The Predictive Content of Commodity Futures

by

Menzie D. Chinn
Robert M. La Follette School of Public Affairs and
Department of Economics
University of Wisconsin, Madison
and NBER

Olivier Coibion
Department of Economics
College of William and Mary

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Correspondence: Chinn: Dept. of Economics, 1180 Observatory Drive, Madison, WI 53706. Tel.: (608) 262-7397. Email: mchinn@lafollette.wisc.edu . Coibion: Department of Economics, 115 Morton Hall, Williamsburg, VA 23188. Tel.: (757)-221-1389. Email: ocoibion@wm.edu .

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Abstract

This paper examines the relationship between spot and futures prices for commodities, including those for energy (crude oil, gasoline, heating oil markets and natural gas), precious and base metals (gold, silver, aluminum, copper, lead, nickel and tin), and agricultural commodities (corn, soybean and wheat). In particular, we examine whether futures prices are (1) an unbiased and/or (2) accurate predictor of subsequent spot prices. We find that while energy futures prices are generally unbiased predictors of future spot prices, there are certain notable exceptions. For both base and precious metals, the results are much less favorable to unbiasedness hypothesis. For precious metals and copper and lead, we strongly reject the null that $\beta=1$ at all three horizons. For the these other base metals, while we cannot reject that $\beta=1$, due to large standard errors. Finally, both corn and soybean futures have β close to 1, while wheat has $\beta<1$. Excepting oil and base metals, futures tend to outperform a random walk specification in out of sample forecasts.

Keywords: futures, energy, petroleum, natural gas, heating oil, gasoline, precious metals, base metals, agricultural commodities, forecasting, efficient markets hypothesis, backwardation, contango

JEL Classification: G13, Q43

"Policymakers and other analysts have often relied on quotes from commodity futures markets to derive forecasts of the prices of key commodities… The poor recent record of commodity futures markets in forecasting the course of prices raises the question of whether policymakers should continue to use this source of information and, if so, how." *Ben Bernanke, June 9, 2008*

This paper examines the relationship between spot and futures prices for commodities. In particular, we examine whether futures prices are (1) an unbiased and/or (2) accurate predictors of subsequent spot prices, in the markets for energy, precious metals, base metals, and agricultural commodities.

In our view, a re-examination is warranted because of recent public policy concerns about sharp movements in energy and commodity prices that have macroeconomic and international repercussions (see for instance Hunt *et al*., 2001; LeBlanc and Chinn, 2004). If futures prices correctly anticipate the direction of these movements on average, then public policy can be based upon such market information.[1] On the other hand, if futures prices are misleading indicators of future price movements, then policy-makers should take into account the deficiencies of futures prices as price predictors, and either appeal to alternative forecasting devices, or undertake public policies to mitigate the effects of energy and food price uncertainty.

To illustrate this point, consider the situation at the beginning of 2001, with respect to energy. Certain policy makers were arguing for a policy of encouraging domestic production of petroleum, in light of the then high prices of crude oil in order to drive down prices. However, in the absence of externalities, if individuals and firms can make "good" forecasts of prices, then hedging activities can nullify arguments for public policy interventions of this nature.

With respect to energy futures, we replicate the results reported in Chinn, Coibion and LeBlanc (2005): Futures prices are unbiased predictors of future spot prices in the petroleum,

[1] Greenspan (2004) has appealed to long dated futures as predictors of petroleum prices. While there is some dispute as to whether such futures have much informational content (Baum, 2004), we focus on futures with maturities within one year.

gasoline and heating oil markets. In contrast natural gas futures prices are a biased predictor of subsequent spot prices at the 3- and 6-month horizons.

For other markets, results vary. For both base and precious metals, the results are much less favorable to unbiasedness hypothesis. For gold and silver, as well as copper and lead, we strongly reject the null that $\beta=1$ at all 3 horizons. For the three other base metals, we cannot reject that $\beta=1$ due to the large standard errors. Finally, both corn and soybean futures have β close to 1, while wheat has $\beta<1$, with fairly small standard errors.

We augment the standard tests for unbiasedness by accounting for GARCH effects in commodity prices. Doing so, we obtain broadly similar results, with slightly greater evidence against unbiasedness.

In out-of-sample forecasting over the January 2003-July 2008 period, we find that for oil market, neither futures prices nor econometric modeling outperforms the random walk, thereby confirming the results of Alquist and Kilian (2008). However, when looking at other commodity markets, we find substantial differences. In other energy markets, precious metals, agricultural commodities, futures prices outperform both a random walk and an ARIMA model at all horizons. Only in the case of base metals do futures prices fail to outperform a random walk.

1. Theory and Previous Literature

The notion that the futures price is the optimal forecast of the spot price is an implication of the efficient market hypothesis. In an efficient market, new information is reflected instantly in commodity prices. If this is true, then price patterns are random, and no system based on past market behavior can do other than break even. The link between efficiency and forecastability arises from realizing the difference between the current futures price and the future spot price represents both the forecasting error and the opportunity gain or loss realized from taking certain positions. The requirement that the forecasting error is zero on average is consistent with both market efficiency (the absence of profitable arbitrage opportunities) and the unbiasedness property of the forecaster (zero forecasting error on average).

The futures price of a storable commodity such as crude oil is determined by the spot price and the cost incurred while the commodity is stored awaiting delivery some time in the future. The cost associated with holding the commodity until the delivery date is known as the cost-of-carry. The cost-of-carry consists of the cost of storing oil in a tank (and perhaps insurance) and the financial cost in the form of the opportunity cost of holding oil, or the cost of funding, and perhaps a risk premium.[2]

The spot/futures pricing relationship is based on the assumption that market participants are able to trade in the spot and futures markets simultaneously, i.e. they can utilize spot/futures arbitrage. The relationship between the futures rate and the current spot rate for petroleum is given by:

$$f_{t|t\text{-}k} - s_{t\text{-}k} = d_{t|t\text{-}k} + Q_{t|t\text{-}k} \tag{1}$$

where $f_{t|t\text{-}k}$ is the observed (log) time t-k futures contract price that matures at time t, and $s_{t\text{-}k}$ is the time t-k spot rate, $d_{t|t\text{-}k}$ the log cost-of-carry (the sum of storage costs minus convenience yield, plus interest costs and a risk premium), and $Q_{t|t\text{-}k}$ is a term accounting for the marking-to-market feature of futures. The object on the left hand side of (1) is called the "basis" in the commodity futures literature.[3]

[2] Williams and Wright (1991) provide an excellent overview to the behavior of commodity prices and futures. See also Pindyck (2001).

[3] The discussion and notation is based upon the exposition in Brenner and Kroner (1995).

