Economic variables today, returns tomorrow

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Abstract

Commodity prices are of interest to investors, central banks and policymakers since they are believed to influence general price levels. Therefore, in this thesis I study whether it is possible to forecast commodities returns using economic indicators over different horizons and economic cycles.

I establish an out-of-sample (OOS) predictability using different economic variables such as: inflation, unemployment rate, dividend price ratio, industrial production, among others. The time span of the analysis is from 1951 to 2014, over a monthly, quarterly an annual horizon.

I observe that inflation is consistently a good predictor for in-sample (IS) and OOS univariate models. Multivariate OOS estimations tend to be more accurate when predicting commodity returns than univariate regressions. Furthermore, the unemployment rate and the commodity currencies are strong statistically significant predictors during economic recessions.

Key words: Commodity price predictability, out-of-sample forecast, economic cycle.

Resumo

Os preços das commodities revestem-se de grade interesse para os investidores, bancos centrais e decisores políticos uma vez que se parte do principio que vêm a influenciar o nível geral de preços. Consequentemente, nesta tese eu fiz um estudo a fim de prever os retornos das commodities, usando indicadores económicos em diferentes horizontes temporais e ciclos económicos.

Estabeleci uma previsão out-of-sample usando diferentes variáveis económicas tais como: inflação, taxa de desemprego, rácio dividendo-preço, produção industrial, entre outros indicadores.

O intervalo de tempo de análise decorre entre 1951 e 2014, num horizonte mensal, trimestral e anual.

Observei que a inflação é consistentemente um indicador fiável nos modelos in-sample e out-of-sample univariados. Regressões out-of-sample multivariadas tendem a ser mais fiáveis ao prever retornos de commodities, do que regressões com uma só variável explicativa. Para além disso, a taxa de desemprego, a taxa de câmbio entre o Dólar americano e o Dólar australiano assim como a taxa de câmbio entre o Dólar americano e a Rupia indiana são indicadores estatisticamente significativas durante as recessões económicas.

Palavras-chave: Previsão do preço das commodities, previsão out-of-sample, ciclo económico.

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1. Introduction

Unprecedented spikes and drops in commodities prices have been a frequent problem for both policymakers and investors, as they are believed to influence general price levels. There are several explanations for this phenomenon such as: political uncertainty, increase in world outputs, low interest rates and monetary expansion.

Commodities have been gaining investor's interest in recent years. According to the Investment Company Institute (ICI), the total net assets of commodity exchange traded funds grew from $1bn in 2004 to more than $58bn in 2014. Although commodity ETFs remained the largest category within the group, with 18% of net assets at the end of 2014, their share decreased substantially. At the end of the previous year, 2013, it represented 24% of total net assets. This was mainly due to a decline in commodity ETF assets demand as well as the drop in silver and gold prices.

Commodity spot prices highly depend on storage costs and convenience yields. These factors are influenced by the mismatches between demand and supply between commodities and the financing costs. Thus, economic indicators are expected to be helpful when predicting commodity returns.

Acharya, Lochstoer, and Ramadorai (2011) develop a model for commodity markets where speculators are capital constrained, and commodity producers hedge commodity futures with demand. They find that limits to financial arbitrage lead to limits to hedging by producers, which impact asset and goods prices

Although previous authors have studied commodity price predictability, little is known on how they depend on macroeconomic and financial variables.

Groen and Pesenti (2009) use ten spot prices indexes to examine if it is possible to forecast commodity prices using three different models: benchmark, based on random walk or autoregressive process; based on exchange rate; and factor augmented. They find that the later two models, on average, do not outperform the naive benchmarks for most commodity indexes.

Chen, Rogoff, and Rossi (2010) defend that a small number of commodity currencies can forecast commodity prices. They state that exchange rates reflect expectations of future changes of economic fundamentals, which can affect both demand and supply in commodity markets. Hence, the natural question that arises is if it is possible to use macroeconomic variables to forecast commodity prices.

Hitherto, the predictability of commodity futures prices has attracted more interest to researchers. Bessembinder and Chan (1992) conclude that the dividend yield and the T-bill yield have limitations when predicting movements in agricultural, metals, and currency futures prices. Hong and Yogo (2009) investigate the determinants of aggregate commodities returns. They state that predictors of stock and bond returns such as the yield spread and the short rate are valid predictors for commodities prices. For example: a high yield spread predicts low commodities returns, which is consistent with the fact that usually commodities are hedge for market.

Moreover, previous studies were concerned with IS forecast of commodities prices. However, Hong and Yogo (2011) find limitations on IS predictability in commodity spot and futures returns through economic variables. Therefore, it would be interesting to analyze the predictability of commodity prices in an OOS context.

Rapach, Strauss, and Zhou (2010) state that stock returns predictability is highly correlated to the underlying economic state. Bond (1984), Chambers (1985) and Frankel (2006) suggest that commodity prices are negatively correlated with interest rates. Furthermore, McQueen and Roley (1993) states that positive surprises in real economic activity news leads to cash flow growth in recessions and raise in discount rates during economic growth. Hence, it is of interest to observe how commodity prices co-vary with the economic cycle.

The paper “Forecasting commodity prices indexes using macroeconomic and financial predictors” (2014) by Antonio Gargano and Allan Timmermann aims to exploit these pitfalls and observe whether is possible to predict commodity prices through economic variables. The authors study the predictability of commodity returns over different horizons and economic cycles by establishing OOS predictability over different economic variables such as inflation, unemployment, long-term return, and industrial production. Some of their results suggest that predictability of commodity returns from macroeconomic variables, such as: inflation and money supply is weaker during economic expansions than during recessions.

In addition, in the past three years, researchers have dedicated more time to exploit commodities returns predictability. Example of that is Rossi (2012) paper, where she studies the linkage between equity and commodity markets. Furthermore, Gruber and Vigfusson (2013) analyze the correlation of interest rates and volatility with commodity returns. They propose that the increase in prices is caused by a decrease in interest rates say, metal prices raise when interest rates decline. Thus, price does not entirely depend on the influence of financial speculators as several theories state.

An economy relies on the imports of commodities to sustain its own production, consumption and services. As a consequence, prices movements are very important for industries with a high degree of dependence on commodities and it is crucial to be aware of future movements. Thus, from my point of view, it is relevant to have a wider approach regarding the forecast of commodity prices. So, a replication and update of Gargano and Timmermann (2014) paper seems to be an interesting analysis of the influence of economic variables as predictors of commodities spot prices.

Hence, the main purpose of this thesis is to use macroeconomic and financial variables to empirically examine the behavior of the underlying spot prices in an OOS context. In line with "Forecasting commodity prices indexes using macroeconomic and financial predictors", I focus on four fundamental questions: 1) Can economic variables predict commodity prices?; 2) How does price predictability vary over time?; 3) Does the state of the economy have influence on commodity price predictability?; 4) Does the commodity prices predictability vary across the different types of commodities?.

I find that univariate predictability of commodity returns varies across indicators, inflation appears to be a good predictor whereas Killian's real economic activity index is weak. OOS multivariate regressions present stronger evidence of predictability than IS ones.

The empirical results suggest that commodity prices predictability relies on the forecast horizon. The returns appear to be more significant at the monthly horizon.

Furthermore, I conclude that commodity returns predictions is linked to the economic state. Price changes in commodities are more predictable in recessions than in expansions.

The returns forecast widely varies across the commodity indexes. Nevertheless, in general terms, the predictability is stronger for Metals, Textiles, Industrials, Livestock and Commodity indexes. In contrast, Foods and Fats& Oils show little predictability evidence.

The thesis structure is presented as follows: section 2 describes the data and methodology as well as the commodity returns summary statistics. Section 3 presents the IS and OOS regressions methodology and their empirical results. Section 4 shows the predictability of commodity returns in expansions and recessions. Finally, the conclusions are reached in Section 5.

2. Data & Methodology

In this section it is described the variables analyzed, the data used as well as the indexes and predictors sources.

The time span for both the commodity spot prices and predictors is 65 years, from January 1951 to December 2014, and it is divided into sub periods. This division may be relevant when explaining why a variable is able to predict or not commodities spot prices. With the aim of observing the influence of the economic cycles as well as relevant economic events on prices, the returns are observed in a monthly, quarterly and annual time horizon, as in Gargano and Timmermann (2014).

Concerning the commodities, due to the long time horizon and the difficulty when assessing commodity data, spot prices and indexes are gathered from Thompson Reuters and the Commodity Research Bureau (CRB). The indexes are calculated as an unweighted geometric mean of individual prices relative to their base periods, which enables to reduce the impact of extreme movements in individual commodity prices within each index. Prices are in US dollars and we consider end-of-month prices at close.

The commodities data is distributed within seven different categories, this division was made by the Commodity Research Bureau[1] and it is also used in the basis paper. The first index is commodities, which encompasses all the categories and, it is divided in two subgroups: raw industrials (cotton, rubber, cooper, tin, burlap, rosin, etc.) and foodstuffs (hogs, lard, corn, cocoa, sugar, beans, etc.). Moreover, these subgroups are composed by four categories: metals (cooper, zinc, tin, steel scrap, etc.), textiles and fibbers (cotton, wool, burlap, print cloth, etc.) that are included in the raw industrials groups. The fats and oils (butter, soybean oil, lard, tallow, etc.) as well as the livestock and products (hides, steers, hogs, lard, etc.) are gathered in the foodstuffs subgroup.

[1] http://www.crbtrader.com/crbindex

Moreover, in order to make a broader analysis, I added the value-weighted CRSP index as a proxy for stocks and the 10-years Treasury as a proxy for bonds. The data is compiled from the Center for Research in Security Prices (CRSP) and the Federal Reserve Bank of St. Louis (FRED)[2].

Regarding the predictors, I consider 16 state variables used in "Forecasting commodity prices indexes using macroeconomic and financial predictors" and three additional world indicators. It encompasses seven variables from literature on stock return predictability previously used by Goyal and Welch (2008): inflation which is the consumer price index logarithmic growth rate, long-term rate of returns (ltr) is the long-term government bond return, treasury bill (tbl) which is the 3-month treasury bill rate, dividend price ratio (dp) calculated as the difference between the logarithm of the 12-month moving sum of dividends and the logarithm of the S&P500 index, term spread (tms) computed as the difference between long term yield on government bonds and the treasury bill rate, default return spread (dfr) measured as the difference between long-term corporate bond and long-term government bond returns, and investment to capital ratio (Ik) which is the ratio of aggregate capital for the whole economy. The predictors data is collected from Goyal and Welch website[3].

Furthermore, it comprises a range of macroeconomic variables that aim to measure the state of the economy. These variables are computed following Gargano and Timmermann (2014) paper. Firstly, the Money Stock (ΔMSL1) is the log growth in the money stock and it is available in the Philadelphia FED database[4]. Quarterly and annual series are computed by averaging the monthly values over each quarter and year. For instance, if $MSL1_{Y2:M2}$ and $MSL1_{Y2:q2}$ are the unemployment rate for the second month (February) and for the second quarter of the year in the sample, respectively. The monthly, quarterly and annual rates are calculated as presented below:

$$\Delta MSL1_{Y2:M2} = \ln(MSL1_{Y2:M2}) - \ln(MSL1_{Y2:M1})$$

$$\Delta MSL1_{Y2:Q2} = \ln(\sum_{m=4}^{6} MSL1_{Y2:Mm}) - \ln(\sum_{n=1}^{3} MSL1_{Y2:Mn})$$

[2] https://fred.stlouisfed.org
[3] http://www.hec.unil.ch/agoyal
[4] https://www.philadelphiafed.org

$$\Delta MSL1_{Y2} = \ln(\sum_{m=1}^{12} MSL1_{Y2:Mm}) - \ln(\sum_{n=1}^{12} MSL1_{Y2:Mn})$$

The Industrial Production Growth (ΔINDPRO) is gathered from Archival Federal Reserve Bank of St. Louis (ALFRED) as the monthly growth in Industrial Production. The quarterly and annual series are computed by averaging the monthly values over each quarter and year. Monthly, quarter and annual growth rates are calculated as in the money stock case. Third, the GDP Growth (ΔGDP) represents the logarithmic growth in the annual GDP, it is collected from the Philadelphia FED. As in the former variables, by averaging the monthly data over each quarter and year, we obtain the quarterly and annual series. Lastly, the monthly unemployment rate (UNRATE) is compiled from the ALFRED. The quarterly and yearly values are calculated by averaging the monthly data by each quarter and year, respectively. Due to the fact that the indicators are commonly revised, it might affect the methodology used to construct the data. Therefore, in order to avoid bias, it is used vintage data to estimate the models. Thus, the predictions are based only on data available at the forecasting time.

Since I am analyzing the impact of economic and financial variables on world commodity spot prices, it seems reasonable to add world indicators and not only US indicators. Hence, I also included some variables from the Organization for Economic Co-operation and Development (OECD) countries, namely: the OECD industrial production (OECD INDPRO), which is the monthly industrial production for the OECD countries, the OECD money supply (OECD MSL1), which represents the OECD countries money supply, and the OECD unemployment rate (OECD UNRATE) that represent the average unemployment rate in the OECD member countries. These indicators are computed as in the US case, where the quarterly and annual series are computed by averaging the monthly values over each quarter and year. The indicators data is collected from OECD database[5].

Finally, I added the world GDP growth and the world inflation that represent the logarithmic growth in the annual world GDP and the world consumer price index log growth, respectively. The world GDP growth data series are computed as in the former cases; by averaging the monthly data over each quarter and year I obtain the quarterly and annual

[5] http://stats.oecd.org

series. The series are available on the International Monetary Fund database[6].

Moreover, to track the demand for industrial commodities, it is used the Killian's real economy index (KREA), which is available on Kilian's website[7]. Due to commodities being traded around the world and following Gargano and Timmermann (2014), it seems interesting to add two commodity currencies: the log difference between the Australian dollar (AUD) and the United States dollar (USD), as well as the difference between Indian rupee (INR) and the USD, since these countries are large exporters of both agricultural and industrial commodities. These exchange rates are collected from Thompson Reuters database.

Hong and Yogo (2012) state that the number of futures contracts of a given commodity is a good proxy of future expected prices. Thus, with the purpose of having information from the financial markets, it is used the futures market open interest of livestock commodities (FMOIL). This information is available on Yogo's website[8]. Additionally, I include the S&P Goldman Sachs Commodity Index (GSCITOTTR), a broadly diversified, unleveraged, long-only investment in commodities futures. The later variable is from Datastream.

If we observe the movements in the nominal commodity prices (Appendix A) for each of the seven indexes, we see that in 1973, during the oil crisis, the seven indexes increased due to the oil prices spikes. Subsequently, the values stabilized until 2006 and then started to rise until mid-2008 where the prices sharply declined, except for the Textiles index, as a consequence of the financial crisis. Between 2009 and 2014 the commodity prices have been increasing.

In Figure 1, it is presented the monthly commodity returns for each index analyzed. The price returns are computed as the percentage change between the end of period t and the end of period t+1. The formula is presented below:

$$r_{t+1} = \frac{P_{t+1} - P_t}{P_t}$$

Where P_t and P_{t+1} are the commodity spot prices in period t and period t+1,

[6] http://www.imf.org/external/pubs/ft/weo/2016/01/weodata/index.aspx
[7] http://www-personal.umich.edu/lkilian/reaupdate.txt.
[8] https://sites.google.com/site/motohiroyogo/home/research.

respectively.

