ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

BSc. Thesis Financial Economics

Predicting Asset Returns using the Copper to Gold Ratio

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Abstract

We show that the ratio of the copper to gold price, is a significant predictor of the 10 year U.S Yield, and of commodity, bonds and large-cap stock market returns. Using regression analysis, we analyse the direction and strength of the relationship and construct a trading strategy. The results of the trading strategy show that the copper-to-gold ratio as a trading signal, is of economic value to the large-cap U.S and Japanese equity indices, and to a global commodities index.

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Contents

1 Introduction

Copper and gold are two of the oldest metals exploited by mankind, copper was first discovered about 4,500 BC and mixed with tin ore to form bronze. Gold was first delved 5,000 years ago by the Egyptians and used to gilt ancient objects. Nowadays, gold is mainly used as a reserve asset by centrals banks and investors and copper is used by a wide range of industries.

Copper and gold both have distinct properties. Copper has useful industrial properties such as it's hardness, corrosion-resistance and electronic conductivity. Today it is used by the power, transport, building and renewable energy sectors and our economy is unimaginable without it (Mikesell, 2013). In recent years the demand for copper has increased significantly both due to an increasing global population as well as increasing demand from fast growing developing countries. According to (Elshkaki et al., 2016) this trend of increasing demand is expected to remain.

Gold serves a completely different role in our society. It is termed a precious metal and its scarcity and softness makes its purpose more financial than industrial. Gold is seen as a safe haven, a store of value and as hedge against market uncertainty. Among its historical uses are the minting of coins used for exchange and as a store of value before credit markets and fiat money existed. Even after the introduction of paper money it served an important role in the Bretton Woods system, spearheaded by Maynard Keynes, gold became the backbone of the global monetary system.

Gold's financial power stems from its scarcity, near indestructibility and mass. Gold serves as a hedge against inflation or a falling dollar since most gold is priced in dollars, the nominal value of gold will tend to rise when the dollar falls (Capie et al., 2005). In times of financial stress, unlike many other financial assets, the price of gold tends to increase as markets fall and offers investors a sense of certainty.

This study attempts to (I) asses the degree in which the ratio of the prices of the metals (copper/gold) convey information about the direction of the economy and specifically the direction of interest rates and asset returns, (II) whether the strength of this relationship changed over time and by the events of the great financial crisis and (III) whether a profitable trading strategy can be formed based on the ratio.

Combining the cyclical characteristic of copper with the financial properties of gold, their prices could provide information about the health of the economy. Jaunky (2013) finds a long run unidirectional causality running from economic growth to copper consumption and finds that, for some countries, copper demand can be used to forecast economic growth. Earlier literature on the relationship between metal prices and the broader economy by T.Orlowski (2017) finds that the price of copper moves in tandem with 5-year implied inflation while gold moves in the opposite direction. Thus, we expect that gold and copper prices convey information about the direction of interest rates through the Fisher equation where the nominal interest is a function of the real interest rate plus implied inflation (Fisher, 1930)[1]. We expect the relationship between the copper to gold ratio and the interest rate to be positive. Seeing the negative relationship between interest rates and bond prices, we expect the Global aggregate bond indices to relate negatively with the ratio.

Considering the relationship between equity markets and the copper to gold ratio, the study by Nguyena et al. (2020) finds that the correlation between positive shocks to equity market returns and copper futures returns, is positive. The study also finds that this relationship is negative for gold futures. As such, gold can be considered as a hedge for equity investments. On a study about co-movements between commodity markets and equity market returns, Lopez and Delatte (2013) finds positive correlations and that integration is greatest for Brent and Copper. Therefore, we expect the relationship between the copper to gold ratio and equity markets to be positive.

Mishkin (2017) studied the way in which monetary policy has changed since the great financial crisis (from here on abbreviated as "GFC") and finds that the set of unconventional monetary policies adopted by central banks leads to a long term suppression of interest rates. This leads us to expect that the strength of the relationship between interest rates and the copper to gold ratio has weakened after the great financial crisis.

The rest of the paper is organised as follows: section 2 covers the data used in this study. Section 3 covers formal testing and the results. Section 4 covers the trading strategy and section 5 discusses and concludes.

[1] $i = r + \pi^e$

2 Data

To examine the predictability of interest rates using metal prices, we utilize daily data of market closing futures prices compiled with Bloomberg. In the essence of representativeness, the liquid and regulated U.S futures markets are used in this study.

2.1 Copper and Gold

The data on copper and gold consists of prices of futures traded on the Chicago Mercantile Exchange. Based on the front month contract, Bloomberg constructs a continuous price series of which the closing prices are used in this study. The price of copper is derived from the Grade 1 Electrolytic Copper Cathodes future (HG), is quoted in U.S dollar cents per pound, the method of settling is physical and the contract size equals 25,000 pounds. The gold contract (GC) is traded in U.S dollar per troy ounce of at least 99.5% fineness, is settled physically and the contract size is equivalent to 100 troy ounces. The sample period covers December 1988, when the copper futures started trading, until January 2020 and consists of daily data. The main variable of interest in this study is the Copper-over-Gold ratio (from here one abbreviated as "CoG"): $\frac{P_c}{P_g}$, where P_c is the price of copper and P_g the price of gold.

2.2 Yield

We construct a time series of the yield on U.S T-Bonds with a maturity of 10 years. The data is derived form the U.S treasury which computes the "Constant Maturity Treasury yield" on various bond maturities. This rate refers to the yield obtained on a security which is held to maturity based on closing market bid prices on actively traded bonds in the over-the-counter markets.

In this way, the daily yield on the 10 year treasury bond can be obtained even when there is no security on the market with the exact remaining time to maturity. Our sample period for this study covers December 1988 until January 2020 which includes a total of 8106 observations. Earlier data on interest rates exists, however this time frame is chosen to match the availability of the data on copper prices which are available from December 1988.