If we assume the log spot rate follows a time random walk with drift, and expectations are rational, then the time t-k *expectation* of the change in the spot rate will equal the basis and the marking-to-market term. Hence, in the regression of change in the spot rate on the basis,

$$s_t - s_{t-k} = \beta_0 + \beta_1 (f_{t|t-k} - s_{t-k}) + \varepsilon_t \qquad (2)$$

β_0 subsumes the terms in the right hand side of (1), as well as the parameters defining the time series process governing the spot rate, while $\beta_0 = 0$ and $\beta_1 = 1$ if the basis is the optimal predictor of the change in the spot rate.

It is important to recall that rejection of the null hypothesis is then a rejection of a composite hypothesis, including both market efficient and unbiased expectations.

The literature examining the behavior of futures markets is fairly extensive. A number of studies have examined the efficiency of futures markets and have investigated the related issue of the forecastability of spot energy prices. Unsurprisingly, the conclusions are quite diverse. A number of studies provide evidence for efficient markets and an equally large number provide evidence that contradicts an efficient market (unbiased futures price prediction) interpretation. For energy markets, Serletis (1991) found evidence consistent with efficient crude petroleum markets. Bopp and Lady (1991), however, found that either the spot or the futures price can be the superior forecasting variable depending on market conditions, and the information content of the two price series is essentially the same.

The more recent literature has focused on the long-run properties of the spot and forward prices, in the context of cointegration.[4] We focus on the change in the spot rate, and its relation to the basis, reserving the analysis of long run dynamics to future study.

2. An Empirical Analysis

2.1 Overview of the Data

We obtained data for four energy prices – petroleum (West Texas Intermediate, or WTI), natural gas (Henry Hub), gasoline (Gulf Coast)[5], and heating oil (No. 2, Gulf Coast), gold, silver, aluminum, copper, lead, nickel, tin, corn, soybean and wheat. All the futures prices pertain to the New York Mercantile Exchange (NYMEX), as reported by Bloomberg.

Figures 1 through 14 depict the current spot and the futures price for 3 months and 6 months ahead (s_t and $f_{t,3}$) for each of these commodities.[6] As is typical of futures prices, the implied future spot rate tracks the actual spot rate with a 3 month lag. This pattern is also evident at longer horizons, but is slightly less pronounced.

Interestingly, an exception to the aforementioned pattern occurs when there are sharp spikes in the spot rate. Then – with the exception of the 1991 price increase – future rates tend to deviate from the spot rate. The most obvious instances of this phenomenon are for the 1996 and 2000 spikes in natural gas prices, and the 2000 spike in heating oil prices.

In order to evaluate more formally the properties of the relationship between the spot and futures prices, we now move to a statistical analysis.

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[4] See for instance, Crowder and Hamed (1993), Moosa and Al-Loughani (1994), Herbert (1993) and Walls (1995).

[5] Starting in 2005, the NYMEX phased in a new set of futures for gasoline to take the place of the previous series. The reason has to do with the changing content of ethanol in gasoline. In order to avoid complications involving changing variable definitions, we restrict our analysis to the older gasoline futures, which end at various points in 2006.

[6] While it is true that in the petroleum market, the nearest month futures price is typically used as a measure of the spot price, the actual difference in the two prices is minimal. Hence, we use the spot price as the relevant price.

2.2 Estimation and Results

Equation (2) is estimated using OLS using spot and futures prices sampled at a monthly frequency. These data are all sampled at the end of month, and hence allow proper synchronization of prices. Note however that because horizons of 3, 6 and 12 months are used, and the data is of monthly frequency, the regression residuals incorporate overlapping information. Under the null hypothesis of efficient markets (risk neutrality and rational expectations), the regression residuals will exhibit serial correlation. In order to obtain consistent estimates of the standard errors, necessary to conduct proper statistical inference, we calculate heteroskedasticity and serial correlation robust standard errors.[7]

The results are reported in Table 1. For the crude oil market, the estimates for β_1 at the 3, 6 and 12-month horizons are not statistically distinguishable from unity, although at the twelve month horizon, the constant is statistically significant. Hence, one cannot reject the efficient markets hypothesis at the shorter horizons. In one instance, the constant is statistically significant, indicating that the 12-month futures rate under-predicts the future spot rate on average by 11 percent.

This *positive* estimate of the constant reflects the fact that typically, the crude oil futures point downward, even though oil futures are not trending downward over time. This configuration of spot and futures prices is referred to as backwardation, and involves the interplay of cost-of-carry and convenience yield in driving a wedge between the futures rate and the expected future spot rate (see Haubrich, et al. (2004); French (2005)).

It is also true that in none of the cases are futures good predictors of subsequent spot prices. At the 3-month horizon, the basis accounts for only 5 percent of total variation in changes

[7] Using monthly data, if the futures mature 12 months (4 quarters) in the future, then a moving average process of 11 (=12-1) is induced. The Newey-West standard errors are calculated using a Bartlett window and lag order set equal to the (k-1).

in spot rates; at the 12-month horizon, this proportion is only 7 percent.[8] Further note that even though the slope coefficient is near unity, the constant is fairly large in economic terms – albeit not statistically significant – indicating that the basis points in the correct direction, but there is a natural drift up in the price change, even after accounting for other factors. This finding is consistent with the idea of backwardation as the normal state of affairs.

Natural gas futures appear to be more correlated with future spot prices, especially at the longer horizon. While the coefficient is quantitatively and statistically different from the posited value of unity at the 3 month horizon[9], at the other horizons, the slope coefficient is not statistically distinguishable from unity, and the proportion of variance explained exceeds 32 percent at the long horizon.

For gasoline futures, one cannot reject the possibility of β_1 being statistically indistinguishable from unity, except at the 6 month horizon. However, as with crude oil markets, these futures are very poor predictors of subsequent prices. In addition the estimated constant shows up with a statistically significant coefficient at the 12 months horizon. The adjusted R^2s are relatively low in these regressions, explaining only between 16% to 26% of total variation. Moreover, the interpretation of the results using 12-month futures price series is complicated by the large and numerous gaps in the data series, which limits the number of observations to 141.

Estimating the same equation for heating oil, we find that we cannot reject the market efficiency hypothesis for our three futures contracts, except at the long horizon, where the constant is statistically significant. As with gasoline, the R^2s remain low, with 3, 6, and 12-month futures accounting for 15%, 13%, and 17% of the variation in future spot prices.

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[8] The crude oil market possesses some unique institutional features. The most important is that it is not possible to truly effect a purchase on the spot market. Rather, toward the end of each month, delivery is arranged for something approaching one month in the future. Hence, the current 1-month futures price is used as a measure of the true spot rate. If one uses the reported spot price instead, the predictive power of the basis is somewhat reduced.
[9] A similar finding is obtained by Chernenko et al. (2004).

3. Accounting for Heteroscedasticity

In the previous analysis, we allowed for serial correlation and heteroskedasticity of a general form, using robust standard errors to make inferences regarding statistical significance. However, we know that asset prices, including derivatives based on underlying commodities, often evidence systematic conditional heteroskedasticity. This understanding motivates a formal GARCH approach to modeling the heteroskedasticity.

