor. The commodity specific factors are a measure of hedging pressures and a measure of supply conditions. Following De Roon *et. al*. (2000) we define the hedging pressure variable (*HP*) as,

$$HP = \frac{number\ of\ short\ hedge\ positions - number\ of\ long\ hedge\ positions}{total\ number\ of\ hedge\ positions} \tag{2}$$

The hedging pressure variables are constructed using weekly trader's commitment data from the Commodity Futures Trading Commission (CFTC).[4] The CFTC requires large

[4] The CFTC uses the nomenclature commercials and non-commercials, which boils down to a distinction between hedgers and speculators, respectively.

traders to report whether their trading activity is for speculative or hedging purposes. Bessembinder (1992) discusses these data in detail.

To capture relative scarcity of the commodity we require a proxy for economic inventory. For crude oil we use data on inventory levels from the American Petroleum Institute's weekly bulletin. The natural gas inventory data is from the Energy Information Administration. For copper and gold, we obtain our inventory data from the New York Mercantile Exchange (NYMEX), which has designated licensed depositories or warehouses from which the appropriate grade of metal may be delivered against a maturing contract. Each of these licensed depositories reports to the exchange on a daily basis the stocks held at that facility and we use the stocks held across all such licensed depositories to compute the aggregate level.[5]

The focus of our analysis is stocks held in storage in excess of those committed to production processes. We assume that the periodic seasonal component of the inventory series represents committed inventory and extract the discretionary component of crude and natural gas inventories using the Seasonal Trend Loess adjustment technique developed by Cleveland, Cleveland, McRae, and Terpenning (1990).[6] We remove a lagged 12-month moving average from the metals inventories to get the discretionary component. Our analysis of relative scarcity of the commodity within the economy uses withdrawals of stocks from storage, $WD_t = Inv_{t-1} - Inv_t$, where *Inv* is the deseasonalized level of the inventory.

C. The Information Variables

Our set of instruments for the macro-economy includes a standard set used in conditional equity pricing models. These are a constant; a January dummy (*Jan*); the average three month Treasury Bill yield from the Fama and French Risk Free Rate files

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[5] Each day all Licensed Depositories report the stocks for which a Warrant has and has not been issued. Metal "on Warrant" is eligible for delivery against a short position on the Exchange. We use both types of stocks in our analysis.

[6] There is little evidence of a seasonal component in the crude oil or natural gas inventory data post-adjustment. and we have checked that our preliminary results are not significantly different when using other methods of deseasonalizing the data.

(*Ave3*); the spread between the BAA and AAA corporate bond yields from the Federal Reserve Economic Database (*Def*); the spread between long-term government bond yields data from the Ibbotson's Stocks, Bonds, Bills and Inflation Yearbook and the three-Month Treasury Bill: Secondary Market Rate from the Federal Reserve Economic Database (*Term*); the aggregate dividend yield (*DY*) of NYSE stocks calculated by summing up 12 lags of $(I_{NYSE,t} * (1+ R_{NYSE,t+1})) - I_{NYSE,t+1}$ and then dividing by $(I_{NYSE,t+12})$, where I_{NYSE} is the level of the value weighted NYSE index excluding dividends and R_{NYSE} is the return on the value weighted NYSE index including dividends found in the CRSP indices files; and expected inflation. To calculate $E_{t-1}(Inf_t)$ we use Fisher's equation which states that the nominal Treasury bill rate for period t known at time $t-1$, TB_t, equals the time $t-1$ expectation of the time t real rate of interest $E_{t-1}(\rho_t)$ plus the time $t-1$ expectation of the time t inflation rate $E_{t-1}(Inf_t)$. Hence, $E_{t-1}(Inf_t) = TB_t - E_{t-1}(\rho_t)$.[7]

Our set of information variables for the specific commodity markets are the basis and the discretionary inventory level, *Inv* described above. For each of the four markets, we compute the basis variable as,

$$basis = \ln\left[\frac{F_{t,T}}{S_t}\right] - y_{t,T} \tag{3}$$

where, S_t is the spot price of the commodity, $F_{t,T}$ denotes the futures price at time t maturing at time T (we use ten months) and $y_{t,T}$ is the corresponding maturity zero-coupon Treasury yield. All the instruments are lagged by one period.