This time frame contains the events of the financial crisis and as expressed by Jarrow and Li (2014), the Quantitative Easing program that the Federal Reserve initiated in response to the crisis generated significant impacts on the prices of U.S treasury bonds.

Our sample covers a period including the financial crisis of 2008 for two reasons: (I) to have enough observations to make statistical inferences about the relationship between the variables studied and (II) to assess whether the strength of the studied relationship changed after monetary policy actions induced by the financial crisis.

2.3 Other asset classes

Daily data on the large-cap developed market equity indices have been gathered. The data has been retrieved from Datastream and includes the indices from the UK (FTSE 100), Japan (Nikkei 225), the U.S (S&P 500) and Europe (Euro Stoxx 50). The S&P GSCI commodity index serves as the benchmark index for the global commodities market, there is an overlap in data since about 8% of the index constitutes of copper and gold prices. However, it is still used because of its importance as a benchmark for other commodities, such as oil. The Bloomberg Barclays Global aggregate bond index is used as a benchmark for High Yield and Investment Grade bonds.

2.4 Control variables

Several variables are added to control for the effects of the economic cycle and for financial effects. The following economic variables are added: the monthly change in the rate of inflation, which is added to control for the positive relationship it has with interest rates and its negative relationship with gold. The manufacturing- and non-manufacturing PMI are added to control for the effects of the economic cycle and its economic production levels. It is expected to relate positively with both interest rates and copper and negatively with gold. The University of Michigan consumer sentiment index is added to control for consumer demand cycles, it has an expected positive relationship with interest rates and copper and negative relationship with gold. The financial control variables are: the stock of M2 money supply, added to control for monetary policy effects. The relationship with interest rates is expected to be negative and its relationship with gold and with copper is expected to be positive. The financial conditions index obtained from the Federal Reserve, is added to control for the effects of the availability of credit in financial markets. It is expected to relate negatively with gold and interest rates and positively with copper. The VIX index is added to control for the effect of investor sentiment. An increase means investors expect more volatility to occur, it is expected to relate positively with gold and negatively with copper and interest rates.

Figure 2.1: The copper to gold ratio and the 10 year U.S government bond yield, 1988:12–2020:01. The solid line delineates the U.S government 10 year and the dotted line displays the copper to gold ratio (from Datastream). Vertical grey bars display recessions as dated by the National Bureau of Economic Research (NBER).

2.5 Sample properties

Table 2.1 and 2.2 contain summary statistics for the predictor variables used in this study over our sample period of December 1988 until January 2020. The tables are organised in four panels. *Panel A to C* contain the summary statistics for the entire sample as well as the period before and after the financial crisis. The mean, median, 1st/99th percentile and standard deviation of the variables are shown in each sub-sample. *Panel D* contains the mean across time.

Comparing panels A to C of table 2.1, it becomes clear that there are different regimes between the sub-samples and subsequent periods. The mean U.S yield in the period before the financial crisis, *Panel B*, is more than twice as high as the mean in the period after the crisis *Panel C*. The mean of the CoG remained stable. At the same time, the mean price of copper and gold almost tripled. The standard deviation of U.S Yield decreased from 1.48 to 0.59. The standard deviation of copper and gold remained relatively stable and that of the CoG decreased from 0.11 to 0.04.

Panel D of table 2.1 shows that the U.S Yield exhibits a strong downward trend over time with the mean decreasing from 7.35% to 2.25% in the first to the last period. This downward trend in interest rates is likely due to accommodative monetary policy. The price of gold shows an upward trend, especially in the last two periods. The mean price increases from 805 to 1422 across time. This is likely due to the feature of gold as a hedge against inflation and financial instability. The price of copper shows an upward trend, the mean increases from 104 to 310. This increase is likely due to increased demand from China, Soulier et al. (2018) finds that China's per-capita in use copper stock has grown from 7kg in 1990 to 60kg in 2015.

Table 2.2 shows summary statistics for the equity, commodity and bond indices used in this study. Comparing Panels A to C, we find that the standard deviation of all indices is lower in the period after the GFC compared to the whole sample and the period before the GFC. Looking at panel D, we find that the mean of all indices but the Nikkei have increased over time. The best performing index in terms of return is the High Yield bond index. The highest returning equity index is the S&P 500.

Table 2.1: Summary Statistics, 1988:12-2020:01.

The database contains 8106 daily observations from December 1988 to January 2020. The table displays summary statistics for the predictor variables copper and gold and the U.S yield. U.S yield is the percentage yield on the 10 year treasury bond and copper and gold are closing prices based on front month futures.

Variable	Mean	Median	1st percentile	99th percentile	Std. dev
Panel A: 1988:12 till 2020:01					
U.S Yield (%)	4.64	4.50	1.56	9.06	2.03
Copper	206	137	66.87	474.86	125
Gold	931	794	384.42	1901.10	408
Copper/Gold	0.22	0.21	0.09	0.52	0.09
Panel B: 1988:12 till 2008:11					
U.S Yield (%)	5.84	5.71	3.51	9.18	1.48
Copper	141	104	65.9	438	99.5
Gold	666	703	382	1069	184
Copper/Gold	0.21	0.18	0.08	0.53	0.11
Panel C: 2008:11 till 2020:01					
U.S Yield (%)	2.47	2.4	1.5	3.82	0.59
Copper	323	324	170	489	68.5
Gold	1408	1358	954	1952	225
Copper/Gold	0.23	0.23	0.16	0.32	0.04

Panel D: Mean across time

Variable	1988-1995	1996-2003	2004-2011	2012-2020
U.S Yield (%)	7.35	5.41	3.85	2.25
Copper	104	93.10	307	310
Gold	805	497	985	1422
Copper/Gold	0.13	0.19	0.32	0.22

Table 2.2: Summary Statistics other assets, 1988:12-2020:01.

The database contains 8106 daily observations from December 1988 to January 2020. The table displays summary statistics for the UK, US, Japan and European equity indices, as well as the S&P global commodity index GSCI. The Bloomberg Barclays High Yield and Investment grade indices are shown as HI and IG index.

