Predictive Dynamics in Commodity Prices

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Questions asked here

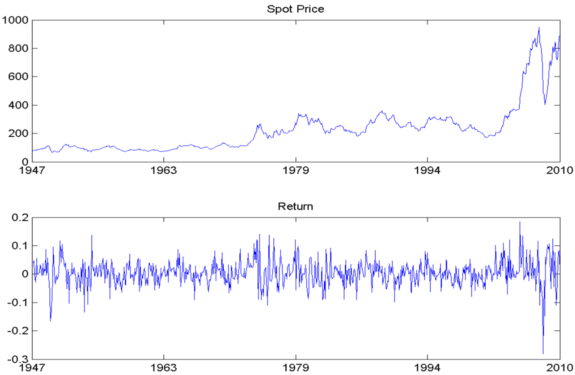
- How strong was predictability of commodity spot returns over the last few decades?
- Which (if any) predictors improve forecasts? financial or macroeconomic variables such as inflation, money supply, industrial production, unemployment rate?
- Does predictability vary across different horizons (monthly, quarterly, annual)?
- Does predictability vary over the economic cycle?
  - Rapach, Strauss and Zhou (2010)
  - Henkel, Martin, and Nardari (2011)
- Can commodity price volatility or price hikes/collapses be predicted?

Data: Commodity prices

- Commodity spot prices measured by Reuters/Jeffries-CRB indexes compiled by Commodity Research Bureau
  - **raw industrials**: burlap, copper scrap, cotton, hides, lead scrap, print cloth, rosin, rubber, steel scrap, tallow, tin, wool tops, and zinc
  - **foodstuffs**: butter, cocoa beans, corn, cottonseed oil, hogs, lard, steers, sugar, and wheat
  - **metals**: copper scrap, lead scrap, steel scrap, tin, and zinc
- Unweighted geometric mean of individual commodity prices
- Sample period: 1947m1 - 2010m12
- Commodity spot returns computed as

$$r_{t+1:t+h} \equiv \frac{P_{t+h} - P_t}{P_t}$$

Spot Prices and Returns (Metals)



Data Characteristics

- Returns on commodity indexes have
  - lower mean than value-weighted stock returns
  - right-skews
  - higher kurtosis than stocks
  - some serial correlation for three of the commodity indexes

Summary Statistics

	Fats & Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
mean (%)	0.841	0.643	0.813	0.754	1.432	0.524	0.676	2.979	1.466
std (%)	11.200	6.464	6.459	8.987	9.466	5.892	5.476	7.804	3.972
skew	0.268	0.255	0.806	0.160	0.030	1.229	0.241	-0.574	0.934
kurt	5.041	4.775	9.859	4.636	4.736	11.482	6.676	4.051	4.414
AR(1)	0.034	0.088	0.299	0.060	0.220	0.157	0.255	0.102	0.019

Introduction

- Some evidence of modest predictability of commodity price movements by means of economic state variables
    - **Bessembinder and Chan (1992)**: T-bill rate, dividend yield, junk bond premium have limited predictive power over movements in agricultural, metals and currency futures prices
    - **Hong and Yogo (2011)**: limited in-sample predictability of commodity spot and futures returns by means of similar economic variables
    - **Acharya et al. (2011)**: mild empirical evidence of predictability of petroleum spot returns from fundamental hedging demand variables and the term spread
    - **Groen and Pesenti (2010)**: factor-augmented and currency-based models outperform naive benchmarks for some commodity spot prices, though not "on average"

Predictor variables

- Dividend Price Ratio (dp)
- Treasure Bill (tbl)
- Long Term Rate of Returns (ltr)
- Term Spread (tms)
- Default Return Spread (dfr)
- Inflation ($infl$)
- Investment to Capital Ratio (ik)
- Industrial Production (ΔIND)
- Unemployment (ΔUN)
- Money Stock ($\Delta M1$)
- Commodity volatility ($cvol$)