Summary statistics for all the data are reported in Table I. The mean return on natural gas is largest, but these returns also have the largest standard deviation. As reported in Bessembinder (1992), the unconditional return on such series are not statistically significant. All futures returns are significantly positively correlated, except for natural gas with copper and gold. The inventory and basis data looks relatively normal

[7] We use the continuously compounded 1-month nominal Treasury-bill rate from the CRSP risk-free file for TB_t. To construct $E_{t-1}(\rho_t)$ we follow Fama and Gibbons (1984) and estimate an MA(2) time series model of the *ex post* real return on Treasury bills, $(TB_t - I_t)$.

across all the commodities while the measure of scarcity, *WD*, exhibits a fat tailed distribution for all the commodities.

The macroeconomic information variables have been previously used for the lagged information set in conditional equities pricing models because they have all been shown to have some predictive ability for market returns. We guard against any spurious regression bias by removing a 12-month lagged moving average as suggested by Ferson, Sarkissian, and Simin (2003) for Ave3, Div, Term, and Def. Each of these variables originally had an autocorrelation greater than 0.96 over our sample period. Overall none of the data exhibit any glaring abnormalities and are consistent with what has been used in previous studies.

IV. The Statistical Evidence

A. The Unconditional Model of Realized Futures Returns

Table II presents the results from the unconditional version of our model. Here neither the exposures nor the expectations of the factors are allowed to vary. Our strongest results are for the energy commodities. Both crude and natural gas futures returns are linearly related to the systematic factor, supply conditions, and the amount of hedging in their respective markets. For these two assets the systematic factor is negatively related to the returns, while the commodity specific factors are both positively related. Both copper and gold futures are positively related to the hedging pressure proxy and copper is positively, but only weakly, related to supply conditions. For the metals, the systematic risk factor is not significant. For all the commodities except gold, the adjusted R^2's are close to 25%.

De Roon *et. al.* (2000) report significant hedging pressure effects across markets, our preliminary results (unreported) show that hedging pressures from the crude oil markets impact natural gas returns, but no other significant cross effects emerge. In our model, the net amount of hedging in the commodity market is significant across the commodities in our sample. As noted above, conclusive empirical evidence on the relationship between futures returns and the physical inventories is lacking, although such a relation is commonly conjectured. Our results provide evidence that scarcity is indeed a significant determinant of futures returns. Overall, we take the results in Table II as confirmation that both hedging pressures and supply conditions are significant determinants of futures returns in our sample.

B. Conditional Models of Returns

When both the systematic and commodity specific risk factors are priced, predictability in returns can be traced to the factors themselves or their loadings. We first consider time varying loadings by allowing betas in our model to fluctuate with commodity specific instruments. In particular, we estimate the following model

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\begin{aligned}
E\{R_{i,t+1}|Z_t\} &= \alpha_{i,t+1} + \beta_{i,r+1}'E\{\boldsymbol{F}_{,t+1}\}, \\
\alpha_{i,t+1} &= a_{i,0} + a_{i,1}'Z^i_{t,} \\
\beta_{i,t+1} &= b_{i,0} + b_{i,1}'\,Z^i_{t}.
\end{aligned}
\tag{3}
$$

In this conditional version of the model Z^i_t contains a constant, the basis and the discretionary inventory level for commodity *i*. Here b_0 is *3x1*, b_1 is *3x3*, a_1 is *3x1*, and a_0 is a scalar, and *F* is a *3x1* vector containing the excess market proxy return, the measure of scarcity, *WD*, and hedging pressure, *HP*. The reduced form of the model is a linear equation with interaction terms which we estimate using ordinary least squares.

Table III contains results of testing restrictions on the time-varying parameters. For instance, the row labeled ‘Int = 0’ contains Wald tests of the null that the time-varying components of the intercept are jointly zero. The following rows have the results for tests of the null that the time-varying components of the betas of each factor are jointly zero. The final row is for a test of the null that all the time-varying components of the model are jointly zero. Since the time-varying beta model nests the unconditional model, this is a test of whether the conditional model is a better specification then the unconditional model.