Variable	Mean	Median	1st percentile	99th percentile	Std. dev
Panel A: 1988:12 till 2020:01					
FTSE 100	5057	5392	2053	7626	1596
S&P 500	1235	1176	296	2985	683
Nikkei 225	16763	16598	8051	35584	6035
Euro Stoxx 50	2701	2845	872	5204	1084
GSCI Commodity	3662	3194	1514	8858	1618
IG index	305	306	98	508	129
HY index	578	461	92	1374	390
Panel B: 1988:12 till 2008:11					
FTSE 100	4356	4380	2031	6653	1458
S&P 500	887	956	292	1522	400
Nikkei 225	17661	16938	8191	36984	6329
Euro Stoxx 50	2536	2554	864	5254	1284
GSCI Commodity	3655	3079	1407	9457	1830
IG index	220	213	98.1	374	75.8
HY index	316	299	90.4	610	151
Panel C: 2008:11 till 2020:01					
FTSE 100	6317	6464	3952	7713	914
S&P 500	1861	1887	814	3110	638
Nikkei 225	15142	15343	7917	23784	5077
Euro Stoxx 50	2997	3016	2079	3715	428
GSCI Commodity	3676	3937	2005	5456	1140
IG index	415	456	359	512	33.6
HY index	1022	1063	438	1380	239
Panel D: Mean across time					
Variable	1988-1995	1996-2003	2004-2011	2012-2020	
FTSE 100	2689	5128	5387	6747	
S&P 500	413	1067	1213	2151	
Nikkei 225	23254	15038	12207	17305	
Euro Stoxx 50	1132	3179	3170	3139	
GSCI Commodity	2189	3227	5697	3366	
IG index	136	218	358	468	
HY index	153	304	602	1143	

3 Predictive regression analysis

3.1 In sample tests

A predictive in- sample regression model is estimated to analyze the predictability of the 10 year U.S bond yield and the other assets using the CoG:

$$Y_t = \alpha + \beta_1 x_t + \beta_2 x_{1t} + ... + \beta_8 x_{8t} + \epsilon_t \quad \text{for} \quad t = 1, ..., T \tag{3.1}$$

Where Y_t is the predicted yield on the 10 year yield/index level for day t and x_t is the CoG for day t. For this study we are interested in finding the significance of β_1 in equation 3.1. Variables x_{2t} to x_{8t} represent the control variables: inflation, the financial conditions index, the consumer sentiment index, M2 money supply, and the manufacturing and non-manufacturing PMI. The regression analysis is split up in three sub-samples covering the entire time frame of the sample and the periods before and after the great financial crisis.

Tables 3.1 to 3.8 show the results of the regression analysis of equation 3.1. The tables reports the OLS estimate of the variables and its corresponding t-statistic for each of the sub-samples. The results of table 3.1 display that, after including control variables, the CoG has significant predictive ability on the U.S Yield at the 1% level in each sub-sample. When CoG increases by one standard deviation (0.09). the yearly U.S yield is expected to increase by 4.111*0.09 (0.369%), all else equal. This effect is, in economic terms, substantial. The expected positive sign of the predictive variable $\hat{\beta}$ of the CoG is present in all sub-samples (columns 2, 4, 6). The R^2 decreases slightly from sub-samples 1 to 3, the highest R^2 is 0.882 and is present in the sub-sample covering the entire time frame. The significance of the CoG in predicting the U.S Yield, as shown by the t-statistic, increases from 8.635 to 13.958 when comparing the pre- to post- GFC sample. This finding rejects the hypothesis that the relationship weakened due to the monetary policy actions induced by the events of the GFC.

The results of the regression on the U.S, UK, Japanese and European indexes are shown in tables 3.2 to 3.5. The predictive ability of the CoG on the equity indices daily returns is significant at the 1% level on the whole sample. This relationship is negative, and contrary to the hypothesis as set out in 1. The relationship between the CoG and equity returns is not significant in the pre- and post QE sub-samples. The R^2 is highest at the full-sample S&p 500 regression. This is likely due to the control variables used are from the U.S, therefore fitting the data at hand best.

Table 3.6 shows the results of the regression on the GSCI Commodity index. On this index, the CoG only has predictive ability, at the 1% level, on the period covering the entire sample. When CoG increases by one standard deviation (0.09). the GSCI daily return is expected to decrease by -0.799*0.09 (-0.072%), all else equal. The results of the regression on the global Investment Grade and High Yield bonds are shown in tables 3.7 and 3.8. The predictive ability of the CoG on the Investment Grade index, is not economically significant on any of the sub-samples. This is likely due to the performance of the index not being too subject to changes in the economic cycle. On the High Yield index, the CoG has significant predictability at the 1% level on the period covering the whole sample. When CoG increases by one standard deviation (0.09). the daily return on the High Yield index is expected to increase by 4.111*0.09 (0.369%), all else equal.

In sum, the in-sample regression analysis shows that, after controlling for economic and financial variables, the CoG has significant predictive ability in estimating the U.S yield across time. For equity, commodity and high yield bond returns, the predictive ability is economically significant in the whole period sub-sample. Our expectation about the positive direction of the relationship between the CoG and the various asset classes as set out in section 1, are confirmed for the U.S Yield and High Yield index and rejected for the equity indices. Overall, and across time the model is most consistent in predicting the U.S Yield.

3.2 Moving average regression

In this section, the predictability of the CoG on asset returns and the U.S Yield at time t using past information is analyzed. A moving average linear regression model is constructed. First, the simple moving average (SMA), which is the unweighted mean of the previous n days of CoG price data, is computed using formula 3.2. Where the closing day CoG prices are $p_M, p_{M-1}, \ldots, p_{M-(n-1)}$.

$$\bar{P}_{SMA} = \frac{p_M + p_{M-1} + \cdots + p_{M-(n-1)}}{n} = \frac{1}{n}\sum_{i=0}^{n-1} p_{M-i} \tag{3.2}$$

Table 3.1: In-sample predictive regression analysis results, 1988:12-2020:01.