In-sample predictability

Univariate return regressions:

$$r_{t+1:t+h} = \beta_{0h} + \beta_{1h} x_t + \varepsilon_{t+1:t+h}$$

- Return predictability varies a great deal across different horizons
- Variables such as the inflation rate are insignificant in monthly regressions but become significant at the quarterly and annual horizons
- Only growth in the money supply seems capable of predicting commodity returns across all three horizons
- Return predictability is stronger for industrials and metals and weakest for fats-oils, foods, and textiles

In-sample Predictability

	Fats & Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
				Monthly					
dfr	0.134	0.066	0.325**	0.435**	0.559**	0.204	0.220	0.109	-0.003
infl	1.065	0.458	0.522	0.551	0.517	0.012	0.493	-0.656	-0.262
Δ IND	0.267	0.204	0.580***	0.267	0.756***	0.340**	0.421***	0.079	-0.127
Δ M1	0.054	0.034	0.094***	0.078	0.108**	0.091**	0.067**	-0.036	0.011
AR(1)	0.088*	0.099**	0.363***	0.097**	0.299***	0.129*	0.278***	0.039	0.072*
				Quarterly					
dfr	0.333	0.220	0.476*	0.484	0.783*	0.033	0.373	0.542**	-0.072
infl	-1.744***	-0.557	-1.222**	-1.386**	-1.452*	-0.600	-0.949**	-0.479	0.335
Δ IND	0.538	0.332	0.645*	0.373	0.665	0.381	0.512*	-0.185	-0.075
Δ M1	0.185	0.141	0.326***	0.284**	0.417**	0.256***	0.246***	-0.107	0.032
AR(1)	0.033	0.087	0.297***	0.058	0.220***	0.157**	0.252***	0.102	0.018
				Annual					
dfr	0.387	0.514	-0.317	0.109	-0.732	-0.099	0.081	-0.358	0.339*
infl	-1.790*	-0.863	-1.864*	-1.408*	-2.672**	-1.022	-1.384**	-0.103	0.719*
Δ IND	-1.019	-0.062	-1.363**	-1.022*	-1.330**	-0.982**	-0.791*	-0.367	-0.140
Δ M1	1.028	0.926**	1.211**	1.055**	1.682**	0.867*	1.091**	-0.514	0.288
AR(1)	-0.075	0.135	-0.128	-0.119	-0.128	-0.073	-0.008	-0.049	-0.094

Out-of-sample predictability

Simulated recursive forecasts:

$$\begin{aligned}
\hat{r}_{t+1|t} &= \hat{\beta}_t' z_t, \\
\hat{\beta}_t &= \Big(\sum_{\tau=1}^{t} z_{\tau-1} z_{\tau-1}'\Big)^{-1} \Big(\sum_{\tau=1}^{t} z_{\tau-1} r_\tau\Big) \\
z_t &= (1 x_t)'
\end{aligned}$$

Performance measured by the relative out-of-sample R^2-value:

$$R^2 = 1 - \frac{\sum_{t=R}^{T-1} (r_{t+1} - \hat{r}_{t+1|t})^2}{\sum_{t=R}^{T-1} (r_{t+1} - \hat{r}_{t+1|t}^{bmk})^2}$$

Clark-West test for statistical significance:

$$\Delta MSE^{adj} = P^{-1} \sum_{t=R}^{T-1} \bar{e}_{t+1|t}^2 - P^{-1} \sum_{t=R}^{T-1} \hat{e}_{t+1|t}^2 + P^{-1} \sum_{t=R}^{T-1} (\bar{r}_{t+1|t} - \hat{r}_{t+1|t})^2$$