First, we test for the presence of conditional heteroskedasticity. Formal tests of the null of no ARCH effects in the simple basis regressions are rejected the 1% level for all commodity markets at all horizons. Thus, modeling the heteroskedasticity in errors is likely to increase efficiency of estimates.

Table 2 presents GARCH(p,q) estimates of the basis specifications. The p and q terms are chosen via the AIC criterion. Overall, the results are qualitatively similar, although much precision has frequently been gained. We can reject the null in more cases for base metals, as the GARCH specification yields much smaller error terms than before. For energy markets, we can reject the null at 12-month horizon for heating oil and, weakly so, natural gas. We also now reject the null for corn market.

Consequently, once we allow for GARCH, we find stronger evidence against efficiency in most markets. For all metals, only in the case of aluminum do we not reject the null at some horizon. For agricultural markets, we reject the null for 2 out of 3 products. Only for energy markets is the evidence much more consistent with the null.

4. Forecast Comparison

We evaluate the relative forecasting abilities of futures, by treating the futures price as the expectation of the future spot rate. We then compare these implied forecasts against a simple naïve forecast and forecasts generated from a simple univariate time series model. The naïve forecast is merely that the current spot rate is the best guess of the future rate (i.e., a random walk without drift). The time series model takes each log price as an ARIMA(1,1,1) process. A description of how the model is selected and estimated is provided in the Appendix. In addition, since there is evidence of backwardation (given the sometimes significant constants in the regression estimates of Table 1), we also estimate a relationship between the change in the spot rate and the basis.

We use a rolling regressions methodology in conjunction with out-of-sample forecasting to assess the estimated specifications. For instance, we estimate the 3 month horizon regression for 1991m01 to 1997m10, forecast out 3 months, predicting the 1998m01 spot rate. Then "roll" the sample up to 1991m02 to 1997m11, re-estimate and then re-forecast, predicting the 1998m02 spot rate. This process is repeated until 2007m02 is predicted. This yields a set of forecasts over the 1998m01-2007m02 period.

As indicated in Table 3, futures prices do a quite good job, in terms of both unbiasedness and smallest forecast errors, for oil, gasoline and heating oil. The ratios of the RMSEs and MAEs for futures prices and ARIMA models relative to that of the no-drift random walk are presented. *Numbers less than one indicate smaller forecast errors than random walk.* Significance levels are also indicated.

For oil market, neither futures prices nor econometric modeling outperforms the random walk in out-of-sample forecasting, thereby confirming the results of Alquist and Kilian (2008).

The sole exception is the ARIMA model slightly outperforms the random walk at yearly horizons when using the RMSE.

However, when looking at other commodity markets, we find substantial differences. First, in other energy markets futures prices outperform both a random walk and an ARIMA model at all horizons. Some of the differences are quite large. Similar results hold in agricultural markets and in the markets for precious metals. Only in the case of base metals do futures prices fail to outperform a random walk. ARIMA models almost always perform worse than the random walk, although this is less true at longer forecasting horizons.

5. Conclusion

- Energy futures prices are generally unbiased predictors of future energy prices (or at least the basis predicts the direction of price change), with certain exceptions in each category. There is no particular pattern to the rejections of unbiasedness, in terms of horizon. Natural gas at 3 months and Gasoline at 12 months exhibits the greatest evidence of bias.
- Futures prices typically explain only a small proportion of the variation in underlying price movements -- no more than 29 percent even at the 12 month horizon, for natural gas.
- Univariate time series models (relating a commodity price to lagged own prices, and estimated errors) do not fare any better – and usually fare worse especially for base metals and agricultural commodities – than futures prices as forecasts.
- A random walk characterization of commodity prices is not a particularly good one. This result contrasts with those found for other asset prices, notably foreign exchange rates.

This result holds true even though our sample period encompasses both rising and falling prices.

Appendix 1

All spot and futures prices are downloaded from Bloomberg. The specific series used and associated mnemonics for spot and futures prices are:

Commodity	Market	Spot Ticker	Futures Ticker
Energy			
Oil	NYMEX	USCRWTIC	CL
Natural Gas	NYMEX	NGUSHHUB	NG
Gasoline	NYMEX	MOINY87P	HU
Heating Oil	NYMEX	NO2INYPR	HO
Base Metals			
Aluminum	LME	LMAHDY	LA
Copper	LME	LMCADY	LP
Lead	LME	LMPBDY	LL
Nickel	LME	LMNIDY	LN
Tin	LME	LMSNDY	LT
Precious Metals			
Gold	NYMEX	GOLDS	GC
Silver	NYMEX	SILV	SIA
Agricultural			
Corn	CME	CORNCH2Y	C_
Soybeans	CME	SOYBCH1Y	S_
Wheat	CME	WEATCH2S	W_

Appendix 2

To generate the forecasts using time series models, the following algorithm was used.

1. An ARIMA(1,1,1) is estimated.
2. Estimate using the in-sample period (up to 2002m12); then roll recursively the estimation until all the out-of-sample observations are exhausted.
3. Forecasts are compared on a 2003m01-2008m07 sample.

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Table 1: Regressions of Price Change on the Basis

	3-months							6-months							12-months						
	α	se(α)	β	se(β)	adj. R^2	SER	N	α	se(α)	β	se(β)	adj. R^2	SER	N	α	se(α)	β	se(β)	adj. R^2	SER	N
Energy Products																					
Oil	0.03*	(0.02)	1.09	(0.52)	0.05	0.16	223	0.06**	(0.03)	0.77	(0.47)	0.05	0.203	223	0.13**	(0.05)	0.83	(0.35)	0.10	0.264	223
Natural Gas	0.00	(0.03)	0.63***	(0.09)	0.14	0.26	208	0.02	(0.04)	0.83	(0.13)	0.23	0.322	205	0.06	(0.07)	1.18	(0.23)	0.29	0.372	199
Heating Oil	0.03*	(0.02)	0.87	(0.15)	0.14	0.16	223	0.05*	(0.03)	0.71	(0.20)	0.12	0.214	223	0.12**	(0.06)	0.93	(0.30)	0.15	0.284	216
Gasoline ***	0.00	(0.02)	0.97	(0.24)	0.16	0.17	203	0.04	(0.03)	0.97	(0.19)	0.22	0.2	205	0.04	(0.03)	0.97	(0.19)	0.22	0.2	205
Precious Metals																					
Gold	0.02**	(0.01)	-0.87***	(0.69)	0.01	0.06	223	0.06***	(0.02)	-0.98***	(0.51)	0.02	0.089	223	0.10***	(0.04)	-0.77***	(0.44)	0.03	0.128	219
Silver	0.04***	(0.01)	-1.57***	(0.64)	0.02	0.10	223	0.07**	(0.03)	-1.20***	(0.73)	0.03	0.137	223	0.13**	(0.06)	-0.99***	(0.59)	0.06	0.181	217
Base Metals																					
Aluminum	0.01	(0.01)	0.16	(0.73)	-0.01	0.08	130	0.02	(0.02)	0.78	(0.80)	0.01	0.116	127	0.06	(0.04)	-0.26*	(0.74)	0.00	0.153	121
Copper	0.03*	(0.02)	-1.47***	(0.50)	0.05	0.12	130	0.06**	(0.03)	-1.43***	(0.65)	0.09	0.178	127	0.11*	(0.06)	-1.55***	(0.58)	0.21	0.231	121
Lead	0.03	(0.02)	-0.35***	(0.45)	0.00	0.15	130	0.06*	(0.04)	-0.49***	(0.54)	0.00	0.209	127	0.16**	(0.07)	-0.67***	(0.58)	0.02	0.298	118
Nickel	0.03	(0.02)	0.85	(1.06)	0.00	0.19	130	0.09	(0.06)	1.16	(1.48)	0.02	0.286	127	0.27**	(0.12)	2.12	(0.97)	0.14	0.407	121
Tin	0.03**	(0.02)	1.24	(0.76)	0.01	0.11	130	0.06*	(0.03)	0.65	(1.37)	0.00	0.177	127	0.13	(0.08)	0.64	(1.59)	0.00	0.287	118
Agricultural Products																					
Corn	-0.03*	(0.02)	1.00	(0.25)	0.17	0.12	223	-0.03	(0.04)	0.80	(0.30)	0.16	0.183	223							
Soybean	0.00	(0.01)	1.26	(0.35)	0.16	0.11	223	0.01	(0.02)	1.02	(0.35)	0.20	0.152	223							
Wheat	0.00	(0.01)	0.60***	(0.15)	0.10	0.12	223	0.00	(0.03)	0.40***	(0.18)	0.05	0.183	220							