The table displays the ordinary least squares estimates and the R^2 of the predictive regression model of equation 3.1. Within square brackets we report Newey-West corrected t-values using 22 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Columns 1-6 displays the sub-samples. (1-2) is 1988:12-2020:01 (3-4) is 1988:12-2008:11 and (5-6) is 2008:11-2020:01. The first column of each sub-sample is the regression without control variables, the second with control variables.

	Dependent variable:					
	U.S Yield					
	(1)	(2)	(3)	(4)	(5)	(6)
Copper/Gold	−8.078	4.113	−7.334	2.729	12.378	15.975
	[−1.118]	[7.077]***	[−2.167]**	[4.569]***	[8.635]***	[13.958]***
CPI		0.212		−0.030		0.199
		[1.352]		[−0.250]		[1.210]
Consumer sentiment		0.048		0.028		0.001
		[7.184]***		[3.117]***		[0.159]
Non-manufacturing PMI		−0.003		0.044		−0.004
		[−0.161]		[1.882]*		[−0.324]
Manufacturing PMI		−0.018		−0.054		−0.017
		[−1.015]		[−2.827]***		[−1.995]**
VIX		0.010		−0.021		0.021
		[1.352]		[−2.703]***		[4.358]***
M2 Money supply		−0.0003		−0.001		0.0001
		[−9.620]***		[−3.709]***		[2.734]***
Financials index		0.159		0.407		0.273
		[1.954]*		[3.558]***		[3.067]***
Constant	6.375	1.789	7.361	5.281	−0.372	−1.758
	[3.369]***	[1.692]*	[6.514]***	[4.289]***	[−1.041]	[−2.463]**
Observations	8,105	8,105	5,209	5,209	2,896	2,896
R^2	0.124	0.883	0.279	0.779	0.590	0.786

Table 3.2: In-sample predictive regression analysis results, 1988:12-2020:01.

The table displays the ordinary least squares estimates and the R^2 of the predictive regression model of equation 3.1. Within square brackets we report Newey-West corrected t-values using 22 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Columns 1-6 displays the sub-samples. (1-2) is 1988:12-2020:01 (3-4) is 1988:12-2008:11 and (5-6) is 2008:11-2020:01. The first column of each sub-sample is the regression without control variables, the second with control variables.

	Dependent variable:					
	.2		S&P 500			
	(1)	(2)	(3)	(4)	(5)	(6)
Copper/Gold	−0.057	−1.867	−0.131	−0.537	0.795	0.805
	[−0.559]	[−7.118]***	[−1.219]	[−1.475]	[1.764]*	[1.014]
CPI		−0.203		−0.239		−0.329
		[−3.032]***		[−2.991]***		[−3.661]***
Consumer sentiment		−0.007		−0.017		−0.023
		[−4.044]***		[−3.809]***		[−4.085]***
Non-manufacturing PMI		−0.019		−0.035		−0.008
		[−2.511]**		[−2.399]**		[−0.712]
Manufacturing PMI		0.008		0.008		0.012
		[1.521]		[0.974]		[1.812]*
VIX		−0.049		−0.055		−0.063
		[−10.527]***		[−8.798]***		[−9.694]***
M2 Money supply		−0.00003		−0.0003		0.00005
		[−4.885]***		[−4.775]***		[1.645]
Financials index		0.309		0.290		0.494
		[6.179]***		[3.798]***		[6.642]***
Constant	0.048	3.119	0.055	6.211	−0.131	2.539
	[2.012]**	[8.664]***	[2.188]**	[6.438]***	[−1.218]	[4.289]***
Observations	8,105	8,105	5,209	5,209	2,896	2,896
R^2	0.178	0.382	0.000	0.040	0.000	0.06

Table 3.3: In-sample predictive regression analysis results, 1988:12-2020:01.

The table displays the ordinary least squares estimates and the R^2 of the predictive regression model of equation 3.1. Within square brackets we report Newey-West corrected t-values using 22 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Columns 1-6 displays the sub-samples. (1-2) is 1988:12-2020:01 (3-4) is 1988:12-2008:11 and (5-6) is 2008:11-2020:01. The first column of each sub-sample is the regression without control variables, the second with control variables.

	Dependent variable:					
	FTSE 100					
	(1)	(2)	(3)	(4)	(5)	(6)
Copper/Gold	−0.037	−1.310	−0.091	−0.445	0.727	1.101
	[−0.322]	[−6.234]***	[−0.762]	[−1.380]	[1.495]	[1.540]
CPI		−0.214		−0.255		−0.282
		[−3.731]***		[−3.057]***		[−3.591]***
Consumer sentiment		−0.005		−0.012		−0.013
		[−3.155]***		[−2.783]***		[−2.710]***
Non-manufacturing PMI		−0.014		−0.029		0.002
		[−2.047]**		[−1.985]**		[0.220]
Manufacturing PMI		0.005		0.008		0.002
		[1.076]		[1.056]		[0.355]
VIX		−0.038		−0.044		−0.043
		[−8.971]***		[−6.526]***		[−8.537]***
M2 Money supply		−0.00002		−0.0002		0.00002
		[−4.355]***		[−3.539]***		[0.741]
Financials index		0.245		0.245		0.363
		[5.908]***		[3.436]***		[6.580]***
Constant	0.031	2.382	0.041	4.713	−0.142	1.466
	[1.148]	[7.508]***	[1.438]	[4.671]***	[−1.245]	[2.938]***
Observations	8,105	8,105	5,209	5,209	2,896	2,896
R^2	0.000	0.023	0.000	0.026	0.001	0.033

Table 3.4: In-sample predictive regression analysis results, 1988:12-2020:01.