There is little evidence in Table III against allowing any of the parameters to vary as functions of the instruments in Z^i. Except for the intercept of the metals regressions, we find evidence that lagged values of the basis and the level of discretionary inventories are drivers of time variation in exposures to the factors of our model. For all the commodities the Wald tests suggest that allowing time-varying risk exposures provides a better specification of the model relative to the fixed beta unconditional version of the model.

Along with the factor exposures, another source of predictable variation in expected returns comes from investors updating their expectations of the factors. We test for changing conditional expectations of the factors by specifying a model where these expectations are linear functions of lagged information and the betas are held constant. In this case the instruments, Z_t, are the set used in conditional equity pricing models mentioned above. In Table IV we present evidence that these instruments also have predictive capability for the commodity specific factors. It is interesting that both *HP* and *WD* are related to many of the lagged instruments. Evidence that changing expectations of hedging pressures are driven by the state of the economy supports the Merton model.

We estimate our conditional model using the following moment conditions:

$$E\begin{pmatrix} F_{t+1} - Z_t\gamma \\ (F_{t+1} - Z_t\gamma)(F_{t+1} - Z_t\gamma)\beta - (F_{t+1} - Z_t\gamma)r_{t+1} \end{pmatrix} \otimes Z_t = 0 \tag{4}$$

Here beta is constant, while the expectations of the factors vary through time.[8] These moment conditions are similar to those used in multifactor equity pricing models, e.g. Ferson and Korajczyk (1995) and Simin (2007). In equation (4), the first moment condition is the expected value of the error term from a regression of each factor, F_t on the instruments, Z_t with $Z_t\gamma$ being an estimate of the conditional expectation of the factors. The second moment condition is the definition of the vector of constant β's, the conditional covariance of the factors and the asset divided by the conditional variance of the factors.

[8] We estimate the model via iterated GMM using Newey-West (1987) standard errors.

The model has 24 parameters and 42 moment conditions and based on the J-statistics we are unable to reject the over-identifying restrictions for any of the commodities. In Table V, we again present Wald tests and (*p*-values) were we restrict subsets of the parameters to zero. For each row in the table we test the null that the time-varying parameters of factor *i*'s conditional expectation are jointly zero. We find strong evidence that the conditional expectations of the factors vary through time with the instrument related to the macro-economy.

We next consider the source of the explanatory power within a more general asset pricing context where we allow risk premia to vary as a function of time-varying factor exposures as well as allowing for time-varying conditional factor means. This changes the previous set of moment conditions to

$$E\begin{pmatrix} F_{t+1}-Z_t\gamma \\ (F_{t+1}-Z_t\gamma)(F_{t+1}-Z_t\gamma)\left(\kappa Z_t^i\right)-(F_{t+1}-Z_t\gamma)r_{t+1} \end{pmatrix}\otimes Z_t=0\,. \tag{5}$$

Where κZ^i is the vector of estimated conditional betas. Note that in this specification that the betas vary with the commodity specific instruments, Z^i, while the conditional factor expectations vary with the macroeconomic instruments, Z.

Table VI contains the Wald tests for this specification. The tests here are consistent with the findings in the previous conditional specifications. We again find strong evidence that the conditional factor means varying with the business conditions, as well as evidence that the variation in the factor exposures is related to the commodity specific instruments. The final row of the table tests the null that all the time-varying components of the model are jointly zero, e.g. this test rejects the unconditional specification in favor of the conditional specification.

C. Digging Deeper

The previous results suggest that indeed hedging pressures and supply conditions are important for explaining commodity futures returns and further that these factors vary with lagged information on the state of the economy and the state of the commodities market. In this section we look further into how well the conditional version of the model in equation (5) performs relative to the unconditional model and quantify the predictable variation that is explained by the model. Finally, we calculate the amount of predictable variation that is explained by the conditional factor exposures and by the conditional factor expectations.[9]

The first two columns of Table VII contain R^2's from regressions of the pricing errors from the unconditional model and the fully conditional model on the lagged instruments. For the unconditional model the pricing errors are simply the error terms from the regression. For the model in equation (5) the pricing errors for commodity *i* are defined as

$$\varepsilon_{it} = R_{i,t} - Z_{t-1}\gamma^{*}kZ^{i}_{t-1}. \tag{6}$$

If the model is well specified, the pricing errors should not be predictable using the lagged instruments. For the unconditional model the pricing error regressions have R^2's that range from 5% to 17% indicating that the model leaves some of the predictable variation unexplained. For each commodity the conditional version of the model pricing errors regression R^2's are smaller. For crude the R^2 decreases by 61%, for copper the R^2 falls 37%, for gold and natural gas the reduction in R^2 is smaller, 14% and 17%. These reductions in the amount of predictability of the pricing errors indicate that the conditional version of the model outperforms the unconditional version.