Note: for oil, corn, soybean, and wheat, spot price is replaced with 1-month futures price. For gasoline, only the old version ("HU") of futures are used in the regressions. Statistical significance at the 10%, 5%, and 1% level are denoted by *, **, and *** respectively. For α, statistical significance is for null that α=0, while for β, the null is that β=1. Newey-West HAC standard errors, using truncation 1-less than futures horizon.

Table 2: GARCH Regressions of Price Change on the Basis

	3-months							6-months							12-months						
	α	se(α)	β	se(β)	adj. R^2	SER	N	α	se(α)	β	se(β)	adj. R^2	SER	N	α	se(α)	β	se(β)	adj. R^2	SER	N
Energy Products																					
Oil	0.05***	(0.01)	0.61	(0.32)	-0.01	0.16	223	0.07***	(0.01)	0.95	(0.17)	0.02	0.208	223	0.04***	(0.01)	1.01	(0.07)	-0.06	0.286	223
Natural Gas	-0.01	(0.02)	0.63***	(0.12)	0.12	0.27	208	0.02	(0.02)	0.86	(0.09)	0.19	0.33	205	0.13***	(0.02)	1.19*	(0.10)	0.25	0.384	199
Heating Oil	0.03***	(0.01)	0.99	(0.14)	0.10	0.17	223	0.09***	(0.01)	1.08	(0.08)	0.04	0.224	223	0.02**	(0.01)	0.75***	(0.09)	0.05	0.3	216
Gasoline ***	0.01	(0.01)	0.99	(0.18)	0.11	0.18	203	0.05***	(0.01)	1.15	(0.11)	0.20	0.202	205							
Precious Metals																					
Gold	0.02***	(0.01)	-1.78***	(0.43)	-0.14	0.07	223	0.06***	(0.01)	-1.46***	(0.23)	-0.03	0.091	223							
Silver	0.01**	(0.01)	-1.76***	(0.33)	-0.06	0.11	223	0.02**	(0.01)	-1.07***	(0.25)	-0.10	0.146	223							
Base Metals																					
Aluminum	0.01	(0.01)	0.54	(0.51)	-0.03	0.08	130	0.01	(0.01)	1.35	(0.41)	-0.04	0.119	127	0.06***	(0.01)	1.01	(0.20)	-0.16	0.164	121
Copper	0.02***	(0.01)	-1.11***	(0.44)	0.02	0.12	130	0.03***	(0.01)	-1.38***	(0.31)	0.02	0.184	127	0.09***	(0.01)	-1.11***	(0.16)	0.17	0.238	121
Lead	-0.01	(0.01)	0.49**	(0.23)	-0.13	0.16	130	0.00	(0.01)	0.32***	(0.25)	-0.22	0.232	127	-0.09**	(0.01)	-0.03***	(0.16)	-0.48	0.367	118
Nickel	0.06***	(0.01)	1.90	(0.68)	-0.09	0.20	130	0.08***	(0.01)	3.29***	(0.56)	-0.13	0.307	127	0.31***	(0.02)	3.03***	(0.16)	0.05	0.428	121
Tin	0.00	(0.01)	1.45	(0.68)	-0.11	0.12	130	0.00	(0.01)	1.97**	(0.38)	-0.17	0.191	127	0.04***	(0.01)	1.32	(0.30)	-0.18	0.311	118
Agricultural Products																					
Corn	-0.06***	(0.01)	1.35**	(0.16)	0.11	0.13	223	-0.05***	(0.01)	0.75***	(0.09)	0.11	0.188	223							
Soybean	-0.01	(0.01)	1.22	(0.17)	0.10	0.12	223	-0.01	(0.01)	0.88	(0.12)	0.16	0.155	223							
Wheat	-0.04***	(0.01)	0.77***	(0.07)	0.00	0.13	223	-0.08***	(0.01)	0.67***	(0.06)	-0.09	0.196	144							

Table 3: Out-of-Sample Forecasting Performance of Commodity Futures relative to Random Walk and Econometric Forecasts:

	Relative Root Mean Squared Forecast Error						Relative Mean of Absolute Value of Forecast Errors					
	Futures			ARIMA			Futures			ARIMA		
	3-mo	6-mo	12-mo	3-mo	6-mo	12-mo	3-mo	6-mo	12-mo	3-mo	6-mo	12-mo
Energy Products												
Oil	1.01	1.09	1.04	1.09	1.03	0.99	1.01	1.09	1.08	1.12	1.02	1.01
Natural Gas	0.99***	0.87***	0.87**	1.20	1.12	1.14	0.98***	0.90***	0.86***	1.19	1.18	1.17
Heating Oil	0.96	1.02	0.99	1.12	1.07	1.05	0.99	1.00	1.02	1.18	0.99	1.03
Gasoline ***	0.94	0.86**	0.97	1.07	1.02	1.05	0.95	0.88**	0.97	1.12	1.01	1.01
Precious Metals												
Gold	0.92	0.85	0.88	1.23***	1.04*	0.93	0.93	0.85	0.85	1.20***	1.05*	0.91
Silver	0.97	0.93	0.94	1.17**	1.05	0.95	0.96	0.90	0.93	1.14	1.04	0.91
Base Metals												
Aluminum	0.97	0.96	1.00	1.22	1.14	0.99	1.00	0.94	0.98	1.26	1.10	1.05
Copper	1.05***	1.11***	1.09**	1.26***	1.14***	1.02*	1.08***	1.12***	1.10**	1.36***	1.12***	1.03*
Lead	1.01**	1.04*	1.03*	1.19***	1.11**	1.06*	1.03*	1.05	1.06*	1.26***	1.10*	1.04
Nickel	1.01	1.02	1.00	1.23***	1.15**	1.23**	1.02	1.02	1.00	1.18***	1.13*	1.22**
Tin	0.99	0.99	0.99	1.21***	1.08***	1.18***	0.98	0.98	0.98	1.20***	1.04***	1.15***
Agricultural Products												
Corn	0.89	0.83		1.32***	1.16***	1.01	0.90	0.90		1.34***	1.22***	1.04
Soybean	0.89	0.86		1.22**	1.19**	1.07	0.91	0.90		1.19*	1.16*	1.09
Wheat	0.89	0.94		1.29***	1.17*	0.99	0.90	0.90		1.29**	1.18*	1.03