The table displays the ordinary least squares estimates and the R^2 of the predictive regression model of equation 3.1. Within square brackets we report Newey-West corrected t-values using 22 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Columns 1-6 displays the sub-samples. (1-2) is 1988:12-2020:01 (3-4) is 1988:12-2008:11 and (5-6) is 2008:11-2020:01. The first column of each sub-sample is the regression without control variables, the second with control variables.

	Dependent variable:					
	Nikkei 225					
	(1)	(2)	(3)	(4)	(5)	(6)
Copper/Gold	0.077	−1.861	0.003	−0.530	0.584	0.746
	[0.487]	[−6.768]***	[0.020]	[−1.233]	[1.021]	[0.929]
CPI		−0.202		−0.168		−0.450
		[−2.612]***		[−1.388]		[−5.033]***
Consumer sentiment		−0.008		−0.015		−0.023
		[−4.138]***		[−3.147]***		[−3.978]***
Non-manufacturing PMI		−0.016		−0.026		−0.008
		[−1.926]*		[−1.711]*		[−0.696]
Manufacturing PMI		0.005		0.002		0.013
		[0.886]		[0.226]		[1.788]*
VIX		−0.050		−0.052		−0.066
		[−9.819]***		[−6.627]***		[−11.372]***
M2 Money supply		−0.00003		−0.0003		0.00004
		[−4.318]***		[−3.385]***		[1.294]
Financials index		0.290		0.224		0.523
		[5.135]***		[2.341]**		[6.984]***
Constant	−0.009	3.106	−0.015	5.493	−0.088	2.624
	[−0.249]	[7.615]***	[−0.388]	[4.666]***	[−0.652]	[4.290]***
Observations	8,105	8,105	5,209	5,209	2,896	2,896
R^2	0.000	0.026	0.000	0.027	0.001	0.0418

Table 3.5: In-sample predictive regression analysis results, 1988:12-2020:01.

The table displays the ordinary least squares estimates and the R^2 of the predictive regression model of equation 3.1. Within square brackets we report Newey-West corrected t-values using 22 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Columns 1-6 displays the sub-samples. (1-2) is 1988:12-2020:01 (3-4) is 1988:12-2008:11 and (5-6) is 2008:11-2020:01. The first column of each sub-sample is the regression without control variables, the second with control variables.

	Dependent variable:					
	Euro Stoxx 50					
	(1)	(2)	(3)	(4)	(5)	(6)
Copper/Gold	−0.033	−1.716	−0.079	−0.594	0.688	0.959
	[−0.267]	[−6.551]***	[−0.627]	[−1.642]	[1.159]	[1.006]
CPI		−0.263		−0.319		−0.349
		[−3.923]***		[−3.210]***		[−3.420]***
Consumer sentiment		−0.006		−0.014		−0.017
		[−2.641]***		[−2.764]***		[−2.528]**
Non-manufacturing PMI		−0.018		−0.032		−0.003
		[−1.953]*		[−1.764]*		[−0.256]
Manufacturing PMI		0.006		0.005		0.008
		[1.068]		[0.461]		[1.085]
VIX		−0.050		−0.060		−0.057
		[−9.663]***		[−7.795]***		[−8.102]***
M2 Money supply		−0.00003		−0.0003		0.00002
		[−4.742]***		[−4.323]***		[0.699]
Financials index		0.325		0.348		0.462
		[6.202]***		[4.103]***		[5.591]***
Constant	0.034	2.968	0.044	6.049	−0.134	2.033
	[1.100]	[7.517]***	[1.393]	[5.354]***	[−0.958]	[3.283]***
Observations	8,105	8,105	5,209	5,209	2,896	2,896
R^2	0.000	0.027	0.000	0.033	0.001	0.033

Table 3.6: In-sample predictive regression analysis results, 1988:12-2020:01.

The table displays the ordinary least squares estimates and the R^2 of the predictive regression model of equation 3.1. Within square brackets we report Newey-West corrected t-values using 22 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Columns 1-6 displays the sub-samples. (1-2) is 1988:12-2020:01 (3-4) is 1988:12-2008:11 and (5-6) is 2008:11-2020:01. The first column of each sub-sample is the regression without control variables, the second with control variables.

	Dependent variable:					
	GSCI Commodity Index					
	(1)	(2)	(3)	(4)	(5)	(6)
Copper/Gold	−0.030	−0.799	−0.082	−0.189	1.171	0.611
	[−0.174]	[−2.837]***	[−0.452]	[−0.431]	[1.891]*	[0.607]
CPI		0.244		0.206		0.219
		[3.295]***		[2.288]**		[1.822]*
Consumer sentiment		−0.0004		0.005		−0.016
		[−0.213]		[0.967]		[−2.328]**
Non-manufacturing PMI		−0.016		−0.024		−0.007
		[−2.046]**		[−1.525]		[−0.501]
Manufacturing PMI		0.001		−0.004		0.004
		[0.138]		[−0.350]		[0.464]
VIX		−0.025		−0.020		−0.040
		[−4.973]***		[−2.507]**		[−5.686]***
M2 Money supply		−0.00002		−0.00002		0.00004
		[−2.844]***		[−0.258]		[1.159]
Financials index		0.136		0.078		0.302
		[2.559]**		[1.025]		[3.670]***
Constant	0.023	1.747	0.049	1.628	−0.281	1.737
	[0.615]	[4.406]***	[1.304]	[1.273]	[−1.898]*	[2.377]**
Observations	8,105	8,105	5,209	5,209	2,896	2,896
R^2	0.000	0.014	0.000	0.015	0.001	0.020

Table 3.7: In-sample predictive regression analysis results, 1988:12-2020:01.

The table displays the ordinary least squares estimates and the R^2 of the predictive regression model of equation 3.1. Within square brackets we report Newey-West corrected t-values using 22 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Columns 1-6 displays the sub-samples. (1-2) is 1988:12-2020:01 (3-4) is 1988:12-2008:11 and (5-6) is 2008:11-2020:01. The first column of each sub-sample is the regression without control variables, the second with control variables.