Empirical Out-of-sample findings

- Predictability is strongest for industrials, metals, and the broad commodity price index, weaker for fats-oils, foods, and livestock
- Many negative R^2 values due to parameter estimation error
- **Monthly results**: the highest R^2 values are obtained for industrial raw materials and metals when the default return spread is used as the predictor
- **Quarterly results**: models based on T-bill rate, inflation, or money supply growth generate positive and statistically significant R^2
- **Annual results**: R^2 around 10-20% found for the T-bill rate, term spread, and some macroeconomic predictors (industrial production, money supply, unemployment rate)

Out-of-sample R^2

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
					Monthly				
dfr	-0.548	-0.799	4.325*	2.094*	4.500*	0.333	1.536	-0.648	-0.599
infl	0.609	0.438	-0.172	0.259	-0.587	-0.942	0.486	-1.704	0.464
Δ IND	-0.193	0.314	3.060	-0.321	1.996	0.142	2.122	-0.494	-2.072
Δ M1	-0.551	-0.664	1.593**	-0.324	0.931*	0.793	-0.140	-0.184	-1.141
AR(1)	0.853	0.313	9.139***	1.018	7.189***	-7.282	5.279**	0.040	0.128
					Quarterly				
dfr	-2.776	-1.727	4.077	-0.580	3.862	-1.223	1.813	0.313	-1.586
infl	5.137**	1.464**	7.673*	5.328**	3.821*	1.322	6.391**	0.223	1.442
Δ IND	-0.380	0.837	-2.855	-0.594	-2.399	-1.257	-0.644	-2.290	-1.216
Δ M1	-0.864	-1.067	6.853**	0.645	3.941**	5.378**	3.255**	-0.811	-2.759
AR(1)	-0.273	-0.082	10.340***	-0.302	5.927*	4.549**	6.026**	-0.296	-0.482
					Annual				
dfr	-9.357	-6.847	-18.734	-13.906	-17.182	-17.513	-18.585	-19.775	5.167*
infl	6.227*	4.518	9.746*	8.099*	8.704*	4.511	9.551*	-0.436	2.545
Δ IND	16.136**	-15.030	18.684**	20.216**	8.286**	12.599*	19.132**	-5.594	-1.423
Δ M1	6.194	13.426*	15.490***	11.818*	7.347**	22.638***	20.624***	-4.546	-15.396
AR(1)	-4.480	1.442	-2.620	0.117	-7.016	-1.632	-2.758	-4.833	-0.119

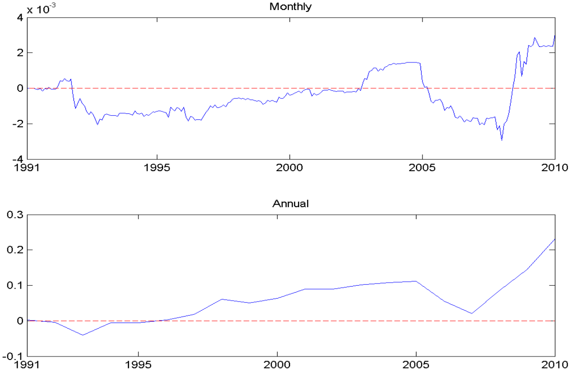
Evolution in OoS return predictability

- What do we learn from out-of-sample forecasts? Diebold (2012)
- Cumulated sum of squared error differential between the benchmark model and a candidate prediction model proposed by Goyal and Welch (2008):

$$\Delta SSE_t = \sum_{\tau=1}^{t} e_\tau^2(Bmk) - \sum_{\tau=1}^{t} e_\tau^2(Model)$$

- $\Delta SSE_t > 0$: benchmark beaten by forecast model
- $\Delta SSE_t < 0$: benchmark better than forecast model

CumSum for Money supply growth



Predictability in recessions and expansions

Evaluate differences in predictability in recessions vs. expansions:

$$(r_{t+1:t+h} - \bar{r}_{t+1:t+h|t})^2 - (r_{t+1:t+h} - \hat{r}_{t+1:t+h|t})^2 = \alpha + \beta NBER_{t+1} + \varepsilon_{t+1:t+h}$$