Note: Table displays the root mean squared forecast error and mean of absolute value of forecast errors at each forecast horizon and commodities product for two forecasting approaches – using futures prices and using an ARIMA model– *relative* to the relevant forecast error measure from a random walk (without drift) prediction. Out-of-sample forecasts are evaluated over 2003M1 to 2008M7. The *, **, and *** denote whether the p-value of the two-sided test of the null that the forecast error measure was generated by a random walk process is less than 10%, 5%, and 1% respectively. P-values are calculated by simulating random walk processes with same variance as in each commodity market and generating a distribution of RMSEs and MAEs for each commodity at each forecast horizon.

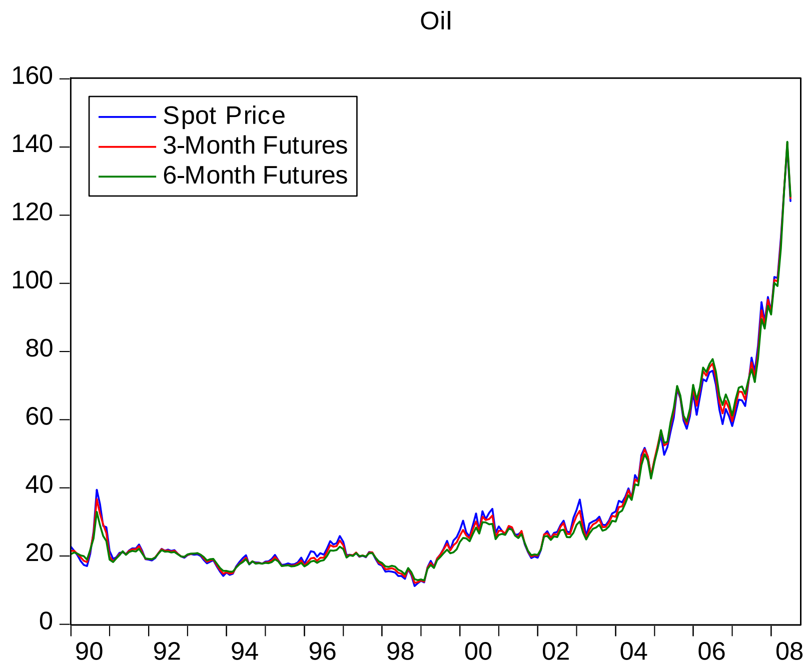

Figure 1: Price of Petroleum (WTI), end of month, and 3 and 6month futures.

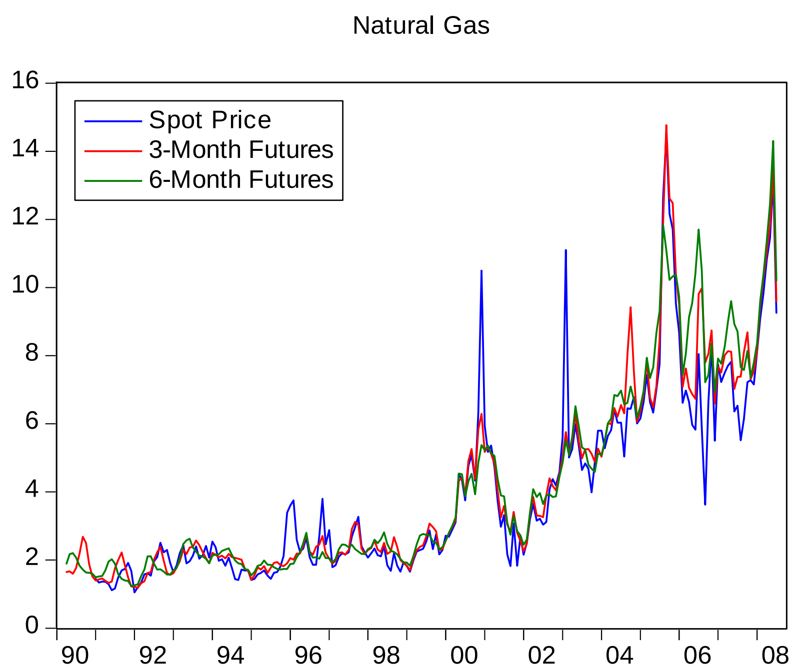

Figure 3: Price of Natural Gas (Henry Hub), end of month, and price 3 and 6 month futures.

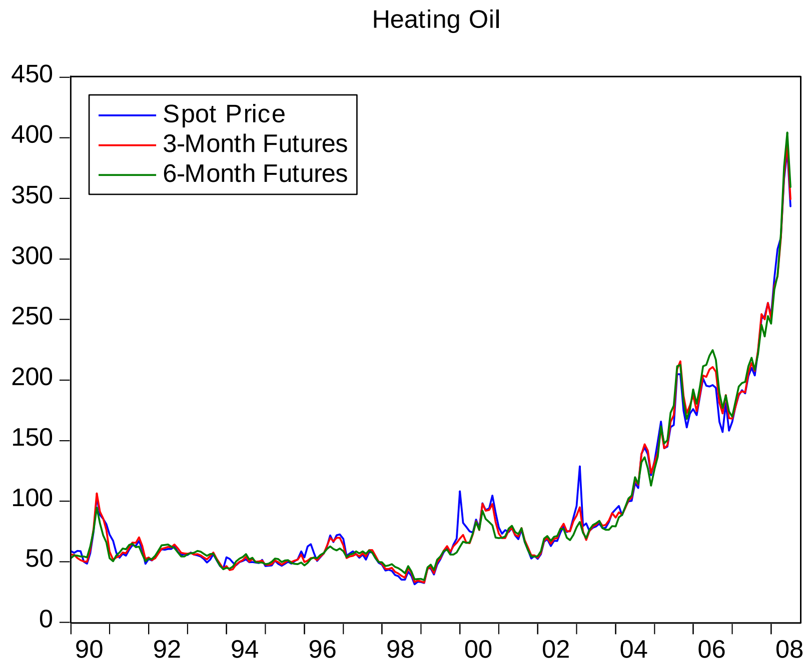

Figure 3: Price of Heating Oil, end of month, and 3 and 6 month futures.