	Dependent variable:					
	Global Investment Grade index					
	(1)	(2)	(3)	(4)	(5)	(6)
Copper/Gold	−0.050	0.065	−0.048	0.076	−0.003	0.272
	[−1.141]	[0.896]	[−1.056]	[0.736]	[−0.019]	[1.106]
CPI		0.008		0.033		−0.033
		[0.425]		[1.393]		[−1.076]
Consumer sentiment		0.0003		0.001		0.001
		[0.560]		[1.048]		[0.764]
Non-manufacturing PMI		−0.0002		0.0002		0.002
		[−0.074]		[0.061]		[0.628]
Manufacturing PMI		0.001		0.001		0.001
		[0.510]		[0.308]		[0.330]
VIX		0.003		0.004		0.001
		[2.174]**		[2.413]**		[0.943]
M2 Money supply		−0.00000		0.00002		−0.00001
		[−0.237]		[1.223]		[−0.692]
Financials index		−0.017		−0.047		0.018
		[−1.134]		[−2.770]***		[0.832]
Constant	0.032	−0.111	0.036	−0.401	0.014	−0.252
	[3.123]***	[−1.102]	[3.379]***	[−1.428]	[0.342]	[−1.478]
Observations	8,105	8,105	5,209	5,209	2,896	2,896
R^2	0.001	0.002	0.000	0.004	0.000	0.004

Table 3.8: In-sample predictive regression analysis results, 1988:12-2020:01.

The table displays the ordinary least squares estimates and the R^2 of the predictive regression model of equation 3.1. Within square brackets we report Newey-West corrected t-values using 22 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels. Columns 1-6 displays the sub-samples. (1-2) is 1988:12-2020:01 (3-4) is 1988:12-2008:11 and (5-6) is 2008:11-2020:01. The first column of each sub-sample is the regression without control variables, the second with control variables.

	Dependent variable:					
	Global High Yield index					
	(1)	(2)	(3)	(4)	(5)	(6)
Copper/Gold	−0.110	−0.758	−0.142	−0.062	0.233	0.177
	[−1.596]	[−4.904]***	[−1.957]*	[−0.290]	[0.837]	[0.399]
CPI		0.00001		−0.0004		−0.069
		[0.0004]		[−0.009]		[−1.538]
Consumer sentiment		−0.003		−0.007		−0.005
		[−3.579]***		[−3.057]***		[−2.316]**
Non-manufacturing PMI		−0.008		−0.011		−0.004
		[−2.027]**		[−1.910]*		[−0.636]
Manufacturing PMI		0.002		0.002		0.004
		[0.740]		[0.563]		[0.999]
VIX		−0.017		−0.019		−0.020
		[−5.516]***		[−3.868]***		[−7.175]***
M2 Money supply		−0.00001		−0.0001		−0.00000
		[−3.794]***		[−3.284]***		[−0.198]
Financials index		0.096		0.020		0.225
		[2.748]***		[0.448]		[6.722]***
Constant	0.059	1.338	0.061	2.292	−0.010	0.956
	[3.528]***	[5.353]***	[3.351]***	[3.716]***	[−0.146]	[3.063]***
Observations	8,105	8,105	5,209	5,209	2,896	2,896
R^2	0.001	0.057	0.001	0.078	0.001	0.122

The previous 1 to 252 days (one business year) CoG SMA's are calculated. The resulting collection of data points is used as the independent variable in an OLS regression of the form:

$$Y_t = \alpha + \beta x_{SMA_n} + \beta_2 x_{1t} + ... + \beta_8 x_{8t} + \epsilon_t \quad \text{for} \quad n = 1, ..., 252 \tag{3.3}$$

Where Y_t is the U.S Yield and the daily return of assets, βx_{SMA_n} is the n'th period SMA and $\beta_2 x_{1t}$ to $\beta_8 x_{8t}$ are the economic and financial control variables as described in section 2.4.

The results of this analysis are presented visually using a figure which shows the t-statistic of the significance of βx_{SMA_n} in equation 3.3. Per asset class, the range of n-day(s) SMA's used in the regression and the corresponding t-statistics are shown in figures 3.1 to 3.3. Figure 3.1 shows the t-statistic of the CoG SMA regression on the U.S