- Little evidence of commodity price predictability during expansions
- Significantly stronger predictability during recessions
  - Industrial production growth, growth in money supply have significantly stronger predictive power during recessions
- Predictability of commodity prices is highly state dependent

Predictability and Business cycle: Recession out-of-sample R^2

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
					Monthly				
dfr	-1.658	-2.211	8.106**	4.128*	11.379***	0.957	2.361	-1.827	-1.364
infl	0.797	1.273***	3.175***	0.813*	1.547***	-0.975	2.478***	-6.643	1.154
Δ IN	-0.088	0.909*	7.771**	0.273	6.244**	-1.383	5.021**	-0.780	-7.411
Δ M1	-0.621	-1.112	2.452*	-0.969	2.613**	0.523	-0.134	-1.169	-1.269
AR(1)	3.577**	0.811	17.239***	5.073***	13.301***	-10.948	7.544*	1.598***	-0.938
					Quarterly				
dfr	-9.034	-4.309	3.486	-7.650	6.894	-4.761	1.229	4.304	-8.747
infl	14.089***	3.686***	17.271***	12.271***	10.422***	23.973***	13.244***	1.614**	9.597***
Δ IN	2.519	4.546***	-2.544	1.385	-3.123	-17.661	2.610	-4.263	-3.454
Δ M1	0.082	-0.257	10.095***	1.531	8.746***	18.120	5.851**	-5.708	-5.336
AR(1)	-0.156	0.358	9.437	-0.165	6.921	0.181	7.095	4.053**	-2.430

Multivariate Regressions

- **Variable selection** based on AIC or BIC across 2^K models
- **Ridge regression** shrinks OLS estimates towards zero. Single parameter λ regulates the amount of shrinkage:

$$\hat{\beta}_{\lambda t} = \arg\min_{\lambda} \left(\sum_{\tau=1}^{t} (r_\tau - z'_{\tau-h}\beta_{\lambda t})^2 + \lambda \sum_{j=1}^{K} \beta^2_{\lambda tj} \right)$$

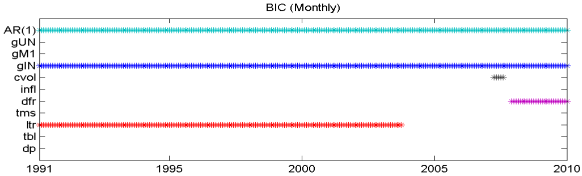
$$\hat{r}^{RIDGE}_{t+h|t} = z'_t \hat{\beta}_{\lambda t}$$

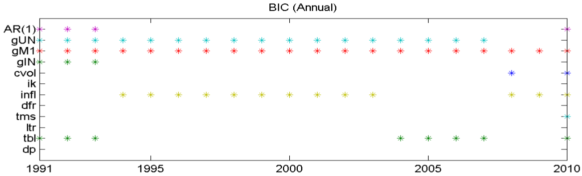
- **Subset regressions** - averaging over $k-$variate models

$$\hat{r}_{t+1|t} = \frac{1}{K} \sum_{i=1}^{K} x'_{ti} \hat{\beta}_{it}$$

Rapach, Strauss and Zhou (2010) obtained as special case

ICs suggest the best model varies over time





Out-of-sample R^2 (Model selection)

- AIC works reasonably well at all horizons for industrials, metals and total index
- BIC produces less reliable performance

	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
					Monthly				
AIC	-1.342	0.313	10.614	0.298	7.478	-9.348	5.403	-5.799	0.305
BIC	-0.975	-0.618	9.417	-2.265	8.679	-11.329	6.403	-6.253	0.698
					Quarterly				
AIC	-5.140	-11.730	12.763	-5.412	5.974	-5.186	10.330	-14.699	-0.182
BIC	0.111	0.000	-11.205	-3.519	-10.697	-6.364	-5.151	-12.589	1.923
					Annual				
AIC	6.565	22.597	22.595	29.393	26.251	6.807	38.418	-57.660	40.517
BIC	0.000	0.000	18.264	11.804	2.111	10.287	30.521	-40.457	40.018