We can observe that price changes are in line with volatility changes. As a consequence, in periods with large price adjustments or uncertain periods such as the global financial, the oil or the beginning of the 50s crises, the levels of volatility sharply increased.

Figure 1 - *Commodity returns*

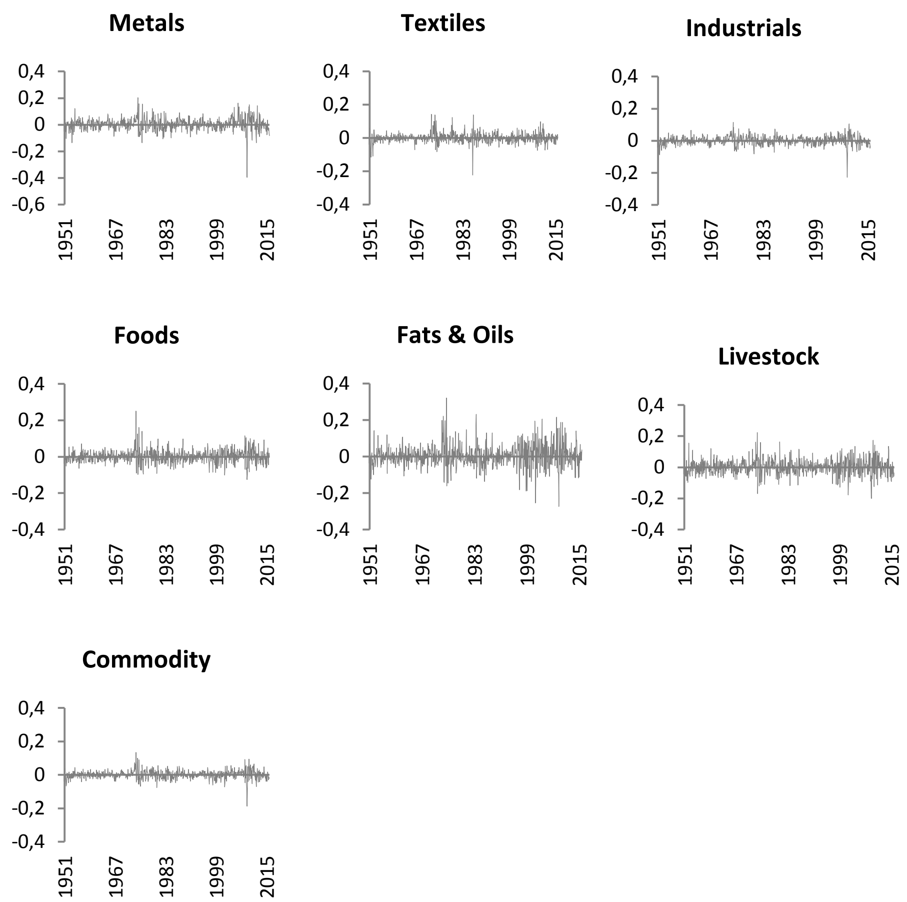


Figure 1 - In these plots we can observe the commodity indexes returns at the monthly time horizon. Prices are measured in USD over the sample period, from 1951 to 2014. The commodity indexes are: Metals, Textiles , Industrials , Foods, Fats & Oils, Livestock and Commodity Index and are compiled by the Commodity Research Bureau (CRB).

Table 1 shows the commodity spot prices variation summary statistics for the entire sample period. In addition, the table is divided in three different panels (A, B and C) with the goal of showing the different time horizons analyzed: month, quarter and year. In order to make a valuable comparison, I add stock market portfolio returns data as well. We can observe that all commodities have positive mean returns over the period. For instance, the textiles index earned the lower monthly return of the seven indexes, 0.081%. By contrast, between 1951 and 2014, the metals index has a 0.3% average return per month. As expected, the stock portfolio presents the higher nominal average returns, close to 1%.

Table 1 - *Commodity returns summary statistics*

	Metals	Textile	Industrials	Foods	Fats & Oils	Livestock	Commodity Index	Stock
Panel A: Monthly								
Mean (%)	0.300	0.081	0.148	0.194	0.272	0.228	0.151	0.941
Std (%)	4.495	2.790	2.717	3.589	6.162	4.980	2.528	4.272
Var (%)	0.202	0.078	0.074	0.129	0.380	0.248	0.064	0.182
Skew	-0.552	-0.017	-0.666	0.626	0.279	0.060	-0.199	-0.525
Kurt	11.794	11.892	10.189	7.101	5.759	4.587	8.823	5.009
AR(1)	0.343	0.143	0.373	0.122	0.099	0.101	0.265	0.038
Panel B: Quarterly								
	Metals	**Textile**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**
Mean (%)	0.460	0.303	0.410	0.677	1.012	0.697	0.460	2.909
Std (%)	7.229	4.599	4.583	5.703	9.554	7.269	4.260	8.198
Var (%)	0.523	0.212	0.210	0.325	0.913	0.528	0.181	0.672
Skew	-0.646	0.267	-0.701	0.793	0.539	0.038	-0.065	-0.565
Kurt	9.181	8.193	9.848	7.627	7.676	5.708	10.452	3.942
AR(1)	0.309	0.170	0.284	0.098	0.064	0.076	0.243	0.099
Panel C: Annual								
	Metals	**Textile**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**
Mean (%)	3.412	0.978	1.842	2.793	4.248	3.183	2.008	12.164
Std (%)	21.67	11.559	13.992	12.546	18.592	15.220	11.499	17.636
Var (%)	4.699	1.336	1.958	1.574	3.457	2.316	1.322	3.110
Skew	0.793	0.709	0.495	1.265	1.056	0.194	0.869	-0.441
Kurt	4.940	4.436	3.818	6.767	6.478	2.780	5.529	3.043
AR(1)	-0.029	-0.085	-0.148	0.111	-0.087	-0.065	-0.012	-0.089

Regarding the volatility, there is not a general tendency across the analyzed indexes. It is possible to observe that Fats & Oils is the more volatile index, it presents a 0.380% variance of returns per month while the Commodity Index shows the lower monthly variance, 0.064%.

Table 1 - This table presents the mean, standard deviation (Std), variance (Var), skewness coefficient (Skew), kurtosis coefficient (Kurt) and first-order autocorrelation (AR(1)) for the seven commodity indexes returns as well as stock market portfolio returns. The table is divided in three time horizons: monthly (Panel A), quarterly (Panel B) and annual (Panel C) over the full sample period, from 1951 to 2014. The commodity returns are measured at the end of the month.

The stock returns are more volatile than the Textiles, the Foods and the Commodity indexes. Stock portfolio, Metals, Textiles, Raw Industrials and Commodity Index are left-skewed while Foods, Fats & Oils and Livestock are right-skewed. This suggests that in the later indexes large increase in prices are more expected than large declines. With the purpose of observing how fat-tailed commodity performs, by assessing kurtosis, it is possible to see that all commodities with the exception of Livestock, exceed the kurtosis of stock returns.

Bond and stock are not serial correlated. Nevertheless, Industrials, Metals and the Commodity Index, present a monthly first order autocorrelation (AR(1)) of around 0.3. This serial correlation is reduced within the quarterly horizon and it is extinguished in the annual series.

In table 2, we can observe the same summary statistics as in the previous one. However, the period analyzed is from 1971 to 2014, I aim to observe whether the results follow the same trend or not. Moreover, I added bonds returns data, measured as the 10-year Treasury Bond with the goal of making a comparison with all the indexes and the stock market portfolio as well. Furthermore, I also include a Panel (Panel D) with the correlation matrix of the commodity indexes as well as the stock and the bond returns.

Table 2 - *Commodity returns summary statistics*

	Panel A: Monthly								
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Mean (%)	0.517	0.234	0.336	0.324	0.458	0.468	0.313	0.942	-0.079
Std (%)	4.935	3.070	2.950	4.048	6.924	5.372	2.839	4.546	4.906
Var (%)	0.244	0.094	0.087	0.164	0.479	0.289	0.081	0.207	0.241
Skew	-0.654	0.130	-0.816	0.572	0.227	-0.038	-0.294	-0.565	-0.223
Kurt	11.636	10.817	10.445	6.242	5.079	4.497	7.995	5.183	7.891
AR(1)	0.434	0.178	0.227	0.182	0.115	0.101	0.197	0.022	0.025
	Panel B: Quarterly								
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Mean (%)	0.806	0.618	0.771	0.988	1.190	1.090	0.810	21.063	2.915
Std (%)	7.973	5.011	4.996	6.522	10.938	7.850	4.869	11.180	8.716
Var (%)	0.636	0.251	0.250	0.425	1.196	0.616	0.237	1.250	0.760
Skew	-0.733	0.560	-0.870	0.666	0.442	-0.037	-0.222	0.320	-0.505
Kurt	9.032	7.123	10.055	6.376	6.431	5.632	8.994	3.277	3.658
AR(1)	0.418	0.137	0.128	0.008	0.064	0.084	0.143	0.009	0.087
	Panel C: Annual								
	Metals	**Textile**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Mean (%)	5.536	2.692	3.869	4.508	6.453	5.825	3.911	12.125	130.29
Std (%)	23.25	12.586	14.763	13.99	19.713	14.345	12.575	18.011	81.089
Var (%)	5.403	1.584	2.179	1.958	3.886	2.058	1.581	3.244	65.755
Skew	0.811	0.743	0.490	1.123	1.155	0.284	0.736	-0.816	1.235

Kurt	4.854	3.591	3.730	5.714	6.622	3.143	4.893	3.168	4.269
AR(1)	-0.020	-0.085	-0.148	0.099	-0.077	-0.065	-0.004	-0.089	0.002

Panel D: Correlation Matrix

	Metals	**Textile**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Metals	1								
Textile	0.188	1							
Indust.	0.828	0.524	1f						
Foods	0.271	0.226	0.388	1					
Fats& Oils	0.232	0.218	0.477	0.735	1				
Livest.	0.266	0.142	0.515	0.654	0.751	1			
Comm. Index	0.667	0.457	0.842	0.821	0.723	0.699	1		
Stock	-0.031	0.065	0.010	-0.070	-0.018	-0.008	-0.034	1	
Bonds	0.216	0.090	0.252	0.122	0.112	0.198	0.227	-0.063	1

Table 2 - This table presents the mean, standard deviation (Std), variance (Var), skewness coefficient (Skew), kurtosis coefficient (Kurt) and first-order autocorrelation (AR(1)) for the seven commodity indexes returns as well as stock market portfolio and bond returns. The table is divided in three horizons: month (Panel A), quarter (Panel B) and year (Panel C) over the sample period, from 1971 to 2014. The commodity returns are measured at the end of the month. Panel D reports the correlation matrix between monthly returns series below the diagonal.

Concerning the monthly data, the mean returns for the commodity indexes and the stock are all positive as in the whole sample period, however, the bond presents negative returns of -0.079%. With the exception of the Metals, all indexes present a higher return, although not very significant, than in the whole sample. Also, the stock portfolio presents a decline in its mean returns of nearly 50%. this might be due to the fact that, in general terms, commodity prices increased during the oil crisis, in the early 70s, and the global financial crisis between 2007 and 2008. The volatility of the indexes was higher in the sub-sample period, this also might be due to the fact of the high levels of uncertainty during the both crisis mentioned before. Regarding the stock, it presents a decrease in its volatility while the bond has the second highest volatility of the analyzed returns, 0.672%. The bond is left-skewed and presents a 7.891 Kurtosis. With the exception of Textiles, the indexes show the same Skewness tendency.

Panel D presents the commodity returns cross-correlation analysis, we can see that Metals and Industrials are strongly correlated (0.828). Moreover, Fats & Oils is strongly correlated with Foods (0.735) and Livestock (0.751).

3. Empirical Results

In order to observe if the indicators are significant for the return prediction, univariate IS and OOS regressions are performed. From these regressions, it is obtained the prices that allow the calculation of returns and afterwards compare them with realized returns. With these results, it is possible conclude which indicators are relevant when predicting commodities returns, if any, and the time horizon in which they do it more precisely.

Following Gargano and Timmermann (2014), as well as Rapach et al. (2010) and Goyal and Welch (2008), it is first computed the univariate return regressions. The goal is to observe the marginal predictive power of each variable in the seven indexes, the prediction models are calculated as follows:

$$r_{t+1:t+h} = \frac{P_{t+h} - P_t}{P_t} = \beta_{0h} + \beta_{1h}X_t + \varepsilon_{t+1:t+h}$$

where: $r_{t+1:t+h}$ is the cumulated return between the end of the period t and the end of the period t+h; h states for each time horizon: monthly, quarterly and annual data; and X_t is the predictor variable.

3.1 ***In-sample predictability***

From the IS estimation models obtained from the univariate return regressions over the entire sample period, 1951-2014, it is possible to observe (Appendix B) that inflation is a strong variable predictor for commodity indexes through a monthly, quarterly and annual horizon.

Other indicators are strong predictors but not in the three different horizons. For instance: long-term return and industrial production growth, have predictive power over the majority of commodity indexes at the monthly horizon while unemployment rate is a strong predictor at the quarterly horizon.

These results are in line with Gargano and Timmermann (2014), the predictability of returns is stronger at a monthly horizon and weaker when analyzed yearly.

In order to compare the results with the OOS regressions, it is computed IS estimation models from 1971 to 2014 (Appendix C). It is observable that more economic indicators have predictability power over the commodity indexes. Inflation, unemployment rate and the commodity currencies are strong predictors over a monthly, quarterly and annual horizon. In general, the predictability is stronger for Metals, Textiles, and Industrials.

Several indicators have predictive power over the market stock portfolio and the 10-year Treasury Bill.

3.2 ***Out-of-sample predictability***

The IS returns predictions are not ex-ante predictions, since it is needed the full sample data to perform the regressions. The data for the whole period would not be available to policy makers and investors in real time. Thus, I compute OOS regressions, where the forecasts are updated recursively and it is used a 22-year rolling window estimation. The OOS forecasts are from January 1971 to December 2014. Moreover, the GDP growth, world GDP growth and world inflation are excluded from this part of the analysis since there is not enough data to perform OOS regressions. The forecast estimations are calculated as follows:

$$\hat{r}_{t+1|t} = \hat{\beta}_t' \mathrm{Z}_t$$

Where $\mathrm{Z}_t = (1\chi_t)'$ and the unknown parameter is computed as:

$$\hat{\beta}_t = \left(\sum_{\tau=t-v+1}^{t} \mathrm{Z}_{\tau-1}\,\mathrm{Z}_{\tau-1}' \right)^{-1} \left(\sum_{\tau=t-v+1}^{t} \mathrm{Z}_{\tau-1}\, r_\tau \right)$$

Table 3a reports, for each univariate regression, the ratio between the OOS forecasted mean squared errors (MSEF) and the MSE from the benchmark model (MSEB). If the ratio is smaller than 1, then the forecasting model performs better than the benchmark. By contrast, if the value is above 1, the forecasting model performs worse than the benchmark.