We use the methods of Ferson and Harvey (1993) to consistently estimate two variance ratios. The first, VR1 is the amount of predictable variation captured by the model, while VR2 is the amount of predictable variation in returns not captured by the model. In particular VR1 is defined as

[9] These tests are similar to those found in Ferson and Harvey (1993).

$$VR1=\frac{Var\left[\sum_{j} E\left(F_{j,t}|Z_{t\text{-}1}\right)\beta_{i,j}\left(Z_{t-1}^{i}\right)\right]}{Var\left[E\left(R_{i,j}\mid Z_{t\text{-}1}\right)\right]} \tag{7}$$

and VR2 is defined as

$$VR2=\frac{Var\left[E\left(R_{i,j}\mid Z_{t\text{-}1}\right)-\sum_{j} E\left(F_{j,t}|Z_{t\text{-}1}\right)\beta_{i,j}\left(Z_{t-1}^{i}\right)\right]}{Var\left[E\left(R_{i,j}\mid Z_{t\text{-}1}\right)\right]}. \tag{8}$$

Estimation of these ratios requires several moment conditions in addition to those in equation (5). We refer the reader to Ferson and Harvey (1993) for the definition of these.

For all the commodities except gold, the amount of predictable variation explained by the model is larger then the amount left in the residuals. While the standard errors of these estimates are typically large, the estimates are consistent and generally support the model. For crude the amount of predictable variation explained exceeds the unexplained variation by 33%. For copper and natural gas the model captures 21% more of the predictable variation than it leaves behind, these tests provide further support for the conditional model.

While the Wald tests clearly reject the hypotheses that the conditional betas and conditional factor means are constant, it is not clear which component of the risk premium is more important. To determine this we use the following decomposition:

$$Var\left\{E\left(\beta'\lambda\mid Z\right)\right\}=E\left(\beta\right)'Var\left\{E\left(\lambda\mid Z\right)\right\}E\left(\beta\right)+E\left(\lambda\right)'Var\left\{E\left(\beta\mid Z\right)\right\}E\left(\lambda\right)+\phi. \tag{9}$$

That is, the predictable variation that is captured by the model can be decomposed into three parts: changes in the expected risk premia, changes in time-varying beta, and a term that captures any movements from the correlation between time-varying betas and factor means.

We again add to equation (5) the additional equations needed to estimate the first two components of equation (9) as described in Ferson and Harvey (1993). The last two columns of Table VII contain the estimated contributions of time-varying beta and time-varying factor means. In the equities literature, time-variation in beta has been repeatedly shown to be less important then variation in factor means for explaining conditional expected portfolio returns. We find similar results for the commodities data. For all commodities, except again gold, we find that the time-variation in expectations of the factors is much more important for explaining predictable variation captured by the model.

V. Conclusion

There is a large literature debating the predictability of returns. One path to reconciling evidence of predictability and the efficient market hypothesis is by way of intertemporal equilibrium pricing models. In these models rational investors expect asset returns to vary with time varying risk premia related to the state of the macro-economy. Also consistent with return predictability are models of inefficient markets such as those by Shiller (1984) and Summers (1986). Irrational bubbles might be indistinguishable from rational time-varying risk premia, as Fama (1991) notes in a sequel to his seminal article on market efficiency. But, as he conjectures, exploring the link between expected returns and the demand for capital goods may be fruitful in judging predictability. By incorporating holdings of hedgers that vary with standard predictor variables, we present evidence on this issue.

The documented evidence suggests strong covariance between hedger's holdings for capital goods like crude oil and macroeconomic state variables. To a lesser extent we find similar results for supply conditions of capital goods. Furthermore, variation in expected commodity futures returns can be explained, in part, by hedging responses to changing macroeconomic conditions. This evidence is consistent with inter-temporal asset pricing models with time varying risk premia that provide a rational explanation for predictability in asset returns. While the evidence speaks directly to questions of market efficiency, precise judgments on the degree of efficiency remain subject to priors.