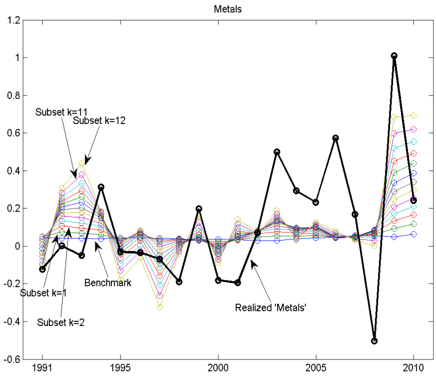
Multivariate results: Ridge and subset

- **Monthly**: positive R^2-values around 10% (industrials), 8% (metals) and 4-5% (broad index)
- **Quarterly**: R^2-values are somewhat higher for industrials, metals and the broad commodity index
- **Annual**: R^2-values in the range 20-35% for the broad commodity index and some of the disaggregate indexes

Out-of-sample R^2 for Ridge Regression

λ	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
					Monthly				
0.5	-2.476	-1.472	10.449***	0.244	8.430***	-8.107	4.430***	-5.249	0.242
10	-2.387	-1.408	10.563***	0.288	8.507***	-7.892	4.536***	-5.073	0.280
200	-1.376	-0.805	11.170***	0.700	8.993***	-5.316	5.280**	-3.057	-0.230
					Quarterly				
0.5	-8.134	-5.527	10.947***	-6.451	8.772***	-13.050	7.736**	-10.083	-10.078
10	-6.809	-4.319	13.224***	-4.892	9.993***	-8.248	9.626**	-8.896	-7.304
200	-1.043	-0.559	14.745***	0.490	9.975***	3.711*	10.689**	-2.342	-2.778
					Annual				
0.5	-2.635	17.729*	23.439**	32.078**	30.197**	9.492**	26.831***	-54.765	13.828***
10	16.044*	17.683	36.867**	30.122**	31.723**	17.606**	36.457***	-35.438	26.091***
200	8.696*	5.013	19.264**	13.899**	12.113*	11.384*	17.278**	-4.040	2.783

Complete Subset Selection



OoS R^2 for complete subset regression

- Including 5-8 predictor variables doubles or triples the value of the out-of-sample R^2 compared with the equal-weighted combination of univariate forecasts

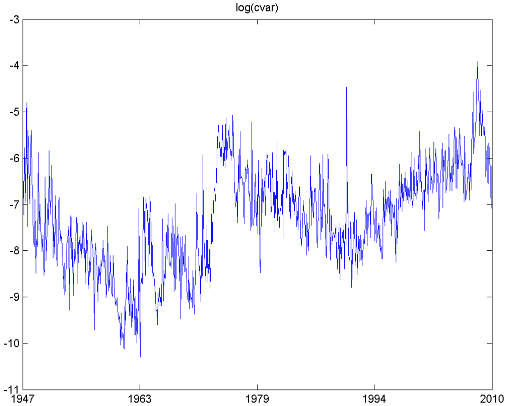
k	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
					Monthly				
1	-0.033	-0.039	3.336***	0.342	2.658***	-0.234	1.637**	-0.228	-0.095
8	-1.374	-0.876	10.866***	0.572	8.816***	-5.052	5.022**	-2.968	-0.120
					Quarterly				
1	0.209	-0.060	4.283***	0.527	2.779**	1.351*	2.846**	-0.042	-0.517
8	-2.727	-1.856	15.446***	-0.747	10.472***	1.115	11.197**	-4.148	-3.444
					Annual				
1	4.884*	2.004	10.618**	7.775**	6.159**	6.535*	9.271**	-1.532	0.645
8	12.877*	14.244	35.503**	28.283**	28.855*	19.403**	34.880***	-25.777	26.133**