The benchmark model only includes a constant, which means that $B_{1h} = 0$. The regression is as follows:

$$r_{t+1:t+h} = \frac{P_{t+h} - P_t}{P_t} = \beta_{0h} + \varepsilon_{t+1:t+h}$$

Following my basis paper, I use the Clark and West test to evaluate the statistical significance of the OOS regressions. The test measures the difference between the OOS MSE of the forecasting model and the benchmark model and it is corrected by basing inference on the mean squared error adjusted. The formula is presented below:

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

Where $\ddot{e}_{t+1|t}^2$ is the squared forecast error of the benchmark model and $\hat{e}_{t+1|t}^2$ is the squared forecast error of the prevailing model, $\ddot{r}_{t+1|t}^2$ is the return from the benchmark model and $\hat{r}_{t+1|t}$ states for the univariate model forecasted returns. Finally, P = T-R states for the size of the sample estimated. If $\Delta MSE^{adj} > 0$, then the benchmark model is associated with larger forecast errors and, as a consequence, the univariate forecasted model prevails. Otherwise, the benchmark model dominates.

At the monthly horizon (Panel A), only some of the MSE present a ratio higher than one. According to Clark and West (2007) and Inoue and Killian (2008), the ratios that exceed 1 reduce the precision of the forecast. As it only occurs in few cases, it is not a significant problem in the analysis.

In panel A below, variables such as inflation, ltr, KREA, and the OECDINDPRO have a MSE ratio smaller than 1 across all commodity indexes and many of them are statistically significant. Therefore, one can observe that the prediction efficiency is improved between 1 and 5%.

In the second panel, quarterly data, we again observe that the MSE ratios are in general smaller than 1. Inflation, UNRATE and ΔUSDINR are significantly strong predictors when compared to the benchmark.

Metals, Textiles, Industrials, Livestock and Commodity indexes have the strongest predictability evidence. In contrast, Foods and Fats & Oils, as in the monthly case, show poor predictability.

In the annual horizon, panel C, we can observe that evidence is strongest in both Livestock and Metals indexes whereas Fats & Oils and Textiles present the weakest evidence. Regarding the predictors, inflation and OECDINDPRO are statistically significant across commodity indexes. For example: at a 5% significance level, inflation is able to predict Metals returns. However, if we compare the IS and OOS regression results, we conclude that the former are stronger. Foods and Textiles show little evidence of predictability while Metals and Commodity Index have the strongest predictability evidence within the indexes studied.

Table 3a - This table reports the ratio between the mean squared forecast error of the univariate prediction model (MSEF) and the benchmark model (MSEB), MSEF/MSEB. The estimation period is from 1971 to 2014, all the forecasts are recursively updated and it is used a 22-years rolling window. Values below one mean that the univariate model performs better than the benchmark, values above one mean the opposite. To measure the statistical significance I use the Clark and West statistic test.

* Statistical significance at 1% level.
**Statistical significance at 5% level.
***Statistical significance at 10% level.

In order to study if the predictability is stronger in different periods and since in the entire sample period we can observe instability on price predictability, I divided the sample in two periods. The former is from 1951 to 1992 (Table 3b) and the second is from 1993 to 2014 (Table 3c).

In the first table, we observe that, at the monthly horizon, the following predictors: inflation, ltr, IK and dfr have predictive power over some of the commodity indexes. In comparison, economic indicators like INDPRO, MSL1, UNRATE, KREA and FMOIL show no evidence of predictability.

Metals, Industrials, Livestock and Commodity indexes have the strongest evidence of predictability. By contrast, Textiles, Foods and Fats & Oils show little or no evidence.

Table 3a - *Out-of-sample forecast performance: univariate prediction models, 1971-2014*

	Metals	Textiles	Industrials	Foods	Fats & Oils	Livestock	Commodity Index	Stock	Bond
	Panel A: Monthly								
Inflation	0.953*	0.998	0.943**	0.984*	0.986**	0.981	0.953**	0.987**	0.965*
tbl	0.993	1.003	0.994	1.000	1.003	1.002	0.995	0.999	0.998
ltr	0.960**	0.991**	0.951**	0.986	0.996***	0.988**	0.955	0.945	0.960
lk	0.991	1.000	0.988	1.000	1.001	1.001	0.990**	1.002	1.001
dp	0.992	0.999	0.990	1.001	1.001	1.001	0.993**	0.992	1.000
tms	0.989	1.001	0.990	1.000	1.000	0.999	0.992	1.002	0.992
dfr	0.991**	0.997	0.990	1.000	1.003	1.002	0.996	0.957	0.952
Δ INDPRO	1.000	1.003*	1.001*	0.998	0.994**	1.002	1.001	0.998	0.999
Δ MSL1	0.994	1.000	0.992	1.000	0.999	0.998***	0.997	0.998	0.987**
UNRATE	0.998	1.003	0.998***	1.003	1.004	1.001	1.001	1.003	0.998
KREA	0.980	0.995	0.981	0.984	0.996	0.995	0.976**	0.997	0.999
GSCITOTTR	0.984	1.002	0.989	0.998	1.002	1.001	0.994	0.987**	0.989
FMOIL	1.001	1.003	1.002	1.003	1.003	1.002	1.002	0.997	0.999
Δ INDPRO'	0.985*	0.994**	0.975	0.997**	0.990	0.995	0.982***	1.000	0.993
Δ MSL1'	1.001	0.999	0.998**	0.998	1.001	1.003	1.002	0.991	1.000
Δ USDUD	0.998**	1.003**	1.001	1.002	1.003	0.996***	1.001	0.922	1.003
Δ USDINR	0.993	0.998	0.995**	1.001	1.001	1.001	0.998**	0.987	1.001
AR(1)	0.998**	0.976	0.932	1.000	1.001	0.954	0.955	0.986	0.995
	Panel B: Quarterly								
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Inflation	0.942	0.998*	0.936	0.955**	0.973***	0.958**	0.928	0.976*	0.964**
tbl	1.001	1.008	1.008	1.007	1.011	1.007	1.007	1.001	0.495
ltr	0.871	0.943	0.825	0.998	0.988*	0.933	0.894	0.922	1.009
lk	0.997*	1.003	0.995***	1.002	1.007	1.003	0.993**	1.006	0.930
dp	0.996	1.004	0.994	1.003	1.004	1.005	0.995	0.974	0.836
tms	0.986	0.987	0.994	1.003	1.007	0.995*	0.994	1.008	0.935
dfr	0.921	0.989	0.927	1.001	1.002	0.969	0.956	0.950	1.008
Δ INDPRO	0.908	0.985**	0.876	0.989	0.977	0.978	0.915	0.967	0.991*
Δ MSL1	0.983***	1.006	0.982**	0.999	1.003	0.997	0.989	1.004	0.890
UNRATE	0.924	0.968*	0.878	0.991**	0.980*	0.964***	0.912	0.978	0.998*
KREA	0.970	0.990	0.981	0.944	0.985	0.998	0.956	0.995	0.935
GSCITOTTR	0.905	0.980**	0.882	0.874	0.931	0.881	0.834	0.970	0.988
FMOIL	1.002	1.010	1.004	0.958	1.002	0.926	0.984	0.994	0.987**
Δ INDPRO'	0.914	0.949	0.889	0.971	0.980**	0.981**	0.919	0.983	0.958
Δ MSL1'	0.990**	1.005	1.003**	1.005	0.997	1.003	1.010	0.992**	0.969
Δ USDUD	0.831	0.987***	0.979**	0.960	0.968	0.955	0.850**	0.943	0.989*
Δ USDINR	0.955	0.972**	0.949	0.987*	0.991**	0.991***	0.959***	0.994	0.992
AR(1)	0.974**	0.998	0.954**	0.997	1.001	1.002	0.974	1.001	0.999
	Panel C: Annual								
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Inflation	0.991**	1.018	0.990***	0.983*	1.005	0.982**	0.973	1.016	0.924
tbl	1.040	1.015	1.046	1.027	1.035	1.034	1.044	1.026	0.750
ltr	0.642	0.943	0.677	1.017	0.909	0.790	0.802	0.950	1.032
lk	0.993**	1.026	0.982***	0.976	0.962	0.987**	0.948	1.032	0.981
dp	0.995	1.019	0.965**	0.992	0.919	0.983**	0.941	0.930	0.895
tms	1.023	1.003	1.020	0.973	0.969**	0.951	0.986**	0.980**	0.960**
dfr	0.800	0.980	0.821	0.999	0.931	0.777	0.867	0.958	1.033
Δ INDPRO	0.887*	1.002	0.927	1.001	0.957	1.008	0.925	0.976	1.012
Δ MSL1	0.965**	1.037	0.967	1.039	1.037	1.008	0.982	0.987*	0.936
UNRATE	0.882	0.973	0.924	1.010	0.989	1.007	0.941	0.981	1.024
KREA	0.801	0.948	0.826	0.874	0.863	0.914	0.779	0.977	1.008
GSCITOTTR	0.945	0.986	0.956	0.930	0.956	0.972***	0.912	0.997**	0.982***
FMOIL	0.859	1.024	0.931	1.032	1.026	0.866	0.974	0.999	0.927
Δ INDPRO'	0.918	0.970**	0.944***	1.019	1.028	1.005	0.962***	1.033	0.949
Δ MSL1'	0.866	0.868	0.874	1.039	1.004	1.024	0.948	1.030	0.958
Δ USDUD	0.788	0.971**	0.823	0.978**	0.920	0.837	0.819	1.000	1.023
Δ USDINR	0.863	0.888	0.862	0.969**	0.988*	1.020	0.858	1.041	1.017
AR(1)	0.905	1.024	0.926	1.046	1.001	0.970**	0.963	1.005	0.993

Most of the results hold in the quarterly and yearly horizon, although we can observe that in the annual horizon there are more statistically significant indicators when predicting commodity returns.

In addition, the MSE ratio between the forecasted univariate and benchmark model, in panel A and B is mostly higher than 1, which means that the forecasts are less precise due to the negative effect of the parameter estimation error. Nevertheless, in the annual horizon we see that the MSE ratio is lower than 1 for most predictors. There is an increase on predictive accuracy between 1 and 7%.

Finally, in table 3c, the predictability evidence is weaker for Foods and Fats & Oils indexes through all time horizons (panels: A, B and C) while Metals and Textiles present the strongest evidence.

At the monthly horizon, inflation, ltr and dfr, continue to be statistically significant in most commodity indexes whereas KREA and the FMOIL show no evidence of predictability. At quarterly and yearly horizon, the default return spread continues to do well, additionally, the US and OECD money supply also produce accurate predictability in several commodity indexes.

In general, inflation is a strong predictor across commodity indexes and over the analyzed period. According to Gorton and Rouwenhorst (2006), inflation is positively correlated with commodity prices which means that when inflation is increasing so are the prices in commodities. Hence, it is possible to infer that to a certain extent, commodities prices follow inflation trends.

Table 3b - This table reports the ratio between the mean squared forecast error of the univariate prediction model (MSEF) and the benchmark model (MSEB), MSEF/MSEB. The estimation period is from 1971 to 1992, all the forecasts are recursively updated and I use a 22-years rolling window. Values below one mean that the univariate model performs better than the benchmark, values above one mean the opposite. To measure the statistical significance I use the Clark and West test.

* Statistical significance at 1% level.
**Statistical significance at 5% level.
***Statistical significance at 10% level.

Table 3c - *Out-of-sample forecast performance: univariate prediction models, 1993-2014*

	Panel A: Monthly								
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Inflation	1.001	0.996**	0.887	0.972**	0.972**	0.963***	0.910**	0.996	0.974
tbl	0.989**	1.003	0.998	1.003	1.003	1.003	1.000	1.003	1.003
ltr	0.964**	0.980**	0.941	0.991	0.990	0.985**	0.955***	0.992	0.623
lk	0.997	0.999	0.981	0.999	1.001	1.001	0.985	1.003	1.003
dp	0.993	1.002	0.994	1.002	1.003	1.003	0.996	0.996	1.002
tms	0.990*	1.002	0.986**	1.002	1.000	0.998	0.991	1.002	0.985
dfr	0.995**	0.992**	0.985**	1.000	1.003	1.001	0.999*	0.916	0.922
Δ INDPRO	0.999	1.003	1.002	0.996	0.996	1.003	1.003	0.998	0.998
Δ MSL1	1.001	0.999	0.982***	0.998**	0.998	0.994***	0.992**	0.995	0.973
UNRATE	0.994**	1.003	1.002	1.003	1.004	1.000	1.002	1.003	1.002
KREA	0.960	0.992	0.960	0.977	0.991	0.991	0.954	1.001	0.998
GSCITOTTR	0.996**	1.000	0.978	0.999	1.002	1.001	0.987	0.973	0.983
FMOIL	1.000	1.003	1.002	1.003	1.003	1.002	1.002	1.001	0.998
Δ INDPRO'	1.001	0.992**	0.954	0.991	0.977	0.986	0.963**	0.997	0.985
Δ MSL1'	0.999**	1.000	1.003	0.997	1.003	1.003	1.002	0.996	1.001
Δ USDUD	1.003	1.004	1.000	1.002	1.003	0.997**	1.002	0.855	1.003

Table 3b - *Out-of-sample forecast performance: univariate prediction models, 1971-1992*

Panel A: Monthly

	Metals	Textiles	Industrials	Foods	Fats & Oils	Livestock	Commodity Index	Stock	Bond
Inflation	1.001	1.000	0.999**	0.996***	0.999**	0.999**	0.996**	0.978	0.956**
tbl	0.989	1.003	0.989	0.998	1.002	1.002	0.990	0.994	0.993
ltr	0.964**	1.002	0.961	0.982**	1.003	0.991*	0.955	0.899	0.583
lk	0.997**	1.002	0.995**	1.000	1.001	1.002	0.994**	1.001	0.999
dp	0.993	0.996	0.986**	1.000	1.000	1.000	0.991*	0.988	0.997
tms	0.990	1.000	0.994	0.997	1.001	1.001	0.993***	1.002	1.000
dfr	0.995**	1.001	0.994**	0.999	1.003	1.002	0.993*	0.998	0.981
Δ INDPRO	0.999	1.003	1.000	1.000	0.993	1.001	0.999	0.998	1.000
Δ MSL1	1.001	1 .001	1.002	1.002	1.001	1.002	1.002	1.002	1.001
UNRATE	0.994	1.003	0.993	1.003	1.004	1.003	1.000	1.003	0.994
KREA	1.000	0.998	1.002	0.992	1.001	0.999	0.998	0.993	1.000
GSCITOTTR	0.996***	1.003	1.000	0.996	1.002	1.002	1.001	1.000	0.996
FMOIL	1.001	1.003	1.003	1.002	1.002	1.003	1.002	0.993	1.000
Δ INDPRO'	1.001	0.996	0.996	1.003	1.003	1.003	1.000	1.002	1.001
Δ MSL1'	0.999*	0.999	0.994**	1.000	1.000	1.003	1.002	0.987	1.000
Δ USDUD	1.003	1.003	1.002	1.002	1.002	0.995*	1.001	0.990	1.004
Δ USDINR	1.002	1.002	0.998	0.001	0.999	0.999**	1.000	1.003	1.001
AR(1)	1.010	1.007	0.958	0.988	1.082	0.987***	0.949	1.005	0.999