Fama and French (1991) note that a problem that "lurks on the horizon in all tests of multifactor ICAPM's," is trying to explain why a state variable that can explain common variation in returns might be of special hedging concern to investors and so earn a special premium. We have in some sense, circumvented this problem by directly incorporating proxies for hedger's holdings and supply conditions that vary with business conditions into a model of expected returns. Our preliminary evidence on net hedging pressure coupled with the cross-market effects of hedging pressure found in DeRoon et al. (2000) may lead to a better understanding of how hedging demands interact with the business conditions to move expectations of returns across assets. Most general equilibrium model of commodity markets assume risk neutrality, our results on how commodity market scarcity relates to risk premia may be similarly beneficial.

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Table I: Summary Statistics

Panel A contains the summary statistics for the excess returns of the Standard and Poor's (*Mkt*) and the macroeconomic instruments over the period 1988/01:2005/12. *Jan* is a January dummy, *Ave3* is the yield on the three month T-bill, *Div* is the dividend yield on NYSE stocks, *Term* is the spread between short and long term government debt, *Def* is the spread between the BAA and AAA corporate debt, and *E(Inf)* is expected inflation. We stochastically detrend Ave3, Div, Term, and Def using a lagged 12-month moving average to remove excess autocorrelation leaving 216 observations. Panel B contains the summary statistics for the commodity specific data. *WD* is withdrawals from storage, *HP* is hedging demand, *Inv* is the lagged discretionary inventory, and *Basis* is a measure of the futures contracts term structure's slope. Precise variable definitions are given in the text. Limited inventory data for copper (CO), gold (GC), and natural gas (NG) restrict the sample to the period 1995/01:2005/12, N= 132. Crude oil (CL) ranges over the same period as *SP500*.

Panel A

	Mkt	Jan	Ave3	Div	Term	Def	E(inf)
Mean	0.005	0.083	-0.075	0.000	-0.001	0.000	0.000
Median	0.008	0.000	-0.101	0.000	0.000	0.000	0.000
Std.Dev	0.040	0.277	0.837	0.000	0.008	0.001	0.001
Skewness	-0.449	3.015	-0.167	0.656	0.206	0.943	0.493
Kurtosis	3.745	10.091	3.009	4.152	2.724	4.696	3.666
Autocorr	-0.056	-0.091	0.968	0.867	0.933	0.882	0.756

Panel B

	CL					CO				
	Return	WD	HP	Inv	Basis	Return	WD	HP	Inv	Basis
Mean	0.006	0.000	-0.002	-0.002	0.000	0.004	0.009	0.159	0.000	0.005
Median	0.012	0.002	-0.002	0.012	0.001	0.001	0.005	0.168	0.174	0.032
Std.Dev	0.094	0.028	0.062	0.075	0.085	0.061	0.320	0.190	1.255	0.055
Skewness	0.018	-0.116	-0.176	-0.217	0.002	-0.333	-1.739	-0.131	-0.551	-0.744
Kurtosis	3.943	3.280	3.257	2.569	3.097	3.931	16.255	2.643	2.714	2.278
Autocorr	-0.013	-0.012	0.634	0.929	0.832	0.023	-0.030	0.617	0.968	0.902
	GC					NG				
	Return	WD	HP	Inv	Basis	Return	WD	HP	Inv	Basis
Mean	0.003	-0.011	0.074	0.000	-0.011	0.014	-0.001	0.056	0.000	-0.011
Median	-0.002	-0.017	0.023	-0.123	-0.006	0.020	0.003	0.047	0.025	0.036
Std.Dev	0.038	0.142	0.262	0.674	0.016	0.161	0.050	0.065	0.127	0.165
Skewness	1.393	0.469	0.319	0.532	-0.119	-0.563	0.241	0.530	-0.484	-1.030
Kurtosis	9.677	5.072	1.755	2.512	2.199	3.849	4.478	2.780	2.698	3.615
Autocorr	-0.086	-0.159	0.884	0.978	0.960	-0.027	0.165	0.545	0.923	0.748

Table II: Unconditional Model

The coefficients, Newey-West *t*-statistics using 12 lags, and adjusted R^2's for the regression of the nearest term futures return on the excess return of S&P 500 Index, *Mkt*, and on the commodity specific factors, *WD* and *HP*.