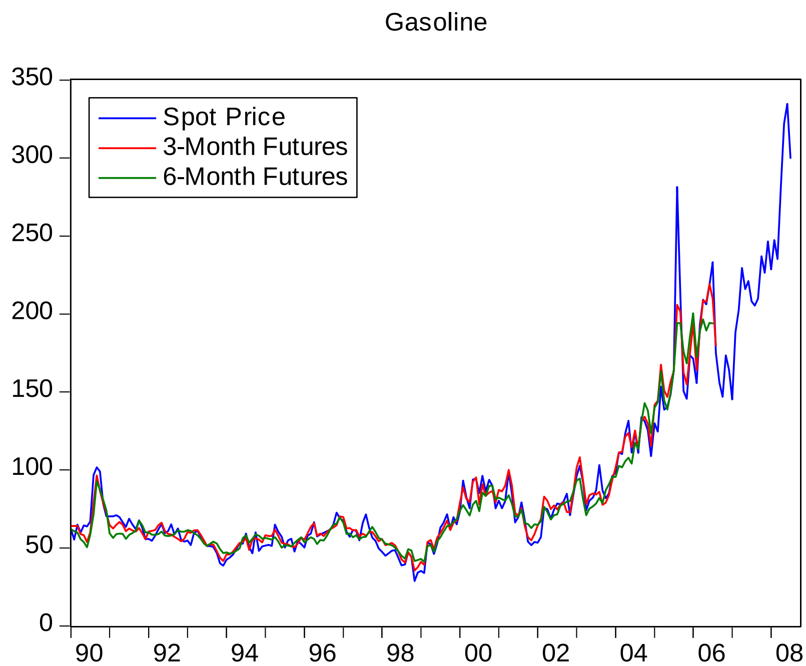

Figure 4: Price of Gasoline (NY Harbor), end of month, and 3 and 6 month futures.

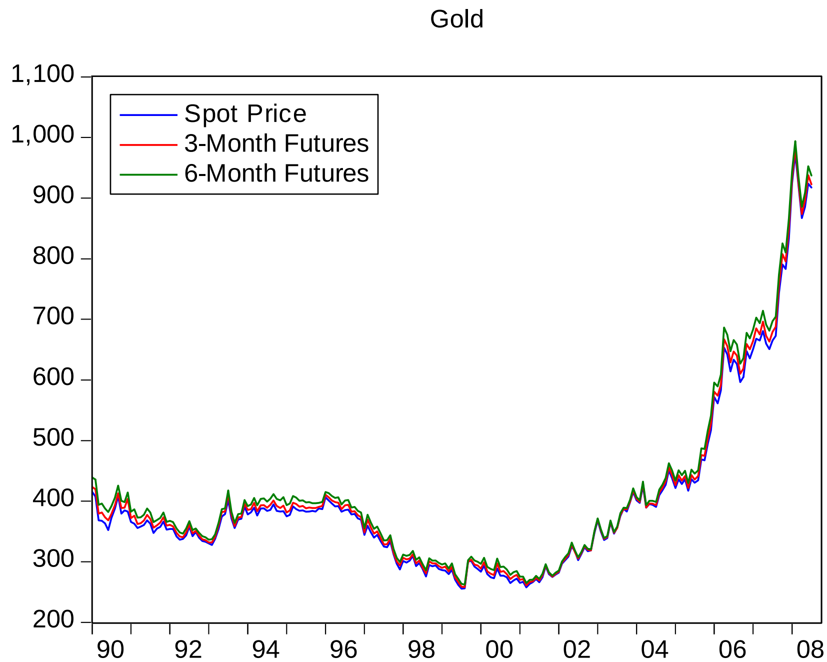

Figure 5: Price ofGold, end of month, and 3 and 6 month futures.

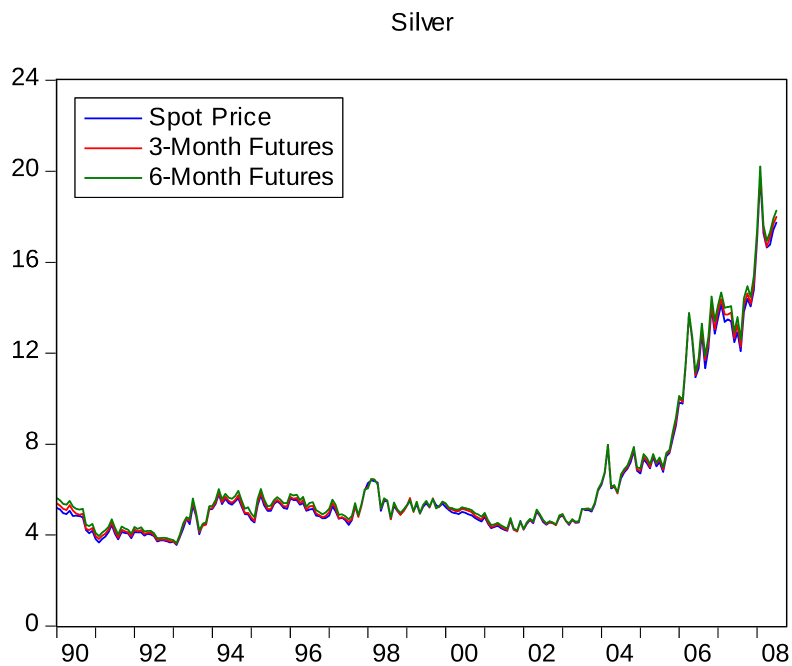

Figure 6: Price of Silver, end of month, and 3 and 6 month futures.

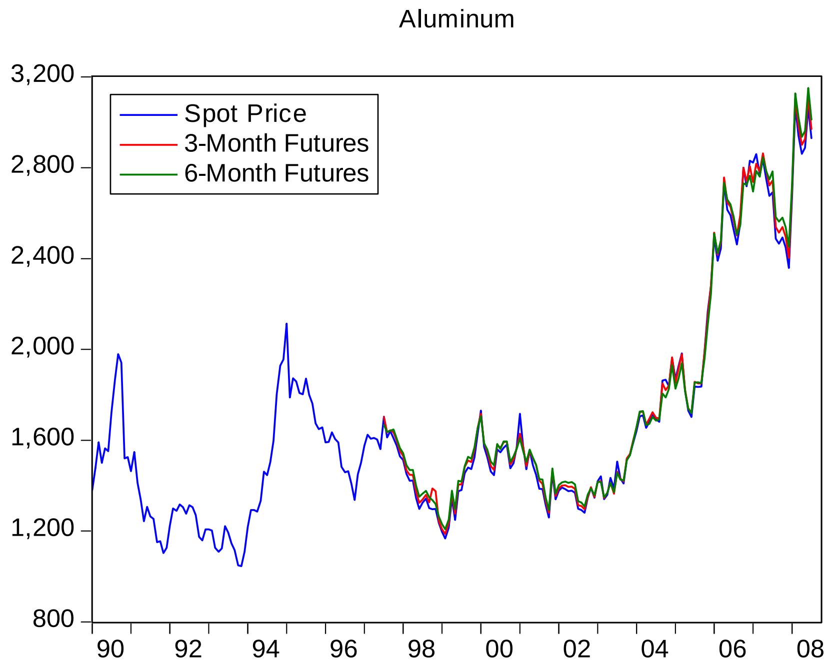

Figure 7: Price of Aluminum, end of month, and 3 and 6 month futures.