Panel B: Quarterly

	Metals	Textiles	Industrials	Foods	Fats & Oils	Livestock	Commodity Index	Stock	Bond
Inflation	1.010	0.998**	1.010	0.991**	1.002	1.001	1.002	0.973	0.966**
tbl	0.998**	1.009	1.007	1.007	1.011	1.011	1.007	0.416	0.992
ltr	0.908**	0.935	0.828	0.998	0.976	0.932***	0.885	1.008	0.905
lk	1.005	1.005	1.003	1.002	1.007	1.008	0.998**	0.902	1.004
dp	1.001	0.998	0.988**	1.001	1.000	1.002	0.992	0.689	0.962
tms	0.991**	0.979	1.004	1.004	1.007	1.008	1.003	0.981**	1.007
dfr	0.923***	1.010	0.948**	1.002	1.004	0.983***	0.966***	1.009	1.005
Δ INDPRO	0.904	0.985**	0.852	0.999	0.961	0.962	0.905	0.986	0.960
Δ MSL1	1.008	1.011	1.008	1.007	1.010	1.006	1.008	0.946	1.009
UNRATE	0.908**	0.959	0.830	0.992	0.959	0.927	0.880	0.988	0.984**
KREA	0.999	0.991	0.940	0.962	0.986	1.008	0.994	0.977	1.000
GSCITOTTR	0.963	0.993	0.948	0.858	0.935	0.876	0.858	1.001	0.967
FMOIL	1.010	1.010	0.998	0.942	0.998	0.884	0.983	0.975	0.998
Δ INDPRO'	0.973	0.959	0.904	1.008	1.007	1.003	0.989**	1.001	0.990
Δ MSL1'	0.985**	1.002	1.000***	1.001	0.995**	1.000	1.011	0.959**	0.989**
Δ USDUD	0.966	0.845	1.010	1.007	1.006	1.007	0.952***	0.978	1.009
Δ USDINR	1.003	1.003	1.009	1.007	0.999***	1.004	1.004***	0.978	1.010
AR(1)	0.993	1.001	0.994**	1.010	1.035	1.041	0.969	0.998	1.042

Panel C: Annual

	Metals	Textiles	Industrials	Foods	Fats & Oils	Livestock	Commodity Index	Stock	Bond
Inflation	1.048	1.034	1.043	0.997**	1.028	1.035	1.030	1.015	1.012
tbl	1.050	1.014	1.051	1.033	1.044	1.040	1.046	1.018	0.820
ltr	0.635	0.947	0.677	1.006	0.832	0.826***	0.759***	0.921**	1.016
lk	1.009	1.036	1.008	0.989	0.987**	1.009	0.979***	1.030	0.966**
dp	1.018	1.012	0.981**	0.987**	0.879	0.966***	0.960	0.881	0.824
tms	1.028	0.985	1.029	0.966	0.994	1.001	0.993**	0.932	1.004
dfr	0.949**	1.026	0.943**	1.018	0.976**	0.847	0.979**	1.013	1.037
Δ INDPRO	0.792	1.001	0.865	0.974	0.883	0.997**	0.850	0.945	0.997
Δ MSL1	0.961***	1.043	0.968**	1.041	1.041	1.027	0.987**	0.963	0.990
UNRATE	0.799	0.965	0.862	1.004	0.970	1.012	0.882	0.971**	1.012
KREA	0.994**	1.007	0.996	0.903	0.919	0.997**	0.939	1.026	1.040
GSCITOTTR	0.966**	0.983	0.980	0.874	0.956	0.938***	0.894	1.011	1.003
FMOIL	0.851	1.029	0.904	1.015	1.022	0.782	0.940	1.017	0.837
Δ INDPRO'	0.874	0.955	0.912	1.014	1.025	1.021	0.934	1.032	1.010
Δ MSL1'	0.887***	0.982**	0.914	1.041	1.010	1.019	0.979***	1.032	0.894
Δ USDUD	0.777	0.973	0.847	0.960**	0.872	0.863	0.827	0.978**	1.022
Δ USDINR	0.828	0.890**	0.836***	0.973	1.006	1.024	0.831	1.037	1.005
AR(1)	0.970***	0.993	0.894	1.003	1.012	0.980**	1.048	1.170	1.165

Δ USDINR	1.002	0.995**	0.993***	1.001	1.003	1.003	0.997**	0.971	1.002
AR(1)	0.948	1.000	0.979**	0.992	1.023	0.983***	0.956	1.002	0.996

Panel B: Quarterly

	Metals	Textiles	Industrials	Foods	Fats & Oils	Livestock	Commodity Index	Stock	Bond
Inflation	0.873***	0.997**	0.859	0.919**	0.943	0.913	0.852	0.958	0.986
tbl	1.004	1.008	1.009	1.008	1.011	1.004	1.007	0.578	1.010
ltr	0.832	0.951	0.822	0.999	1.000	0.935**	0.903	1.010	0.941
lk	0.988**	1.001	0.986	1.003	1.007	0.998**	0.987	0.961	1.009
dp	0.990	1.011	1.000	1.005	1.007	1.010	0.999	0.993	0.984

tms	0.981**	0.995**	0.985**	1.003	1.006	0.982*	0.985**	0.889	1.008
dfr	0.917	0.969	0.906	1.001	1.000	0.955	0.945	1.008	0.894
Δ INDPRO	0.912	0.985**	0.900	0.979	0.993	0.995**	0.924	0.997	0.973
Δ MSL1	0.958	1.001	0.956	0.992	0.995	0.989	0.969	0.831	0.999
UNRATE	0.940	0.977	0.928	0.990	1.002	1.001	0.944	1.008	0.972
KREA	0.940	0.988	0.952	0.934	0.987	0.988*	0.918	0.893	0.991
GSCITOTTR	0.845	0.967	0.825	0.896	0.931	0.890	0.814	0.974	0.974
FMOIL	0.993**	1.009	0.998	1.008	1.006	0.971	0.986***	0.998	0.990
Δ INDPRO'	0.853	0.940	0.828	0.912	0.952	0.958	0.847	0.914	0.976
Δ MSL1'	0.995**	1.008	1.008	0.968	0.999	1.006	1.009	0.978	0.995
Δ USDUD	0.692	0.895	0.687	0.928	0.928	0.902	0.747	1.000	0.876
Δ USDINR	0.906**	0.939**	0.896	0.974***	0.983***	0.977**	0.912	1.005	0.977
AR(1)	0.968**	0.952	0.964	1.003	1.036	0.999	0.984	1.004	0.981

	Panel C: Annual								
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Inflation	0.928**	1.000	0.932	0.972**	0.984***	0.927	0.911	1.019	0.829
tbl	1.029	1.014	1.040	1.021	1.025	1.029	1.041	1.031	0.692
ltr	0.641	0.936	0.665	1.039	0.995	0.739	0.849	0.982	1.049
lk	0.983**	1.018	0.958	0.963	0.937	0.963**	0.919	1.037	1.002
dp	0.969	1.030	0.948	0.991	0.947	1.012	0.914	0.974	0.993
tms	1.019	1.026	1.012	0.988**	0.941	0.891	0.985**	1.021	0.909
dfr	0.632	0.942***	0.694	0.976	0.878	0.701	0.744	0.905	1.028
Δ INDPRO	0.998	1.009	1.006	1.038	1.037	1.030	1.019	1.014	1.027
Δ MSL1	0.975	1.030	0.969**	1.035	1.032	0.989**	0.976***	1.007	0.872
UNRATE	0.986**	0.987**	1.003	1.022	1.013	1.007	1.019	0.994	1.033
KREA	0.593	0.881	0.636	0.862	0.817	0.818	0.606	0.929	0.974
GSCITOTTR	0.942	0.996**	0.942	1.028	0.986	1.011	0.960**	0.995	0.968
FMOIL	0.857	1.022	0.965	1.048	1.027	0.965	1.005	0.975	1.021
Δ INDPRO'	0.980**	0.996	0.992**	1.040	1.039	0.988**	1.014	1.038	0.884
Δ MSL1'	0.835	0.739	0.821	1.036	0.999	1.033	0.908	1.032	1.014
Δ USDUD	0.798	0.972**	0.795	1.016	0.984**	0.809***	0.819	1.031	1.030
Δ USDINR	0.887***	0.872	0.874	0.958	0.966	1.014	0.870	1.044	1.026
AR(1)	0.784	1.029	1.115	1.009	1.007	0.997**	1.014	1.021	0.976

Table 3c - This table reports the ratio between the mean squared forecast error of the univariate prediction model (MSEF) and the benchmark model (MSEB), MSEF/MSEB. The estimation period is from 1993 to 2014, all the forecasts are recursively updated and I use a 22-years rolling window. Values below one mean that the univariate model performs better than the benchmark, values above one mean the opposite. To measure the statistical significance I use the Clark and West test.

* Statistical significance at 1% level.
**Statistical significance at 5% level.
***Statistical significance at 10% level.

Commodity currencies also show predictability power across indexes. Since commodities are in USD, the movements in exchange rates will have a direct impact on the prices. A USD appreciation will lead to positive commodity returns. Additionally, FMOIL it is a non directional variable, thus, it does not reflect real market information. Consequently, it presents no predictive power.

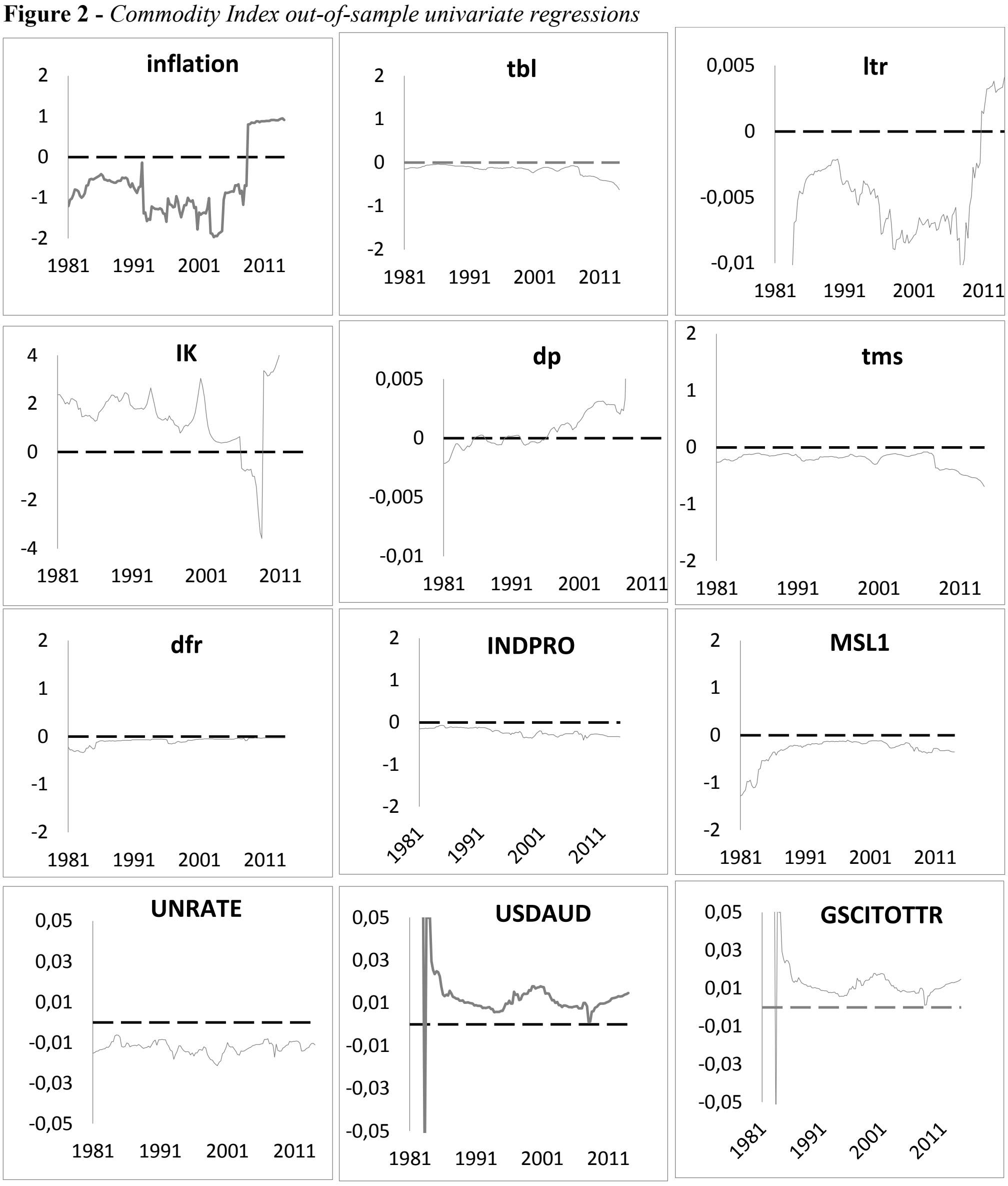
Furthermore, one can observe that in the second subsample, the predictability significance is lower than in the first, this might be caused by the 2008 global financial crisis.

To observe the return predictability evolution over the sample period, I follow Goyal and Welch (2008) and compute the difference between cumulated sum squared error of the benchmark model and the forecasted model. The equation formula is presented below:

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

If $\Delta SSE > 0$, then that the prediction model has a lower MSE than the benchmark model, meaning that the forecasted model is more accurate than the benchmark one. In contrast, if the difference of sum squared errors is negative ($\Delta SSE < 0$), then the forecasting model is less accurate than the benchmark model. Therefore, I plot some graphics (Figure 2) of ΔSSE with the aim of observing periods of outperformance or underperformance.

Figure 2 - *Commodity Index out-of-sample univariate regressions*



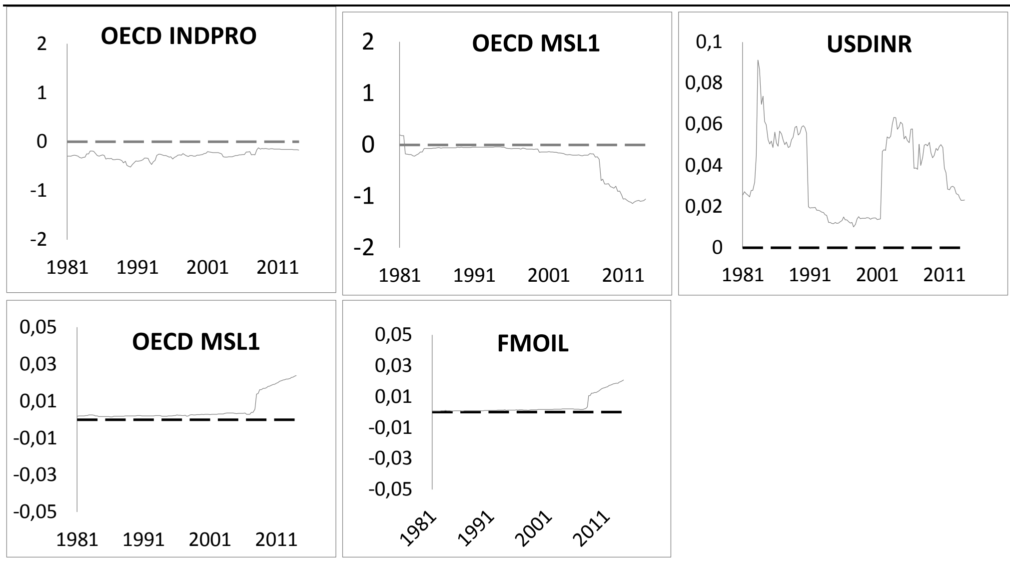


Figure 2 - These graphs show the quarterly cumulate difference between the squared forecast errors of the benchmark model and the univariate models. The univariate regressions contain the following predictor indicators as the independent variable: Inflation (infl), treasury bills (tbl), the long-term rate of returns (ltr), the Investment to the capital ratio (Ik), the dividend price ratio (dp), the term spread (tms), the default return spread (dfr), the industrial production growth (INDPRO), the money supply growth (MSL1), the unemployment rate (UNRATE), the S&P Goldman Sachs Commodity Index (GSCITOTTR), the OECD industrial production growth (OECDINDPRO), the OECD money supply growth (OECDMSL1), the log difference between the Australian dollar (AUD) and the United States dollar (USDAUD), as well as the difference between Indian rupee (INR) and the USD (USDINR), the Killian's real economic activity index (KREA), and the futures market open interest of Livestock (FMOIL). The dependent variable in the regression is the Commodity Index spot price compiled by the CRB.