	CL	CO	GC	NG
Intercept	0.009	-0.020	0.001	-0.040
	(1.72)	(-2.48)	(0.49)	(-2.44)
Mkt	-0.425	0.119	-0.043	-0.363
	(-2.17)	(0.92)	(-0.54)	(-2.00)
WD	0.368	0.023	0.003	0.873
	(2.48)	(1.76)	(0.10)	(2.22)
HP	0.620	0.144	0.019	1.001
	(6.30)	(5.08)	(2.05)	(4.85)
Adj. Rsqr	0.220	0.230	0.000	0.280

Table III: Time-Varying Beta

The table contains the Wald statistics and (*p*-values) for several sets of restrictions on the following time-varying parameter model of futures returns, *R*.

$$E\{R_{i,t+1}|Z_t\} = \alpha_{i,t+1} + \beta_{i,r+1}'E\{\boldsymbol{F}_{,t+1}\},$$
$$\alpha_{i,t+1} = a_{i,0} + a_{i,1}'Z^i_{t,}$$
$$\beta_{i,t+1} = b_{i,0} + b_{i,1}'\,Z^i_{t}.$$

In this conditional version of the model Z^i_t contains a constant, the basis and the discretionary inventory level for commodity *i*. Here b_0 is *3x1*, b_1 is *3x3*, a_1 is *3x1*, and a_0 is a scalar, and *F* is a *3x1* vector containing the excess market proxy return, the measure of scarcity, *WD*, and hedging demand, *HP*. The row labeled Int = 0 is for tests of the null that the time-varying components of the intercept are jointly zero. The rows labeled $B_i = 0$ are for tests of the null that the time-varying components of the betas of each factor are jointly zero. The row labeled Cond. vs. Uncond. is for a test of the null that all the time-varying components of the model are jointly zero.

Null	CL	CO	GC	NG
Int = 0	8.935	3.970	5.728	8.590
	(0.03)	(0.26)	(0.13)	(0.04)
$B_{MKT} = 0$	22.071	18.301	6.912	11.205
	(0.00)	(0.00)	(0.07)	(0.01)
$B_{WD} = 0$	16.604	16.446	0.782	35.370
	(0.00)	(0.00)	(0.85)	(0.00)
$B_{HD} = 0$	89.132	49.565	10.494	32.777
	(0.00)	(0.00)	(0.01)	(0.00)
Cond. Vs. Uncond.	71.640	43.330	37.832	136.815
	(0.00)	(0.00)	(0.00)	(0.00)

Table IV: Regressions of Commodity Specific Factors on Instruments

This table contains the Newey-West *t*-statistics using 12 lags and adjusted R^2's from a regression of the commodity specific factors, *WD* and *HP*, on the lagged instruments. All data are described in Table I. The data in the regressions for the crude oil factors are from the period 1988/01:2005/12. In the remaining regressions the data are from the period 1995/01:2005/12.

	CL		CO		GC		NG	
	WD	HP	WD	HP	WD	HP	WD	HP
Intercept	2.23	-0.53	1.97	7.29	0.98	0.00	-0.43	5.48
Jan	-4.25	2.09	-0.02	-1.83	-1.51	-0.02	0.06	2.27
Ave3	1.99	4.41	1.23	3.06	-2.38	2.96	0.24	0.93
Div	0.44	-3.89	-0.33	-2.93	-0.73	1.27	0.43	-2.31
Term	0.23	2.57	-0.19	2.63	-1.09	0.21	-0.90	-0.21
Def	1.24	2.72	0.60	-0.99	-0.79	-0.47	-0.13	0.38
E(inf)	-3.04	-4.00	1.62	-1.49	0.75	0.06	-0.56	-0.42
Inv	5.87	-0.70	3.11	3.44	2.30	1.91	2.51	-1.63
Basis	-3.80	-3.48	-2.88	-3.03	2.57	-3.31	-1.91	1.32
Adj. R^2	0.15	0.29	0.06	0.32	0.04	0.55	0.04	0.17