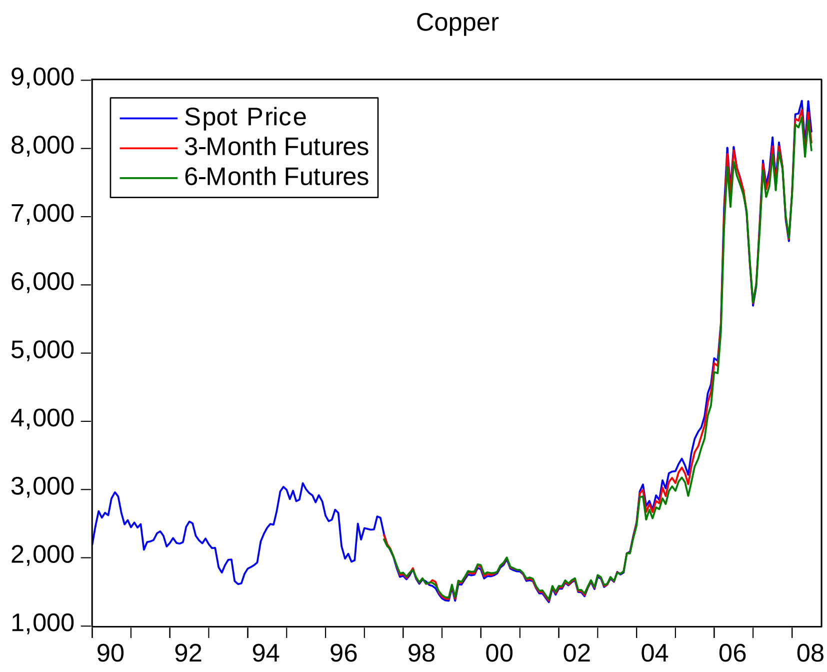

Figure 8: Price of Copper, end of month, and 3 and 6 month futures.

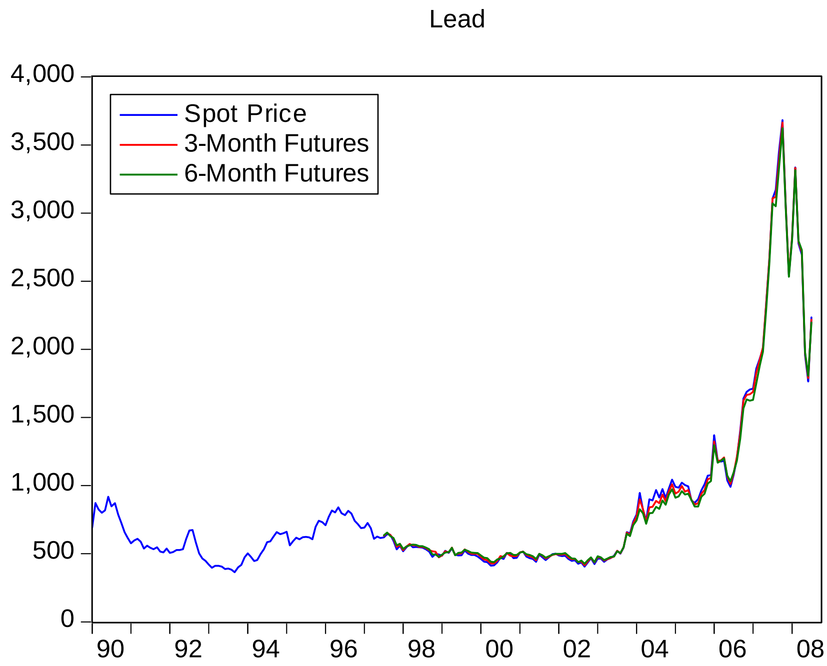

Figure 9: Price of Lead, end of month, and 3 and 6 month futures.

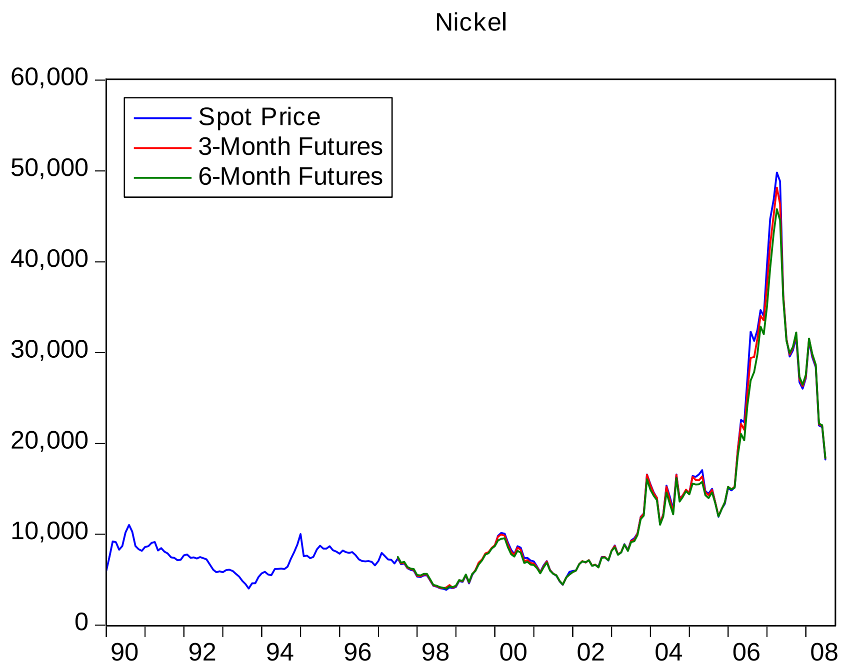

Figure 10: Price of Nickel, end of month, and 3 and 6 month futures.