The graphic presented above, shows the cumulated difference between quarterly squared forecasted errors of the benchmark and forecasted model of the Commodity Index prices, using as predictors each of the 17 individual variables.

On one hand, the IK and the currency exchange rates outperform the benchmark, this results are in line with our finding in table 3a. Furthermore, we can observe that KREA and FMOIL perform well through the entire period and even better after 2008 (global financial crisis). The inflation rate performs poorly through most of the sample period, however, after 2008 there is a shift and the predictor does well until the end of the analyzed period.

On the other hand, economic indicators such as UNRATE, MSL1 and INDPRO both US and OECD variables, perform poorly over the period which does not contradicts the results that are reached in the OOS performance table.

3.3 *OOS multivariate regressions*

To observe the effect of joint predictor variables, multivariate regressions are performed. In order to do so, it is used shrinkage methods which aim to reduce the effect of parameter estimation error on forecasts. For that purpose, I use ridge regressions and the subset regression approach.

On one hand, the ridge regression uses a parameter λ that controls the amount of shrinkage on the regression coefficient. I compute the ridge forecasts as it is presented below:

$$\hat{r}_{t+1|t} = X'_t \hat{\beta}_\lambda$$

Where: $\lambda \longrightarrow \infty$; and $\hat{r}_{t+1|t} \longrightarrow \frac{1}{T}\sum_{j=1}^{T} r_j$; which means that the ridge forecast converges to the sample mean. Following Inoue and Killian (2008), I use a set of shrinkage values $\lambda \in \{0.5, 5, 10, 20, 50, 100, 150, 200, 1000\}$.

Regarding the ridge regression parameter, it is calculated from a linear regression model subject to a penalty term given as:

$$\hat{\beta}_\lambda = \arg min_\beta \left(\sum_{t=1}^{T} (r_{t+1} - \chi_t')^2 + \lambda \sum_{m=1}^{k} \beta_m^2 \right)$$

The ridge regression results are presented in the table below (Table 4). At the monthly horizon, the shrinkage method, presents improvements in most of the indexes with the exception of Foods and Fats & Oils. I find significant improvement between 5 and 1%. At the quarterly horizon, the improvements are lower in percentage terms. Although, all the indexes present improvement some are not statistically significant which is the case of the Livestock index.

Concerning panel C, the yearly horizon, the forecasting improvements are even lower. Metals, Textiles, Foods, Fats & Oils and Livestock indexes present no improvements while Textiles and Commodity Index present small significant improvements, between 1 and 2%.

On the other hand, the subset approach, which is also approached in Gargano and Timmermann (2014) paper, uses equally-weighted combinations of forecasts based on all possible models that include a particular subset of the predictor variables. The range of possible predictors includes k different variables, in this analysis K=17. Each subset encompasses a group of regression models that include a certain number of predictor variables, k ≤ K.

Table 4 - *Out-of-sample forecast performance: multivariate models, 1971-2014 - Ridge Regression*

	Panel A: Monthly								
λ	**Metals**	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
0.5	1.042	1.002	0.983***	1.224	1.111	1.237	1.172	1.140	1.001
5	0.999	1.002	0.963***	1.096	1.180	1.200	1.097	1.089	1.000
10	0.991	1.003	0.924***	1.008	1.023	1.212	1.005	1.006	0.999
20	0.990	0.998**	0.977***	1.100	1.001	1.135	1.002	1.014	0.987***
50	0.999	0.997**	0.963***	1.003	1.073	1.004	1.000	1.001	0.976***
100	0.974***	0.984**	0.969***	0.988	1.016	0.994	0.992***	0.987***	0.963***
150	0.968***	0.973**	0.996***	1.000	1.000	1.414	0.990***	0.965***	0.952***
200	0.972***	0.987**	0.974***	0.997	1.001	1.092	0.985***	0.962***	0.955***
1000	0.988***	0.991**	0.943***	0.990	0.993	0.988*	0.974***	0.987***	0.974***
5000	0.990***	0.999**	0.997***	1.000	1.000	0.994*	0.968***	0.991**	0.982***
	Panel B: Quarterly								
λ	**Metals**	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
0.5	0.973**	0.990**	0.960***	0.999*	0.986*	0.974*	0.997***	1.088	1.028
5	0.976**	0.980**	0.974***	0.997*	0.997*	0.995*	0.980***	0.953***	1.025
10	0.967**	0.999**	0.976***	0.922**	0.995*	0.992*	0.986***	0.987**	1.012
20	0.992**	0.997**	0.978***	0.969**	0.992	0.999*	0.972***	0.975**	0.995

50	0.995**	0.993**	0.998***	1.005	0.976*	0.994*	0.969***	0.982**	0.997
100	0.996**	0.982**	0.972***	1.018	1.381	1.010	0.954***	0.982**	0.997**
150	0.985**	0.984**	0.984***	1.023	0.989	0.995	0.952***	0.980**	0.999**
200	0.988**	0.985**	0.985***	1.026	0.990	0.997	0.952***	0.976**	0.981**
1000	0.997**	0.989**	0.996***	1.032	0.995	1.004	0.972***	0.990	0.998**
5000	0.998**	0.990**	0.998***	1.033	0.995	1.005	0.990***	1.026	1.000

Panel C: Annual

λ	**Metals**	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
0.5	1.197	2.606	1.709	1.005	1.896	2.557	2.128	1.970	2.027
5	1.168	1.677	1.414	1.005	1.880	1.732	1.317	1.571	1.529
10	1.005	1.596	1.283	1.006	1.617	1.703	1.234	1.359	1.256
20	1.008	1.559	1.119	1.011	1.272	1.706	1.085	1.170	1.093
50	1.001	1.349	1.038	1.036	1.137	1.685	0.997**	1.034	1.007
100	1.002	1.351	0.998**	1.057	1.297	1.652	0.9885	0.994	0.986**
150	1.007	1.727	0.989**	1.079	1.191	1.613	0.978**	0.985	0.982**
200	1.014	1.304	0.974**	1.121	1.088	1.571	0.977**	0.983	0.980**
1000	1.021	1.287	0.984*	1.138	1.051	1.221	0.986**	0.989	0.992**
5000	1.021	1.025	0.994*	1.162	1.079	1.333	0.998**	0.992	0.996**

Table 4 - This table presents the ratio between the mean squared forecast error of the multivariate prediction model (MSEFM) and the benchmark model (MSEB), MSEFM/MSEB. The method used was the ridge regressions that include all the predictor indicators in the forecasted model but, through λ, shrinks towards zero the least squares coefficient estimate. The OOS evaluation period is from 1971 to 2014, all the forecasts are recursively updated and I use a 22-years rolling window. The commodity indexes returns: Metals, Textiles, Industrials, Foods, Fats & Oils, Livestock and Commodity Index represent the dependent variables. The table is divided in three panels: A, B, and C for the monthly quarterly and annual horizon, respectively. I use the Clark and West test to observe the statistical significance, using a regression that only includes a constant as the benchmark model.

* Statistical significance at 1% level.
**Statistical significance at 5% level.
***Statistical significance at 10% level

I estimate the regression by using a specific set of predictors, as presented in Gargano and Timmermann (2014). Afterwards, in order to compute regression parameter estimator ($\hat{\beta}$), the results over all k ≤ K subsets are averaged . K states for the number of regressors in the full model and k is the number of predictors in the subset model.

The forecast formula from the subset regressions is presented below, it is an equally-weighted combination of the individual models. This strategy was used in Rapach, Strauss, and Zhou (2010) to study the US stock returns predictability.

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

Where: $C_k^K = \frac{K!}{k!(K-k)!}$; and dim (X_{ti}) = K, so that X_{ti} has k elements.

In the univariate case (k=1) each K regression uses a single variable. Therefore, the combination of forecasts is given as:

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

Table 5 reports the multivariate regressions results. At the monthly horizon, the regression presents no improvement on Foods and Fats & Oils. In addition, there are no significant improvements in Livestock whereas in the remaining indexes we can observe improvements between 1 and 6%..

In panel B, Fats & Oils, as in the monthly horizon, present little or no improvements. Furthermore, Textiles and Livestock also do not show significant improvements. The remaining indexes present lower improvements than in the monthly horizon, between 1 and 3%.

Finally, at the annual horizon, the regressions accuracy, as in the previous panel, is lower than in the monthly case. The Textiles index shows no improvements in annual forecasts whereas Foods and Fats & Oils present some improvement in predictions. I find significant improvements between 1 and 4%.

Both methods present low evidence when forecasting annual returns. In addition, there are several cases where the models that include many producers apply less shrinkage and, consequently, present bad OOS forecasts. This might be due to the fact that I only use 22 observations to compute the multivariate regression forecasting parameter.

Figure 3 plots the quarterly OOS estimations for the Commodity Index subset regression that combines all possible models with k predictors (k = 1, 2, …, 17). The k states for the number of variables that are included in each prediction model. We can observe that the smaller the number of indicators included in the model, the smoother the averaged estimations are.

Furthermore, in the figure we can observe that the models disregard the 2008 global crisis. Despite the fact that there were some signs, namely economic contraction, the modelswere not able to reflect them since they rely on a larger observation than prvious year. Nonetheless, they show the increase after the crisis between 2009 and 2010.

Table 5 - *Out-of-sample forecast performance: multivariate models, 1971-2014 - Subset Regression*

K	Metals	Textiles	Industrials	Foods	Fats & Oils	Livestock	Commodity Index	Stock	Bond
	Panel A: Monthly								
1	0.953***	0.968**	0.980***	0.988**	1.005	0.993**	0.977***	0.986**	0.986***
2	0.932***	0.973**	0.975***	0.989**	0.995	0.995**	0.984***	0.963**	0.984***
3	0.942***	0.973**	0.988***	0.984**	0.990	0.999**	0.980***	0.986**	0.982***
4	0.947***	0.982**	0.990***	0.985**	0.991	0.999**	0.987***	0.983**	0.984***
5	0.943***	0.982**	0.990***	0.990	0.994	0.993**	0.965***	0.963**	0.983***
6	0.979***	0.986**	0.956***	0.996	0.993	0.989**	0.961***	0.976**	0.986***
7	0.978***	0.973**	0.960***	1.006	0.996	0.989**	0.957***	0.979**	0.991***
8	0.978***	0.977**	0.969***	1.003	0.997	0.990**	0.957***	0.980**	0.984***
9	0.967***	0.978**	0.961***	0.000	1.000	0.997**	0.957***	0.988**	0.981***
10	0.967***	0.979**	0.967***	1.014	1.001	0.999**	0.956***	0.989**	0.975***
11	0.969***	0.978**	0.973***	1.017	1.003	0.999	0.962***	0.991**	0.970***
12	0.969***	0.981**	0.989***	1.051	1.002	1.000	0.967***	0.997	0.971***
13	0.969***	0.991**	0.983***	1.051	1.014	1.000	0.955***	1.001	0.966***
14	1.000	0.987**	0.989***	0.967	0.988	0.999	1.007	0.990	1.004***
15	0.970***	0.994**	0.987***	1.011	1.063	1.049	0.968***	1.010	0.968***
16	0.978***	1.003	0.973***	1.015	1.078	1.020	0.969***	1.017	0.979***
17	0.989***	1.015	0.986***	1.010	1.087	1.036	0.979	1.017	0.968***
	Panel B: Quarterly								
K	**Metals**	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
1	0.989**	1.000	1.057	0.990	0.977**	0.993	0.982**	0.994*	0.998*
2	0.994**	0.992	1.080	0.993	0.994	0.994	0.987**	1.011	0.993*
3	0.990**	0.992	1.017	0.996	0.996	0.982	0.998**	0.999	0.996*
4	0.985**	0.987	0.999	0.987	0.980*	0.987	0.985**	0.997	0.992*
5	0.992**	0.995	0.994	0.961	0.994	1.009	0.980**	1.006	1.002
6	0.979**	0.994	0.996	0.980	0.986*	0.998	0.989**	1.000	1.000
7	0.988**	0.993	0.997	0.977	0.984*	0.985**	0.984**	0.999	1.003
8	0.988**	0.997	0.970***	0.976	0.990	0.983**	0.983**	1.000	1.002
9	0.988**	0.997	0.972***	0.977	0.990	0.983**	0.985**	0.999	1.018
10	0.990	0.998	0.972***	0.977	0.990	0.985**	0.987**	0.999	1.010
11	0.990	0.998	0.975***	0.977	0.991	0.985**	0.988**	1.000	1.012
12	0.990	0.998	0.976***	0.977	0.991	0.988**	0.989**	1.000	1.021
13	0.992	0.999	0.977***	0.977	0.991	0.991**	0.991	1.000	1.026
14	0.992	0.999	0.979***	0.979	0.994	0.991*	0.991	1.000	1.027
15	0.992	1.000	0.980***	0.979	0.995	0.991*	0.992	1.000	1.031
16	0.992	1.000	0.982***	0.979	1.000	0.991*	0.992	1.000	1.036
17	0.993	1.000	0.983***	0.980	1.000	0.992*	0.994	1.000	1.040
	Panel C: Annual								
K	**Metals**	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
1	0.962**	1.001	0.969**	0.968**	0.964**	0.949*	0.962**	0.976**	0.979***
2	0.964**	1.004	0.961**	0.956**	0.968**	0.935*	0.953**	0.982**	0.979***
3	0.961**	1.085	0.961**	0.955**	0.970**	0.943*	0.951**	0.992	0.982***
4	0.963**	1.039	0.960**	0.951**	0.974**	0.954*	0.951**	0.995	0.984***
5	0.959**	1.060	0.967**	0.951**	0.974**	0.957*	0.962**	0.999	0.985***
6	0.952**	1.095	0.973**	0.955**	0.983	0.977*	0.966**	1.023	0.995
7	0.953**	1.129	0.986**	0.956**	0.991	0.979*	0.971**	1.037	0.999
8	0.957**	1.235	0.989**	0.985**	1.037	0.984*	0.985**	1.081	1.006
9	0.957**	1.309	0.999	0.989**	1.085	0.987*	0.992**	1.116	1.273
10	0.968**	1.501	1.000	0.989**	1.238	0.991	1.001	1.219	1.314
11	0.970**	1.733	1.000	0.998	1.316	0.997	1.138	1.397	1.403
12	0.971**	1.900	1.000	1.019	1.398	0.997	1.238	1.422	1.775
13	0.976**	2.105	1.012	1.101	1.418	1.000	1.454	1.532	1.925
14	0.983**	2.473	1.019	1.325	1.599	1.010	1.713	1.658	2.036
15	0.991	2.715	1.226	1.503	1.668	1.021	1.859	1.728	2.200
16	1.004	2.932	1.231	1.981	1.742	1.131	2.099	1.842	2.295
17	1.015	3.010	1.702	2.233	1.953	1.212	2.105	2.099	2.319

Table 5 - This table displays the ratio between the mean squared forecast error of the multivariate prediction model (MSEFM) and the benchmark model (MSEB), MSEFM/MSEB. The method used was the subset regressions approach, which is computed as an equally weighted average of forecasts taking into consideration all possible models with k predictor variables included (K is between 1 and 17). The OOS evaluation period is from 1971 to 2014, all the forecasts are recursively updated and it is used a 22-years rolling window. The commodity indexes returns: Metals, Textiles, Industrials, Foods, Fats & Oils, Livestock and Commodity Index represent the dependent variables. The table is divided in three panels: A, B, and C for the monthly quarterly and annual horizon, respectively. I use the Clark and West test to observe the statistical significance of the prediction results. Furthermore, the benchmark model is computed a regression that only includes a constant.