Table V: Time-Varying Expected Factors

The table contains the Wald statistics and (*p*-values) for several sets of restrictions on the following time-varying expected factor, fixed parameter model of futures returns, *R*.

$$E\begin{pmatrix} F_{t+1} - Z_t\gamma \\ (F_{t+1} - Z_t\gamma)(F_{t+1} - Z_t\gamma)\beta - (F_{t+1} - Z_t\gamma)r_{t+1} \end{pmatrix} \otimes Z_t = 0$$

In this conditional version of the model Z_t contains a constant, *Jan*, *Ave3*, *DY*, *Term*, *Def*, and *E(Inf)*. *F* is a *3x1* vector containing the excess market proxy return, the measure of scarcity, *WD*, and hedging demand, *HP*. The γ vector contains the intercept and slopes from a regression of the each factor on the instruments and β is the vector of constant betas. The models are estimated via iterated generalized method of moments using a Newey-West (1987) spectral density estimate. Each row labeled $E_t(F_i) = 0$ is for a test of the null that the time-varying parameters of factor *i*'s conditional expectation are jointly zero.

Null	CL	CO	GC	NG
$E_t(MKT) = 0$	37.193	37.550	27.076	32.447
	(0.00)	(0.00)	(0.00)	(0.00)
$E_t(WD) = 0$	63.866	23.696	20.727	39.946
	(0.00)	(0.00)	(0.00)	(0.00)
$E_t(HP) = 0$	91.861	56.476	53.341	93.946
	(0.00)	(0.00)	(0.00)	(0.00)

Table VI: Time-varying Beta Models

The table contains the Wald statistics and (p-values) for several sets of restrictions on the following time-varying expected factor, time-varying parameter model of futures returns, R.

$$E\begin{pmatrix} F_{t+1}-Z_t\gamma \\ (F_{t+1}-Z_t\gamma)(F_{t+1}-Z_t\gamma)(\kappa Z_t)-(F_{t+1}-Z_t\gamma)r_{t+1} \end{pmatrix}\otimes Z_t=0$$

The model is identical to the model in the previous table but here kZ_t represents the time varying factor betas. The models are estimated via iterated generalized method of moments using a Newey-West (1987) spectral density estimate. The row labeled $E_t(F) = 0$ is for a test of the null that the time-varying parameters of the all the conditional factor expectations are jointly zero. The row labeled $B_t = 0$ is for a test of the null that the time-varying parameters of the all the conditional betas are jointly zero. The row labeled Cond. vs. Uncond. is for a test of the null that all the time-varying components of the model are jointly zero.

Null	CL	CO	GC	NG
$E_t(F) = 0$	75.089	169.800	109.721	103.755
	(0.00)	(0.00)	(0.00)	(0.00)
$B_t = 0$	124.724	48.703	5.617	51.811
	(0.00)	(0.00)	(0.47)	(0.00)
Cond. vs. Uncond.	458.750	498.242	197.447	444.930
	(0.00)	(0.00)	(0.00)	(0.00)

Table VII: The Fit of the Conditional Model

The column labeled Uncond. contains the R^2 from a regression of the pricing errors from the unconditional regressions of Table II on the lagged instruments. The column labeled B_t and $E_t(F)$ are the same regressions where the pricing errors are from the time-varying beta, time-varying expected factor values specification. The columns labeled VR1 and VR2 contain the estimated variance ratios (standard errors) described in Ferson and Harvey (1993). VR1 represents the amount of predictable time-variation explained by the model and VR2 is the amount of predictable variation left unexplained. The final two columns are the parameters (standard errors) from the moment conditions in also found in Ferson and Harvey (1993) which measure which component is more important for explaining time-variation in the model.

	Uncond.	B_t and $E_t(F)$	VR1	VR2	Beta	Risk Premia
CL	0.083	0.032	0.985	0.658	0.005	0.891
			(0.70)	(0.44)	(0.02)	(0.18)
CO	0.175	0.110	1.363	1.073	0.085	0.921
			(1.37)	(3.10)	(0.17)	(0.23)
GC	0.050	0.043	0.279	1.057	0.216	0.062
			(0.38)	(0.30)	(0.28)	(0.21)
NG	0.171	0.142	0.951	0.748	0.131	0.640
			(0.39)	(0.34)	(0.27)	(0.38)