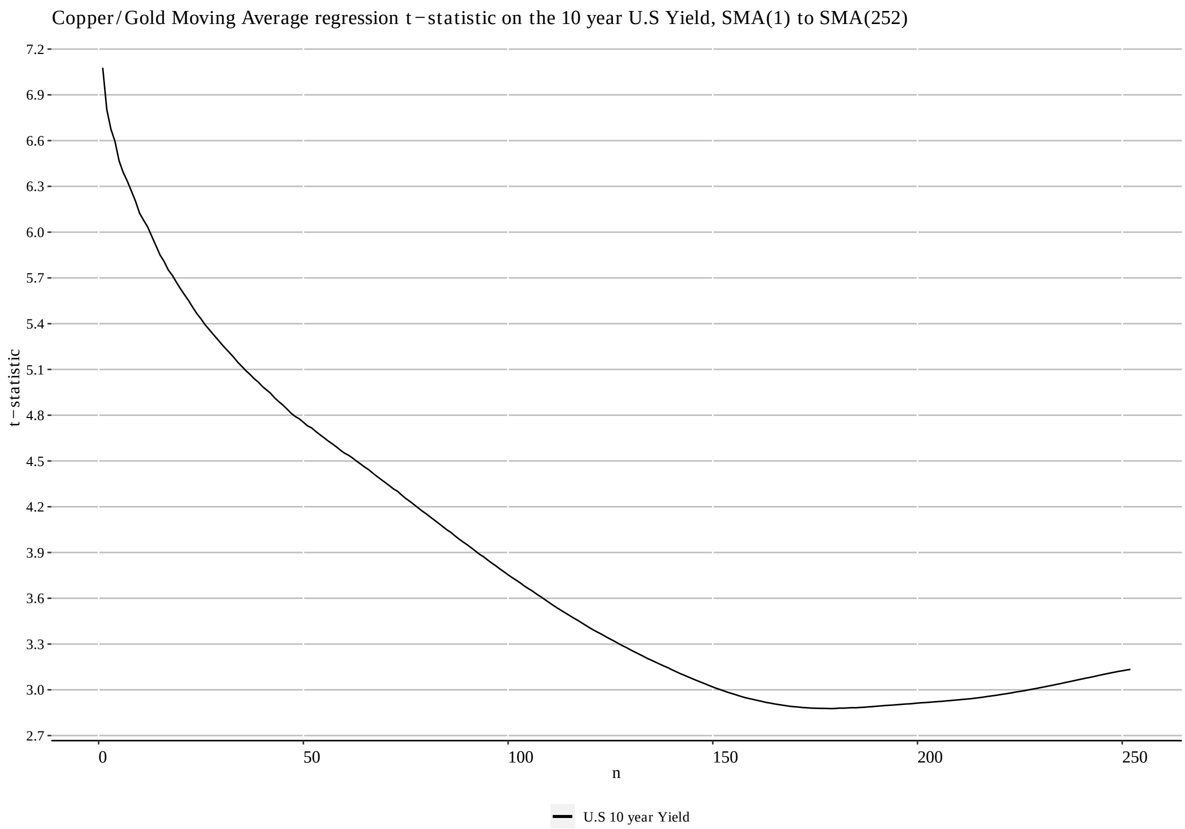

Figure 3.1: The copper to gold ratio moving average regression, t-statistic on the 10 year U.S government bond yield. The solid line delineates the U.S Yield, the y-axis displays the t-statistic and the x-axis displays the n-day(s) simple moving average used as the independent variable in the regression.

Yield. The results show that the regression has significant predictability at at least the

5% level over the entire range of SMA regressions. The relationship between past returns and the U.S Yield is positive. The t-statistic is highest at smaller values of n for the U.S Yield, where the statistic is significant at the 0.1% level. The t-statistic for the U.S Yield bottoms at an SMA of about 170, after which it increases in significance over the remaining range of SMA periods. Figure 3.2 shows an overall pattern of the regression

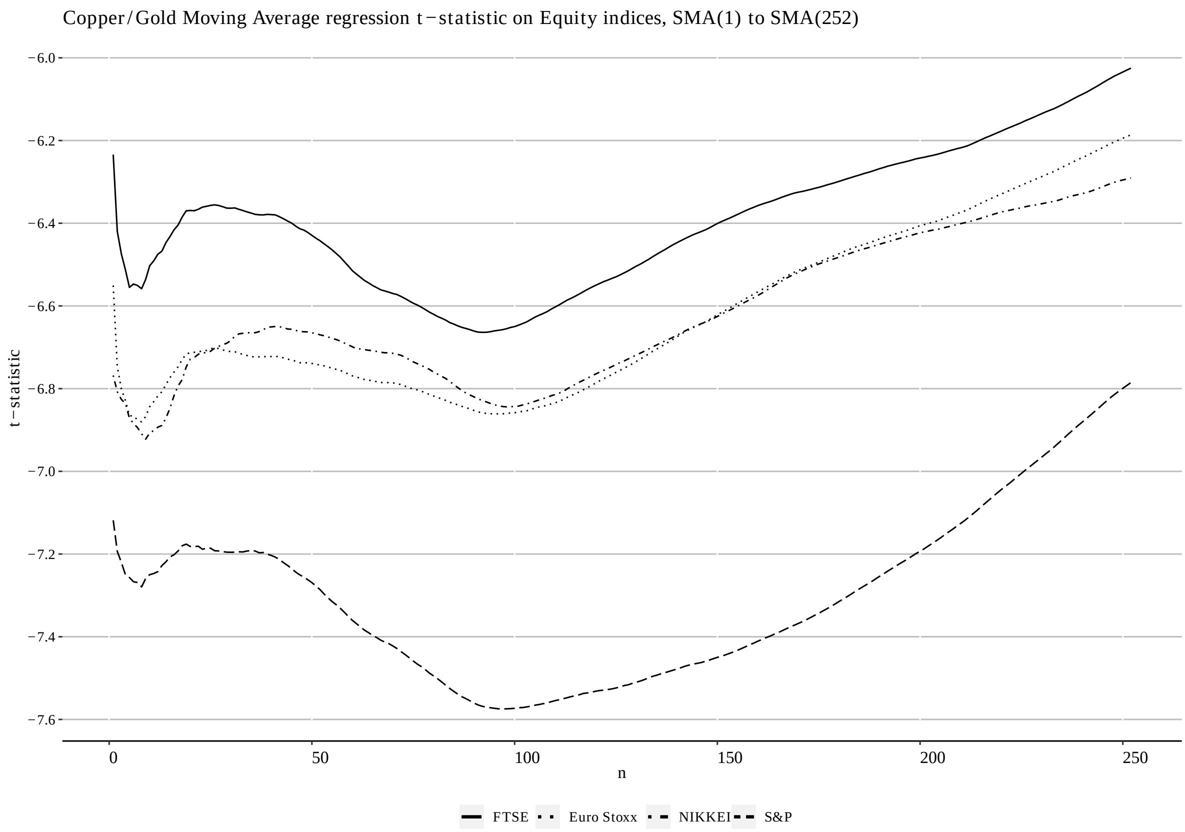

Figure 3.2: The copper to gold ratio moving average regression, t-statistic on the Japanese, European, UK and U.S equity market. The lines delineate the regression t-statistic per equity index, the y-axis displays the t-statistic and the x-axis displays the n-day(s) simple moving average used as the independent variable in the regression. The FTSE is the solid line, the Euro Stoxx the dotted line, the Nikkei the dot-dashed line and the S&P the dashed line.