* Statistical significance at 1% level.
**Statistical significance at 5% level.
***Statistical significance at 10% level.

Figure 3 - *Commodity Index subset regressions*

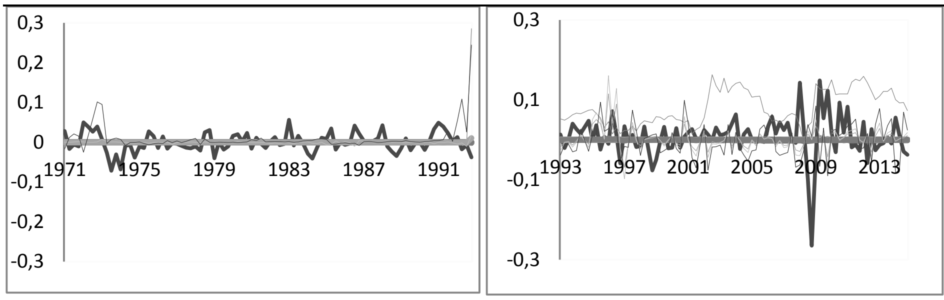


Figure 3 - This plot shows the Commodity Index forecasts from the subset regressions.The returns are quarterly forecasts that combine estimations for all possible models:K = 1, 2, 3.....15, 16, and 17 predictor variables. The black line represents the realized return on the Commodity Index spot price. The actual returns series were collected from Reuters data base. The first plot presents the returns from 1971 to 1992 and the second shows the returns from 1993 to 2014.

Figure 4 shows the monthly cumulate difference between the squared forecast errors from the Benchmark and the forecasted models with k = 1, k = 3, and k = 5 predictor variables, for each of the seven indexes. In this graphics we can see whether the forecasted model is able to outperform the benchmark or not.

Figure 4 - *Subset regression*

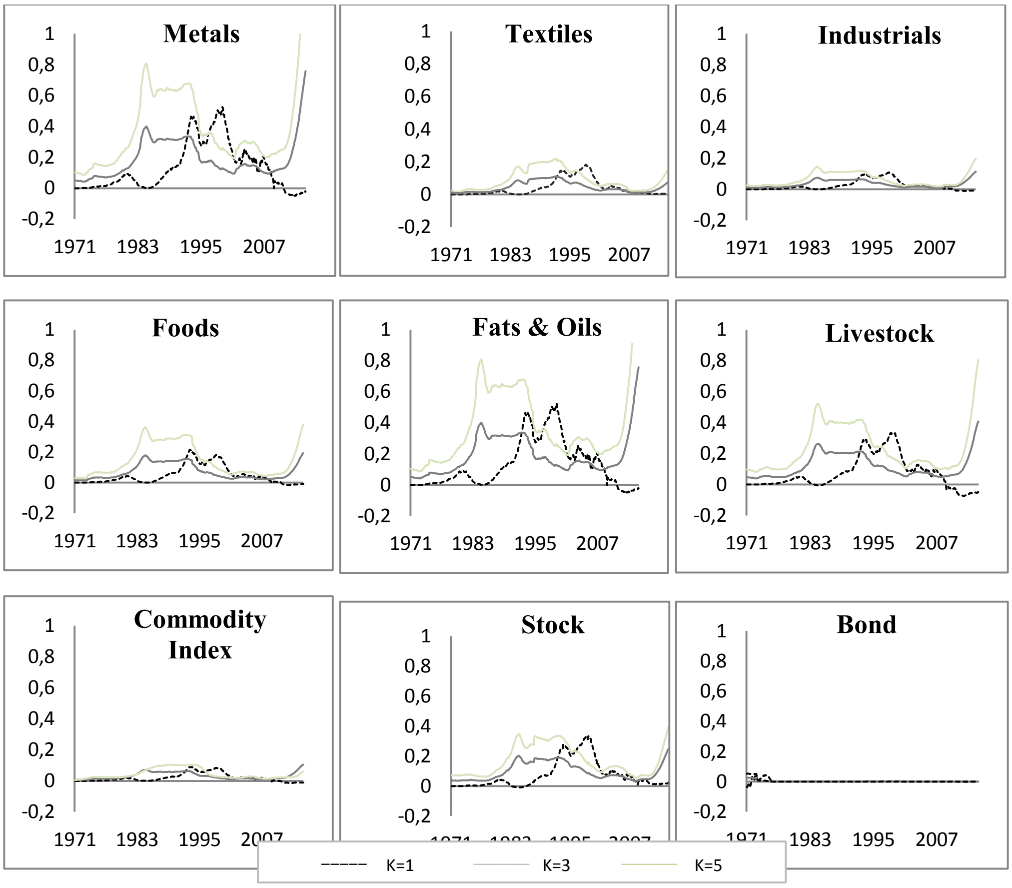


Figure 4 - This figure presents the cumulate difference between the squared forecast errors of the benchmark and the subset regression. The Subset regression combines forecasts from all possible models with k=1, k=3, and K=5 predictors for the seven Commodity Research Bureau indexes : Metals, Textiles (textiles and fibbers, according to the CRB), Industrials (raw industrials, according to the CRB), Foods (foodstuffs, according to the CRB), Fats & Oils, Livestock (livestock and products, according to the CRB) and Commodity Index.

In the plots presented above, we can observe that Textiles, Industrials, Foods and Commodity Index consistently outperform the benchmark through the entire sample. Moreover, the forecast model presents a good performance through the 80s and 90s, less turbulent periods. In contrast, Metals, Fats & Oils, and Livestock show some instability specially the univariate model (k = 1) during the global financial crisis of 2008. The later indexes also present a good performance during the 80s and 90s.

For most of the commodity indexes, these plots suggest that when the subset approach is used as shrinkage method, the multivariate models present consistent better estimations than the benchmark model.

If we compare the number of predictors included in the models, we see that through the majority of the sample most of the indexes when I use 5 predictors. Nevertheless, after 1995 there are some periods where Metals, Textiles, Foods, Fats & Oils, and Livestock present better results in the univariate model (k = 1). Thus, I may infer that usually multivariate models are better when predicting commodity returns but in some periods this might not be true.

4. Economic cycle: *Recessions vs Expansions*

Several literature is addressed to the fact that stock market performance relies on the economic cycle. Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011) state that stock returns predictability is weaker during expansion states. Additionally, many economic predictors are related to the economic state, in specific the macroeconomic ones, say: money supply or unemployment rate. Therefore, it seems interesting to address the variations in commodity price predictability across recessions and expansions with the goal of observing to what extent such predictability varies with the state of the economy.

Since the National Bureau of Economic Research (NBER) recession index[9] is not suitable for predicting OOS regressions because it is an ex-post measure, I follow Stock and Watson (2010) and use an indicator variable based on the unemployment recession gap to identify recessions:

$$\widetilde{\cup}_t \begin{cases} 1 \; if \; \cup_t^* = \cup_t - \dfrac{1}{36}\displaystyle\sum_{\tau=1}^{36} \cup_{t-\tau} > 0.5 \\ 0, \qquad\qquad\qquad Otherwise \end{cases}$$

[9] The data is available on https://fred.stlouisfed.org/series/USREC

Where $\cup_t$ is the vintage monthly unemployment ratio. The authors find that this indicator is in line with the NBER recession measure.

In order to analyze the statistical significance in recessions relative to expansions predictive power, I compute the difference between the squared error return of the benchmark and the forecasting model:

$$\left(r_{t+1:t+h} - \ddot{r}_{t+1:t+h|t}\right)^2 - \left(r_{t+1:t+h} - \hat{r}_{t+1:t+h|t}\right)^2 = \alpha + \beta\, \tilde{\cup}_{t+1} + \varepsilon_{t+1:t+h}$$

Where $\left(r_{t+1:t+h} - \ddot{r}_{t+1:t+h|t}\right)^2$ is the squared forecast error of the benchmark model and $\left(r_{t+1:t+h} - \hat{r}_{t+1:t+h|t}\right)^2$ is the squared forecast error of the forecast (univariate or multivariate) model. Positive and significant values of the estimation parameter (β) indicate that the prediction model is more accurate during recessions than during expansions, relative to the benchmark. Moreover, it is important to note that since I consider forecasting models, there is a need to control for the fact that the commodity price volatility may be higher during economic slow than economic growth.

Table 6 presents the monthly ratio between MSE from the prediction model and the benchmark, in recessions and expansions. If the values are lower than 1, then the MSE is smaller in recessions when compared to expansions. In the table below, we can observe that most of the ratios are lower than one, which means that most models tend to be better during recessions than during expansions. This results are in line with Gargano and Timmermann (2014) paper.

At the monthly horizon, ΔMSL1, UNRATE, and the commodity currencies exchange rates (ΔUSDAUD and ΔUSDINR) are statistically significant across several commodity indexes, the predictive power is measured through the coefficient slope (β) from the equation presented above. regressions results are stronger, particularly for Metals, Textiles, Industrials and Commodity indexes.

Furthermore, we can observe in panel B and C, presented above, the Foods index is not statistically significant.

In addition, it is analyzed the reasons why the estimation is weaker during expansions than during recessions. I decompose the coefficient of determination R^2 which is computed as: $R^2 = \frac{\beta^2\sigma_\chi^2}{(\beta^2\sigma_\chi^2+\sigma_\varepsilon^2)}$. Through this indicator we can observe if the precision of the forecast is: 1) Decreasing with the noise of the regression estimation (σ_ε^2); 2) increasing with the magnitude of the regression coefficient (β); and 3) increasing with the individuals predictor variance σ_χ^2, as it can be deducted from the R^2 formula.

Table 6 - *Out-of-sample forecast performance: univariate models, 1971-2014 - Recessions vs Expansions*

	Panel A: Monthly								
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Inflation	1.253	1.139	1.042	1.085	1.011	1.002	1.008	1.018	1.027
tbl	1.001	1.116	0.999	1.007	1.003	1.012	1.012	1.001	1.000
ltr	1.168	1.008	0.993	0.999	1.018	0.991	0.994	1.003	1.003
Ik	1.001	1.010	1.000	0.991	1.010	1.004	1.016	1.006	1.010
dp	1.132	0.988	0.999	0.997	1.012	0.996	0.994	0.996	1.016
tms	0.918***	0.969	0.988	0.990	1.000	1.002	0.996	0.977	0.983
dfr	0.932***	0.987	0.987**	0.959	0.989	0.982	0.982	0.978**	0.989
Δ INDPRO	1.011	1.036	0.998	0.970	0.999	0.999	0.996	0.998	0.997
Δ MSL1	0.999	0.995	0.994	1.001	0.996	1.002	0.999	1.029	1.002
UNRATE	1.013	1.031	0.980**	0.976**	0.984**	0.987**	0.984**	0.988**	0.989
KREA	0.996	0.998	0.998	1.044	1.001	0.999	0.998	0.983	0.996
GSCITOTTR	0.997	1.102	0.992	0.984	0.984	1.114	0.985***	0.998	1.060
FMOIL	1.306	0.998	0.979**	1.135	1.001	1.002	0.990	1.000	0.994
Δ INDPRO'	0.977**	1.000	1.007	1.067	1.002	1.001	1.001	0.996	0.994
Δ MSL1'	0.984**	0.972**	0.982**	0.977	0.996**	0.997	0.987	0.982	0.972
Δ USDUD	0.977**	0.989**	0.982	0.982***	0.996*	0.999	0.998**	0.995	0.992
Δ USDINR	0.987**	0.992**	0.986**	0.985***	0.987**	0.983	0.985**	0.991**	0.998**
AR(1)	0.987**	0.993	0.927***	0.988	0.991	1.002	0.965	1.030	1.010
	Panel B: Quarterly								
λ	**Metals**	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
0.5	1.024	1.024	0.964	1.024	1.041	0.974	0.957	1.074	1.016
5	1.002	0.997	0.958***	1.033	1.008	0.971	0.955	1.087	1.017
10	1.000	0.978*	0.956***	1.008	0.999	0.970	0.942	1.065	1.018
20	0.999	0.974*	0.951***	1.002	1.001	0.970*	0.941	1.010	1.009
50	0.998	0.971**	0.947***	1.002	1.000	0.965**	0.949*	1.006	1.007
100	0.989	0.969**	0.942**	1.001	0.998	0.967**	0.952*	1.001	1.005
150	1.000	0.967**	0.939**	1.001	0.994	0.970**	0.958**	1.003	1.007
200	0.996*	0.967**	0.926**	1.002	0.990	0.974**	0.956**	1.001	1.010
1000	0.980*	0.981**	0.976**	1.001	0.987	0.981**	0.951**	1.011	1.021
5000	0.989*	0.992**	0.981**	1.000	0.990	0.994**	0.951**	0.999	1.004
	Panel C: Annual								
K	**Metals**	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
1	0.979**	0.995**	0.972***	1.000	0.991**	0.996	0.988	1.000	1.013
2	0.988**	0.991**	0.970***	1.001	0.990**	0.990	0.987	1.000	1.020
3	0.980**	0.990**	0.968***	1.002	0.993***	0.990	0.987	1.000	1.024
4	0.978**	0.988**	0.962***	1.002	0.993	0.988	0.980	1.000	1.030
5	0.977**	0.985**	0.958**	1.004	0.994	0.984	0.978	1.001	1.039
6	0.975**	0.982**	0.950**	1.004	0.988	0.981	0.973	1.002	1.042
7	0.973*	0.980**	0.950**	1.012	0.986	0.979	0.970	1.003	1.046
8	0.973*	0.980**	0.945**	1.020	0.990	0.978	0.970	1.012	1.054
9	0.968*	0.980**	0.935*	1.024	0.990	0.973	0.967**	1.020	1.057
10	0.964*	0.976**	0.930	1.026	0.993	0.970	0.967**	1.020	1.060
11	0.962*	0.964**	0.925	1.029	0.994	0.965	0.965**	1.029	1.063
12	0.960	0.960**	0.921	1.029	0.998	0.971	0.960**	1.031	1.065
13	0.954	0.969*	0.920	1.032	1.001	0.970	0.958**	1.043	1.069
14	0.968	0.975	0.916	1.034	1.001	0.970***	0.953**	1.050	1.068
15	0.977	0.971	0.918	1.020	1.003	0.969***	0.949*	1.064	1.072
16	0.982	0.982	0.934	1.010	1.015	0.967***	0.948*	1.068	1.078
17	0.987	0.986	0.956	1.009	1.027	0.967***	0.948*	1.061	1.070

Table 6 - This table reports the ratio between the mean squared forecast error of prediction model in recession (MSEFrec) and the monthly mean squared forecast errors in expansions (MSEFexp). Recessions are based on the "unemployment recession gap" indicator, computed by Stock and Watson (2010). The series are on a monthly basis and the evaluation period is from 1971 to 2014, all the forecasts are recursively updated and I use a 22-years rolling window. The commodity indexes returns: Metals, Textiles, Industrials, Foods, Fats & Oils, Livestock and Commodity Index are based on spot prices indexes compiled by the CRB. The table is divided in three panels: A, B, and C, which represent the univariate, ridge and subset regressions, respectively. Through the statistical significance, we can observe whether the squared forecast error of each computed model in relation to the benchmark model, is significantly lower in expansions compared to recessions.