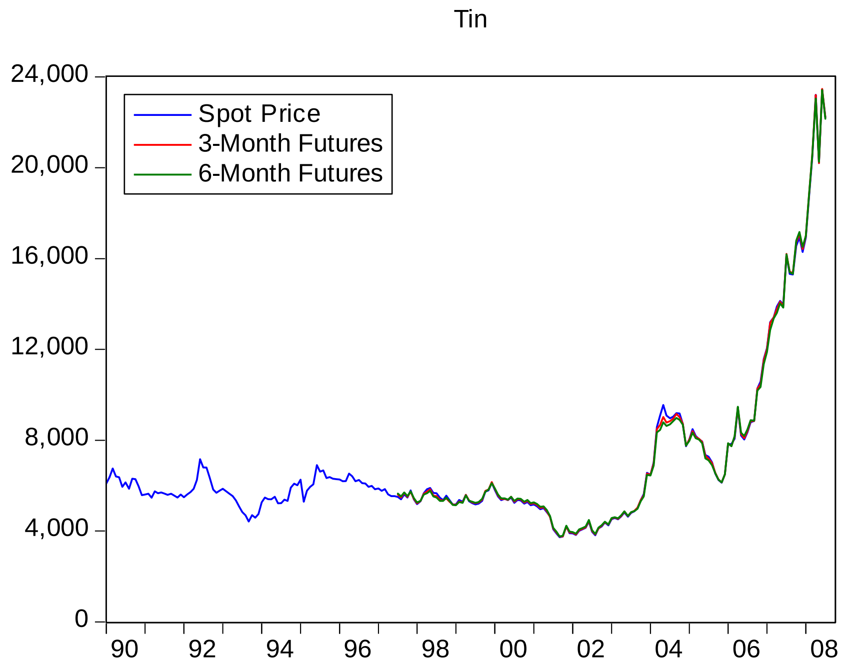

Figure 11: Price of Tin, end of month, and 3 and 6 month futures.

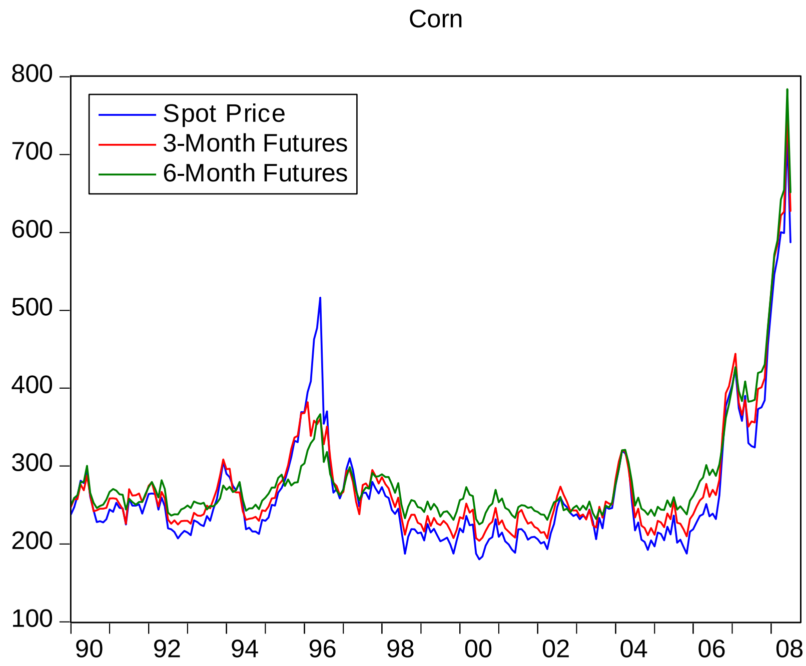

Figure 12: Price of Corn, end of month, and 3 and 6 month futures.

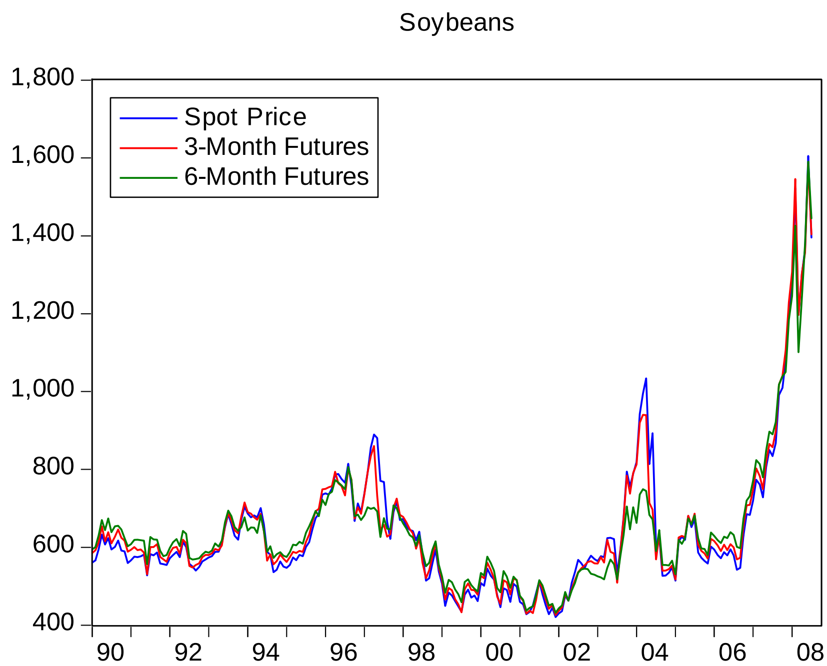

Figure 13: Price of Soybeans, end of month, and 3 and 6 month futures.

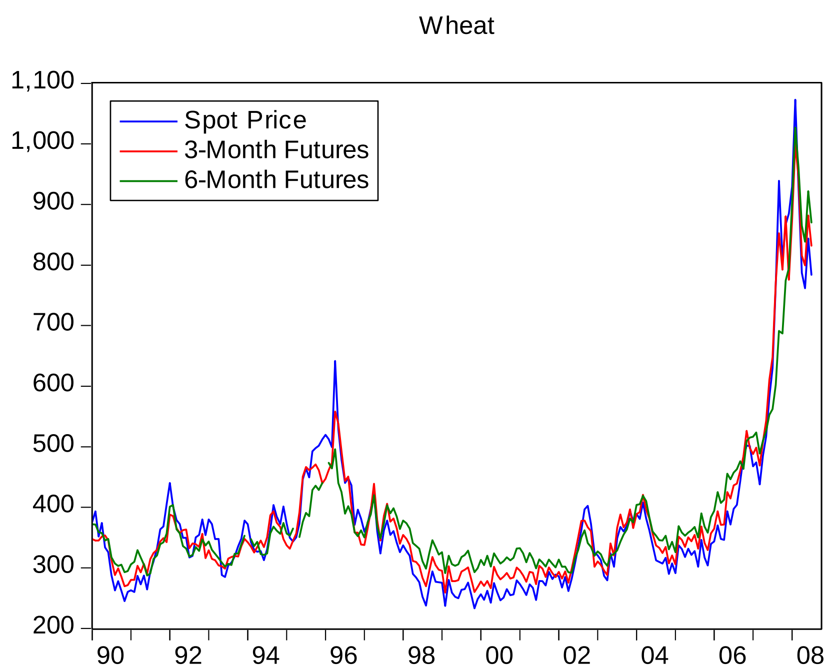

Figure 14: Price of Wheat, end of month, and 3 and 6 month futures.