Forecasting commodity price volatility

$$\log(cvol^2_{t+1}) = \beta_0 + \beta_1 \log(cvol^2_t) + \beta_2 x_t + u_{t+1}$$

- Estimate of β_1 is close to 0.8 and highly significant
- No evidence that time-varying predictors (other than the lagged volatility) help predict realized variance
- During recessions several macroeconomic variables (growth in industrial production, money supply growth, and changes in the unemployment rate) improve the OoS forecasts of monthly commodity volatility when added to the AR(1) model

Realized Volatility, Dow Jones-AIG Commodity Index



Commodity Variance Predictability

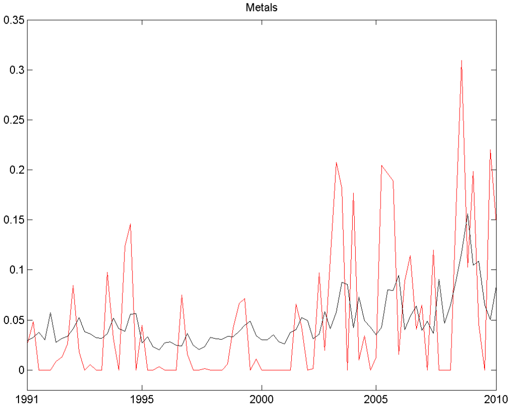
	Monthly			
	β	$OoSR^2$	$OoSR^2_{Expan}$	$OoSR^2_{Recess}$
dp	-0.123***	-1.449	-3.115	1.825*
tbl	0.633	-4.198	-5.203	-2.222
ltr	-0.964	0.125	0.462	-0.536
tms	4.403***	1.332**	0.691	2.592**
dfr	-1.174	-0.450	-0.521	-0.310
infl	10.870*	-5.838	-5.605	-6.297
Δ IN	-2.384	0.277	-0.250	1.314***
Δ M1	1.158**	-3.897	-6.989	2.178**
Δ UN	0.250	-0.034	-0.235	0.362***
AR(1)	0.811***	72.695***		

Predictability of price increases/decreases

$$\max(0, r_{t+1:t+h}) = \beta_{0h} + \beta_{1h} r_{t-h+1:t} + \beta_{2h} \sigma_{t-h+1:t} + \beta_{3h} x_t + \varepsilon_{t+1:t+h}$$

- **Monthly**: Lagged volatility and lagged returns are significant
- **Quarterly**: Money supply growth and inflation are significant for raw industrials and metals
- **Annual**: Broad range of predictor variables are significant (inflation, investment-capital ratio and unemployment)
- Different predictors work for $\max(0, r_{t+1})$ and $\min(0, r_{t+1})$
  - Money supply growth, lagged volatility, and the lagged return predict **increases** in commodity prices
  - inflation and industrial production are better predictors of **decreases** in commodity prices

Predictability of price increases based on money supply growth



Predictability of price increases

	Monthly								
	Fats-Oils	Foods	Industrials	Livestock	Metals	Textiles	Commodity	Stock	Bond
infl	0.003	2.123**	-0.396	0.340	-0.529	-0.558	0.456	-1.717	-1.156
Δ IN	-0.120	0.202	1.115*	-0.246	0.089	-0.139	0.679	-0.391	-1.788
Δ M1	-0.087	-0.232	1.584**	-0.139	0.873**	3.911**	0.494	-0.125	-1.887
cvol	3.113***	0.608**	4.054***	3.245***	5.904***	4.491**	2.484***	-0.555	-0.611
AR(1)	0.159	-0.237	8.405***	0.245	7.190***	-2.015	0.914**	-0.500	0.167

Conclusion

- Movements in commodity prices or functions of these are partially predictable
- Predictability varies with the economic state
- No single best model across all horizons
  - Best model varies over time
- Evidence that multivariate approaches and forecast combinations produce better forecasts
- Commodity price predictability is relevant for risk management (volatility, downside risk)