* Statistical significance at 1% level.
**Statistical significance at 5% level.
***Statistical significance at 10% level.

In order to measure the effects of each of this variables, it is computed two regressions, one for recessions and another for expansions. I use the recession indicator, the difference between the squared error of the benchmark and the prediction model, to determine the state of the economy:

$$r_{t+1} = \begin{cases} \alpha_{rec} + \beta_{rec}\chi_t + \epsilon_{t+1}\epsilon_{t+1} \sim N\left(0, \sigma^2_{\epsilon,rec}\right), & recession\text{: } \cup^*_t > 0.5 \\ \alpha_{exp} + \beta_{exp}\chi_t + \epsilon_{t+1}\epsilon_{t+1} \sim N\left(0, \sigma^2_{\epsilon,exp}\right), & expansion\text{: } \cup^*_t = 0 \end{cases}$$

Afterwards, following Gargano and Timmermann (2014), the R^2 ratio between recessions and expansions: $\Delta_{R^2} = \frac{R^2_{rec}}{R^2_{exp}}$ is calculated. Results below 1 suggest that the estimations are lower in recessions than in expansions whereas values above 1 mean the opposite, estimations are higher in recessions than in expansions.

Subsequently, I compute the variation in the coefficient slope (β) variation as follows: $\Delta\beta = \frac{\hat{\beta}^2_{rec}}{\hat{\beta}^2_{exp}}$. If the ratio between recessions and expansions is above 1, then the estimation parameters tend to increase during recessions. In addition, it is calculated the variance of residuals ratio in recessions compared to expansions: $\Delta_{\sigma^2_\varepsilon} = \frac{\hat{\sigma}^2_{\varepsilon,rec}}{\hat{\sigma}^2_{\varepsilon,exp}}$. Values above 1 mean that the residual variance usually increases during recessions. Lastly, it is computed the χ_t variance both in recessions and economic growth: $\Delta_{\sigma^2_\chi} = \frac{\sigma^2_{\chi,rec}}{\sigma^2_{\chi,exp}}$. If $\Delta_{\sigma^2_\chi} > 1$, then the variance of the predictors decreases during expansions.

Table 7 presents the results from this computations for each of the commodity indexes and using 17 predictor variables. Since recession data is more accurate at a monthly basis than quarterly or yearly, monthly series are used.

In recessions, the measures tend to increase. The predictor variance as well as the residual variance increase in economic slow. By contrast, the coefficient slope tend to increase for fewer predictor variables. For instance: the ratio between the slope coefficients in recessions versus expansions, from the Livestock prediction model that uses money supply as the independent variable, is below one (0.729). Nevertheless, we can also observe that the slope coefficient presents the higher ratios of the analyzed measures.

Therefore, one may infer that according to the results, the net effect in predictive R^2 is to increase during recessions.

If the coefficient determination ratio between recessions and expansions is higher than 1, it increases the predictability. Consequently, it requires that there is an increase in the slope coefficients from the regression (positive $\Delta\beta$), or an increase in predictors variance (positive

$\Delta_{\sigma_\chi^2}$), or negative $\Delta_{\sigma_\varepsilon^2}$, which means a decrease in residuals variance, or a combination of this events.

Following Gargano and Timmermann (2014), it is computed the fraction of predictors where is possible to observe a Δ_{R^2} and $\Delta\beta$ bigger than 1, for each commodity index:

$$Slope = \frac{1}{K}\sum_{k=1}^{K} I\left(\Delta_{R^2,k} > 1\right)I\left(\Delta_{\beta,k} > 1\right)$$

Afterwards, it is computed the same but for Δ_{R^2} and $\Delta_{\sigma_\chi^2}$ above 1:

$$Predictor\ Variance = \frac{1}{K}\sum_{k=1}^{K} I\left(\Delta_{R^2,k} > 1\right) * I\left(\Delta_{\sigma_\chi^2,k} > 1\right)$$

Finally, I calculate the values of Δ_{R^2} higher than 1 and $\Delta_{\sigma_\varepsilon^2}$ lower than 1:

$$Residual\ Variance = \frac{1}{K}\sum_{k=1}^{K} I\left(\Delta_{R^2,k} > 1\right) * I\left(\Delta_{\sigma_\varepsilon^2,k} < 1\right)$$

Where I(.) states for a function that takes the value of 1 if the argument is true and 0 if the argument is not true.

Table 8 reports the slope, predictor variance and residual variance estimation results. For the majority of indicators a higher β as well as higher σ_χ^2 leads to an increase in R^2. Nonetheless, we do not observe many cases where the σ_ε^2 decreases.

Therefore, one may infer that the commodity returns predictability is highly dependent on the economic cycle (recessions and expansions). In general, economic variables tend to have higher predictive power during recessions. This occurs due to the fact that both slope coefficients and predictor variance are large.

These results were to be expected. According to previous literature, e.g. McQueen and Roley (1993), during economic slows, when the interest rate is low, there is a positive relation between commodity prices and macroeconomic surprises. Hence, macroeconomic indicators are stronger predictors during economic slows than in expansions.

Table 7 - *Forecast performance: Recessions vs Expansions*

$\Delta\beta = \frac{\hat{\beta}^2_{rec}}{\hat{\beta}^2_{exp}}$	Metals	Textiles	Industrials	Foods	Fats & Oils	Livestock	Commodity Index	Stock	Bond	$\frac{\sigma^2_{\chi,rec}}{\sigma^2_{\chi,exp}}$
Inflation	0.860	5.623	3.091	1.393	1.446	6.796	2.026	2.464	3.360	1.013
tbl	1.217	2.298	1.720	14.452	2.169	5.511	1.048	6.176	6.891	1.957
ltr	1.267	1.027	3.822	3.460	1.374	1.194	4.916	1.483	4.506	1.998
Ik	1.081	1.342	1.620	3.044	1.747	3.868	2.271	2.632	1.961	2.225
dp	1.243	2.205	2.585	2.269	2.540	1.986	24.433	7.869	5.393	1.078
tms	1.873	3.284	6.825	13.170	1.642	19.859	1.028	0.814	2.701	1.001
dfr	1.294	3.016	2.433	5.783	66.606	1.122	7.120	2.077	0.917	2.041
Δ INDPRO	5.674	1.152	1.542	1.813	0.817	1.386	2.205	3.939	1.110	1.984
Δ MSL1	1.786	1.824	1.215	1.163	12.611	0.729	1.548	2.689	1.300	2.767
UNRATE	0.542	1.013	25.507	0.996	0.907	2.086	2.622	1.901	1.198	1.718
KREA	12.275	2.143	17.465	3.029	2.483	7.995	4.339	1.253	2.098	1.208
GSCITOTTR	1.863	1.667	2.995	2.032	1.340	2.015	1.114	2.765	3.630	1.997
FMOIL	3.100	2.173	0.433	1.370	1.656	1.785	1.625	0.425	1.762	2.034
Δ INDPRO'	2.469	1.051	1.053	0.742	1.536	0.859	1.241	0.829	0.917	1.652
Δ MSL1'	1.997	1.602	1.190	0.787	2.134	1.019	1.067	1.961	1.048	1.096
Δ USDUD	1.475	5.654	9.125	0.921	1.456	1.784	2.561	2.226	1.519	1.457
Δ USDINR	2.724	3.401	1.723	4.265	7.463	5.921	2.298	2.340	1.343	1.121
AR(1)	2.386	0.806	1.043	2.628	2.287	2.759	1.726	1.299	1.135	1.069

$\Delta_{\sigma^2_\chi} = \Delta\sigma^2_\varepsilon = \frac{\hat{\sigma}^2_{\chi,rec}}{\hat{\sigma}^2_{\chi,exp}}$	Metals	Textiles	Industrials	Foods	Fats & Oils	Livestock	Commodity Index	Stock	Bond
Inflation	1.112	1.406	1.097	1.043	1.011	1.458	1.150	1.313	1.374
tbl	1.111	1.409	1.162	1.040	1.079	1.259	1.172	1.224	1.131
ltr	1.248	1.095	1.035	1.111	1.049	1.273	1.088	1.108	1.116
Ik	1.766	1.237	1.359	1.137	1.034	1.098	1.146	1.133	1.201
dp	1.016	1.038	1.025	1.123	1.030	1.168	1.199	1.083	1.223
tms	1.180	1.172	1.006	1.128	1.065	1.173	1.037	1.172	1.258
dfr	1.197	1.180	1.021	1.128	1.039	1.254	1.028	1.274	1.322
Δ INDPRO	1.158	1.324	1.057	1.061	1.047	1.167	1.002	1.199	1.305
Δ MSL1	1.321	1.350	0.996	1.076	1.131	1.050	1.116	1.151	1.169
UNRATE	1.146	1.211	0.992	1.028	1.112	1.190	1.020	1.164	1.148
KREA	1.160	1.402	1.402	1.069	1.069	1.011	1.090	1.251	1.301
GSCITOTTR	1.323	1.201	1.112	1.061	1.061	1.129	1.143	1.134	1.110
FMOIL	1.249	1.010	1.010	1.043	1.043	1.074	1.024	1.170	1.127
Δ INDPRO'	1.010	1.309	1.023	1.170	1.170	1.273	1.098	1.141	1.231
Δ MSL1'	1.162	1.409	1.105	1.293	1.159	1.044	1.015	1.114	1.129
Δ USDUD	1.125	1.095	1.078	1.171	1.171	1.174	1.135	1.114	1.129
Δ USDINR	1.125	1.237	1.114	1.050	1.050	1.060	1.016	1.042	1.026
AR(1)	1.387	1.311	1.029	1.066	1.193	1.117	1.141	1.205	1.327

Table 7 - This table presents (1) the slope coefficient estimates slopes for recession periods in comparison to expansion ones, $\Delta\beta = \frac{\beta^2_{rec}}{\beta^2_{exp}}$; (2) the ratio between the predictor variance in recessions versus expansions, $\Delta_{\sigma^2_\chi} = \frac{\sigma^2_{\chi,rec}}{\sigma^2_{\chi,exp}}$; and (3) the variance of the residuals in periods of recession and expansion ratio, $\Delta_{R^2} = \frac{R^2_{rec}}{R^2_{exp}}$. The data is from 1951 to 2014, the entire sample period.

Table 8 - *Forecasting performances: Recessions vs Expansions*

	Metals	Textiles	Industrials	Foods	Fats & Oils	Livestock	Commodity Index	Stock	Bond
Slope	91.666	100.000	91.666	100.000	100.000	100.000	100.000	91.666	91.666
Predictior Variance	75.000	83.333	83.333	75.000	58.333	75.000	66.666	66.666	33.333
Residuals Variance	16.666	8.333	8.333	16.666	33.333	16.666	25.000	25.000	58.333

Table 8 - This table reports the proportion of univariate indicators for which it is analyzed: (1) Δ_{R^2} and $\Delta\beta$ larger than one in both cases, as measured by the following slope: $\frac{1}{K}\sum_{k=1}^{K} I\left(\Delta_{R^2,k} > 1\right) I\left(\Delta_{\beta,k} > 1\right)$, (2) Δ_{R^2} and $\Delta_{\sigma^2_\chi}$ both greater than one, as predictor variance: $\frac{1}{K}\sum_{k=1}^{K} I\left(\Delta_{R^2,k} > 1\right) * I\left(\Delta_{\sigma^2_\chi,k} > 1\right)$, and (3) Δ_{R^2} bigger than one and $\Delta_{\sigma^2_\varepsilon}$ smaller than one, as residuals variance: $\frac{1}{K}\sum_{k=1}^{K} I\left(\Delta_{R^2,k} > 1\right) * I\left(\Delta_{\sigma^2_\varepsilon,k} < 1\right)$. K is the total number of predictor variables (from 1 to 18) and the I(.) states for a function that takes the value of one if the argument is true and zero if the argument is not true. The data is monthly and encompasses entire sample period, from1951 to 2014.

5. Conclusion

In this thesis it is examined commodity returns predictability over monthly, quarterly and annual horizon. It is used commodity indexes spot prices over a 64 years sample, from 1951 to 2014. By computing OOS regressions both univariate and multivariate, I conclude that some indicators are good return predictors. Furthermore, the results are stronger in multivariate predictability and at is seems to be more significant at the monthly horizon.

The predictability varies across indicators, for example: inflation, individually, appears to be a good predictor of commodity returns while KREA is weak. In general, the predictability is stronger for Metals, Textiles, Industrials, Livestock and Commodity indexes. In contrast, Foods and Fats& Oils show poor return predictability.

The addition of the OECD indicators does not improves significantly the predictability of returns in the multivariate regression models. Although in some univariate models the OECD industrial production and money supply show evidence of predictability. Nevertheless, since the United States economy is the largest world economy, its economic indicators are representative of the world economy.

Moreover, as in the predictability of stock returns studied by several authors, I find that commodity returns estimation is connected to the economic cycle (recessions and expansions). One can observe that price changes in commodities are more predictable in economic slows than in grows. This mainly due to the fact that several indicators are more volatile during recessions as well as due to the high slope coefficients and predictors variance during recessions.

The predictive power of the variables varies across commodity indexes. However, the results indicate that commodity prices have an important predictive component that could be valuable when pricing futures contracts.

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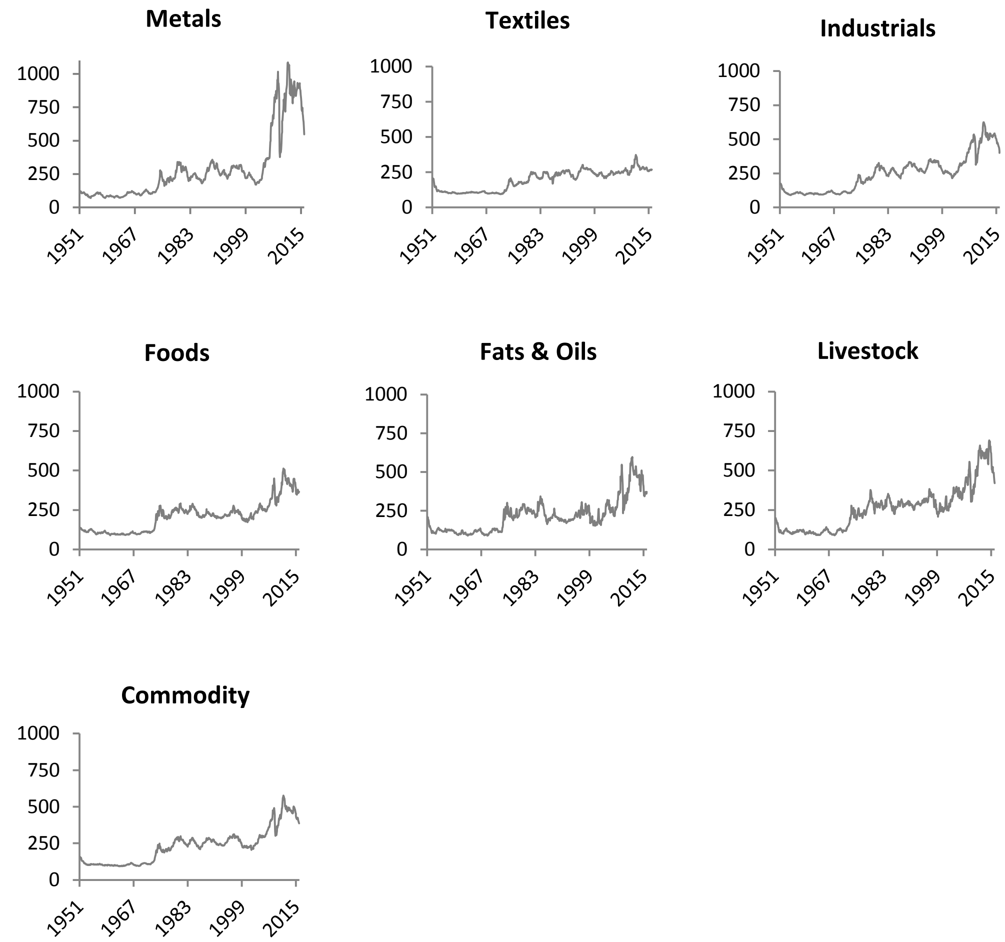
Appendix

Appendix A - *Commodity spot prices*



Appendix A - This figure presents the monthly values of commodity spot prices indexes. The prices are un USD and the indexes are based on 22 commodities over the sample period, from 1951 to 2014. The commodity indexes are divided as follows: Metals, Textiles (textiles and fibbers, according to the CRB), Industrials (raw industrials, according to the CRB), Foods (foodstuffs, according to the CRB), Fats & Oils, Livestock (livestock and products, according to the CRB) and Commodity Index.

Appendix B - *Coefficients In-sample forecast performance: univariate prediction models*

	Panel A: Monthly							
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**
Inflation	2.335*	1.278**	1.831	2.398**	3.194*	2.548	2.052	-1.160
tbl	-0.027	0.051	0.012	0.014	0.026	-0.001	0.013	-0.062**
ltr	-0.390*	-0.082	-0.242	-0.156	-0.177**	-0.228	-0.208*	0.158
Ik	-0.205	0.088	-0.053*	0.397	0.224	0.091***	0.130	-0.973*
dp	-0.01**	-0.004**	-0.006	-0.003	-0.008	-0.007	-0.005*	-0.002**
tms	0.147	-0.01***	0.105**	0.010	0.085	0.191*	0.065	0.190
dfr	0.250	0.175	0.175**	-0.037	0.085	0.085	0.094**	0.69***
Δ INDPRO	-0.216*	-0.21***	-0.234	-0.205*	-0.470**	-0.234*	-0.225	0.252*
UNRATE	0.056	0.013	0.042*	-0.002	0.008	-0.020***	0.024	-0.058
AR(1)	0.261	0.028*	0.322***	0.120	0.091	0.109	0.270**	0.074
	Panel B: Quarterly							
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**
Inflation	1.469*	0.968	1.322*	1.888***	2.514	1.936	1.496*	-0.885*
tbl	-0.036	0.143*	0.064	0.052	0.072	0.065*	0.057*	-0.162
ltr	-0.535*	-0.219	-0.371**	-0.127	-0.283***	-0.344	-0.274	0.040
Ik	-0.818	0.286	-0.256	1.293	0.725	0.445	0.365**	-3.031
dp	-0.014	-0.010	-0.012	-0.009	-0.011	-0.008	-0.012	-0.008
tms	0.367	-0.140*	0.164*	-0.074	-0.030	0.237*	0.076	0.614*
dfr	0.902*	0.339**	0.617*	0.143	0.430*	0.533	0.423	1.016***
Δ INDPRO	0.829*	0.325	0.606	0.111	0.286	0.266*	0.409**	-0.056*
Δ GDP	0.000	0.000	0.000*	0.000*	0.000*	0.000	0.000	0.000
UNRATE	-0.200*	-0.056*	-0.123*	-0.035	-0.016	-0.068***	-0.085*	0.006
AR(1)	0.077*	-0.023	0.169	0.061**	0.017	0.130	0.161	0.068
	Panel C: Annual							
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**
Inflation	0.872	0.639**	0.702*	1.444	1.608	0.535*	0.971***	-0.891
tbl	0.292	0.894	0.600	0.378	0.526**	-0.025	0.502	0.135
ltr	-0.970*	-0.220	-0.530	-0.124	-0.319	-0.312	-0.361**	-0.140
Ik	0.649	4.007*	1.944	4.547***	4.873***	1.719	3.037	-7.279
dp	-0.078	-0.030	-0.046	-0.023	-0.038	-0.067	-0.039*	-0.034
tms	-0.321	-0.780	-0.135	-1.411	-0.258**	1.343	-0.626	0.245
dfr	2.104*	0.626	1.293	0.136	0.799	0.848	0.830	1.389
Δ INDPRO	0.120	0.139*	0.151	0.176	0.171*	-0.046	0.176	-0.728*
Δ GDP	-1.236	-1.290	-1.686**	0.491***	-1.069	-1.525	-0.812*	-0.848
UNRATE	0.219	0.170**	0.237	-0.068	0.096	0.134	0.113	0.101
AR(1)	-0.097	0.043**	-0.287	0.146	0.106	-0.030*	0.126	-0.115

Appendix B - This table reports the OLS mean slope coefficient estimates. I use the commodity returns as the dependent variable and economic indicators as the independent variables. All the regressions use non-overlapping series over the sample period, the table is divided in three time horizons: month (Panel A), quarter (Panel B) and year (Panel C) over the sample period, from 1951 to 2014. The predictor indicators are inflation, treasury bill rate (tbl), long term return (ltr), capital ratio (IK), dividend-price ratio (dp), long term spread (tms), default return spread (dfr), industrial production growth (ΔINDPRO), unemployment rate (UNRATE), and one-period lagged return (AR(1)).

* Statistical significance at 1% level.
**Statistical significance at 5% level.
***Statistical significance at 10% level.

Appendix C - *Coefficients In-sample forecast performance: univariate prediction models, 1971-2014*

	Panel A: Monthly								
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Inflation	2.856*	1.133	2.042*	2.498	3.455	2.408	2.226*	-1.069*	3.163
tbl	-0.065	0.024	-0.023	-0.013**	-0.025	-0.049*	-0.018	-0.027	0.097***
ltr	-0.403**	-0.091	-0.266*	-0.193	-0.236*	-0.277	-0.236*	0.162	-0.989
Ik	-0.541	-0.013**	-0.335	0.164	-0.216	-0.466*	-0.134	-0.779	0.326*
dp	-0.005	0.001	-0.002	-0.002	-0.005*	-0.004	-0.002	-0.002***	0.003
tms	0.094	-0.104	0.046	-0.037*	0.050	0.170	0.011	0.151***	0.042
dfr	0.318**	0.198	0.244*	-0.007	0.014	0.221	0.142	0.748	0.760
Δ INDPRO	-0.357	-0.079*	-0.204	-0.455*	-0.724	-0.236	-0.303	0.615	0.219*
Δ MSL1	-0.427	-0.163	-0.306**	0.160	-0.327	-0.341	-0.126	-0.265*	-1.037**
UNRATE	0.129***	0.035*	0.087	0.048	0.030***	-0.060	0.071	-0.086*	0.045
KREA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GSCITOTTR	0.145*	0.028	0.077	0.057*	0.043	0.061*	0.069	0.110*	0.156
FMOIL	0.020	0.001	0.009**	-0.012	-0.006*	0.003	0.000	0.051	0.002*
Δ INDPRO'	0.656	0.406*	0.588	0.320***	0.690***	0.505	0.471*	0.140	0.589*
Δ MSL1'	-0.035	0.177	0.103	-0.102***	-0.168	0.042*	0.018	0.299	0.342
Δ USDUD	-0.116*	-0.032***	-0.050	-0.029	-0.050***	-0.017	-0.041	-0.442***	0.024***
Δ USDINR	-0.196	-0.057***	-0.071	-0.041*	-0.061	0.037	-0.059	-0.293	0.068*
AR(1)	0.273**	0.133	0.326	0.125	0.088	0.035	0.275*	0.071	0.265*
	Panel B: Quarterly								
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Inflation	1.780*	0.823	1.431**	1.983*	2.832*	1.910***	1.633*	-0.582	5.635*
tbl	-0.110	0.095*	0.000*	-0.004	0.030*	0.002	-0.008	-0.057	2.799*
ltr	-0.551*	-0.246	-0.399	-0.168*	-0.337*	-0.404	-0.309*	0.024	0.029
Ik	-1.553	0.358*	-0.725*	1.047	0.398	-0.706***	-0.029	-2.417	7.459
dp	-0.009	0.000**	-0.003	-0.007*	-0.008*	-0.001*	-0.005	-0.009	0.171*
tms	0.383	-0.385*	0.034*	-0.254**	-0.155	0.141*	-0.075	0.538	-1.889*
dfr	0.994*	0.362	0.676	0.228	0.484	0.718*	0.491*	1.017*	0.133*
Δ INDPRO	1.401*	0.608*	1.093	0.621*	1.090*	0.943*	0.911*	-0.120	-0.556
Δ MSL1	-0.728***	-0.058	-0.405	-0.251	-0.724*	-0.374	-0.342	-0.295	-0.505
Δ GDP	0.000	0.000	0.000**	0.000	0.000	0.000*	0.000	0.000	0.000
UNRATE	-0.406*	-0.195	-0.298**	-0.170	-0.256	-0.233	-0.249*	-0.029	0.119*
KREA	0.001**	0.000**	0.000	0.001*	0.001	0.001*	0.001*	0.000	0.000
GSCITOTTR	0.342*	0.136	0.245	0.353*	0.477	0.376	0.288*	0.007	0.060
FMOIL	0.046	0.006	0.031**	0.081	0.095	0.155**	0.052	0.050	-0.060
Δ INDPRO'	1.683*	1.092**	1.412**	0.897	1.300	0.845	1.216**	0.358	0.053
Δ MSL1'	0.300	0.195	0.178	-0.144	-0.313	-0.090**	0.041*	0.411	2.169
Δ USDUD	-0.818	-0.372	-0.573	-0.373	-0.657	-0.520	-0.493	-0.443	0.354*
Δ USDINR	-0.319	-0.085	-0.191	-0.122	-0.104	-0.082*	-0.165*	-0.316*	0.090***
AR(1)	0.045	-0.049	0.134	0.047	0.010	0.110	0.137**	0.061**	0.964
	Panel C: Annual								
	Metals	**Textiles**	**Industrials**	**Foods**	**Fats & Oils**	**Livestock**	**Commodity Index**	**Stock**	**Bond**
Inflation	1.072	0.671	0.806	1.364**	1.574	0.230	0.984	-0.503	13.710*
tbl	-0.083	0.675	0.267	0.116	0.057	-0.566	0.190	0.590	19.177*
ltr	-1.176*	-0.360**	-0.710	-0.267	0.057**	-0.516	-0.525*	-0.049	0.717
Ik	-3.725	2.878	-0.963	3.439	-3.725	-3.050	0.804	-3.974	4.023
dp	-0.036	0.020	0.004	-0.002	0.002	-0.032	-0.001	-0.036	1.318*
tms	-0.742	-1.720	-0.741	-2.403	-1.223	0.864	-1.383	-0.288	-3.657
dfr	2.513*	0.806**	1.575*	0.364	1.133**	1.287*	1.090*	1.329*	1.400
Δ INDPRO	0.301	0.456	0.500	0.592	0.711	0.296	0.572	-0.402	-0.683
Δ MSL1	0.912	0.213	0.670	-0.009	0.116	0.624	0.394	-0.120	0.542
Δ GDP	1.309	1.525	1.622	0.069	0.789	1.121	1.069	0.082	3.584
UNRATE	-0.126	-0.057	-0.092	-0.069	-0.061	0.015	-0.092	0.025	0.275
KREA	0.005*	0.001***	0.002*	0.003*	0.004*	0.002*	0.003*	0.000	-0.004
GSCITOTTR	-0.131	0.068	-0.036	0.209**	0.115	0.022	0.062	-0.287**	0.372
FMOIL	0.293	0.114	0.207**	0.010	0.042	0.293*	0.131	0.068	-1.098**
Δ INDPRO'	-0.159	0.490	0.216	0.801	0.760	-0.155	0.482	-0.666	0.685
Δ MSL1'	0.322	0.466***	0.410	-0.105	-0.170	-0.243	0.192	0.476	7.276*
Δ USDAUD	-1.001*	-0.360	-0.610**	-0.608*	-0.170*	-0.771*	-0.616*	0.344	2.430***
Δ USDINR	-0.996***	-0.421	-0.647**	-0.590**	-0.726***	-0.521***	-0.623**	0.276	2.093
AR(1)	-0.111	-0.053	-0.081	0.162	0.069	-0.051	0.068	-0.059	0.905

Appendix C - This table reports the OLS mean slope coefficient estimates. I use the commodity returns as the dependent variable and economic indicators as the independent variables. All the regressions use non-overlapping series over the sample period, the table is divided in three time horizons: month (Panel A), quarter (Panel B) and year (Panel C) over the sample period, from 1951 to 2014. The predictor indicators are inflation, treasury bill rate (tbl), long term return (ltr), capital ratio (IK), dividend-price ratio (dp), long term spread (tms), default return spread (dfr), industrial production growth (ΔINDPRO), GDP Growth (ΔGDP), Money Stock (ΔMSL1), unemployment rate (UNRATE), Killian's real economic activity index (KREA), S&P Goldman Sachs Commodity Index (GSCITOTTR), futures market open interest of Livestock (FMOIL), OECD industrial production (ΔINDPRO'), OECD money supply (ΔMSL1'), the log difference between the Australian dollar (AUD) and the United States dollar (ΔUSDAUD), as well as the difference between Indian rupee (INR) and the USD (ΔUSDINR), and one-period lagged return (AR(1)).

* Statistical significance at 1% level.
**Statistical significance at 5% level.
***Statistical significance at 10% level.

Appendix D - General Stata Code:

Summary statistics: sum commodity index

Univariate IS regression: regress depvar indepvar

Benchmark Univariate IS regression: regress depvar

Univariate OOS regression: rollreg depvar varlist indepvar varlist timevar, move(#) stub(abbrev)

Benchmark Univariate OOS regression: rollreg depvar timevar, move(#) stub(abbrev)

Ridge regression: rolling _b _se, recursive window(#) clear:ridgereg depvar indepvar varlist, model(orr) kernel(λ).