on the equity indices in which the 10 and 100 day SMA of the CoG, are most significant in predicting current returns. For the S&P 500 and FTSE index, the highest t-statistics is found at the 100 day SMA. This indicates that longer term past returns in the CoG are more significant in predicting current returns than shorter term past returns. The opposite is found for the Euro stoxx and Nikkei index, where the 10 day SMA is more significant than the 100 day SMA. The relationship between past changes in the CoG and all equity indices is negative. Figure 3.3 displays the t-statistic of the SMA regression

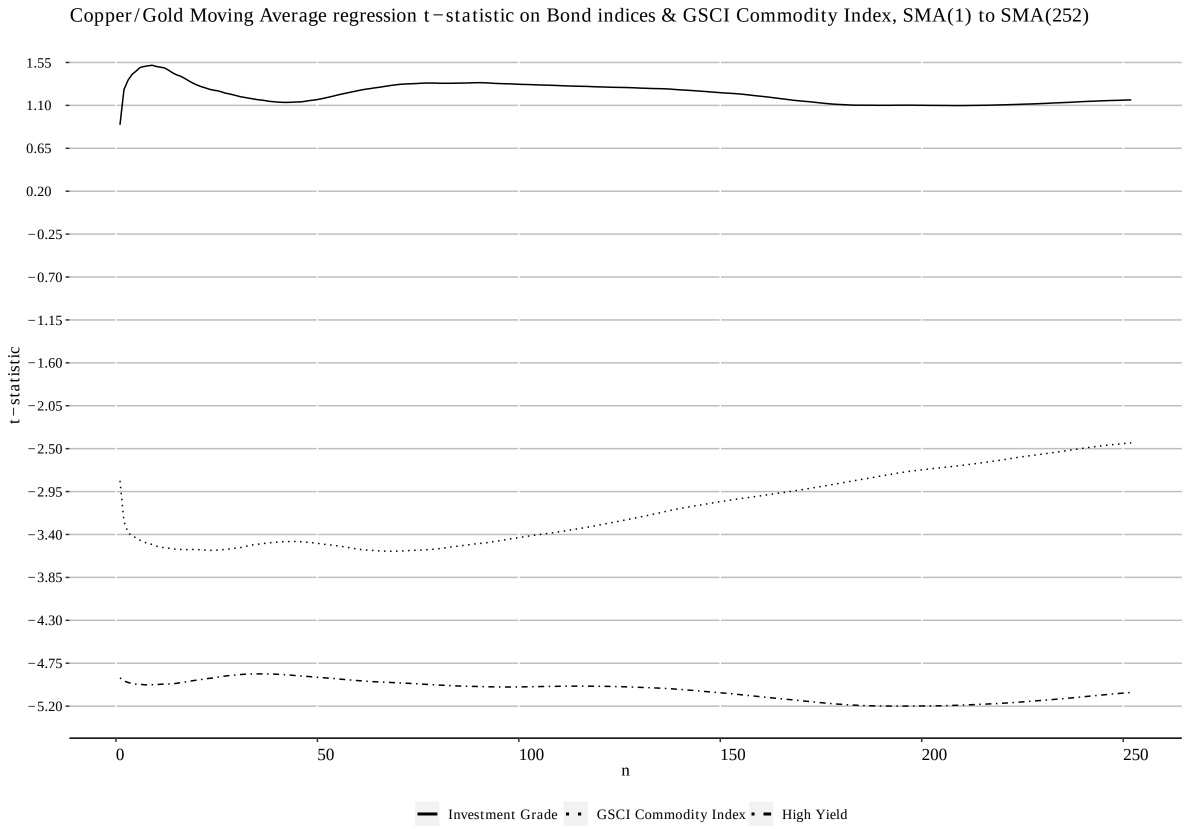

Figure 3.3: The copper to gold ratio moving average regression, t-statistic on the Bloomberg Barclays Global Investment Grade and High Yield bond index and the GSCI Commodity Index. The lines delineates the regression t-statistic per bond index, the y-axis displays the t-statistic and the x-axis displays the n-day(s) simple moving average used as the independent variable in the regression. The Investment Grade index is the solid line, the Commodity index the dotted line and the High Yield index the dot-dashed line.

of the CoG on Bond indices and the Commodity index. The relationship between the Investment Grade index and the SMA component of the regression is positive. While that of the High Yield and Commodity index is negative. The CoG SMA does indicate that it is not helpful in predicting investment grade bond returns, as the t-statistic is insignificant for all n-day(s) SMA. For the Commodity index, the t-statistics at smaller values of n are strictly more negative than larger values. Indicating that short term returns contains more information for current prices than long term returns. The results on High Yield index returns show that its t-statistic is significant at the 0.1% level for all SMA periods. Moreover, long run past returns have more predictive ability than short term past returns.

3.3 Out of sample tests

To assess the forecast performance of the CoG on an independent data set, a rolling out-of-sample R^2 test is conducted. The data is split up in a part used for model parameter specification (the training set) and a part used to evaluate forecasting performance (the testing set). To compare performance, two differently sized estimation windows are used in the training set. One covering two thirds of the sample and one covering four fifths.

Given the difficulties of predicting daily asset returns, for this test, monthly returns are used. The estimated model used for the tests is the 22 days simple moving average regression of the CoG on the various asset returns. A random walk model, which is constructed as the sample historical average return, is used as a benchmark to weigh the results of the regression forecast against. For each prediction, the monthly cumulative forecast return at time t is subtracted from the real cumulative return of the asset at time t. Formula 3.4 is used to compute the out of sample R^2.

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(r_i - \hat{r}_i)^2}{\sum_{t=1}^{T}(r_i - \overline{r})^2} \tag{3.4}$$

Where $\hat{r}_i$ is the predicted value from the regression through period $t-1$ and $\overline{r}$ is the random walk historical average return estimated through period $t-1$. Table 3.9 displays the results of the out of sample test. It is immediately obvious that the results of the the out of sample test are not more predictive than their in sample counter part. The test for all assets, except for the GSCI Commodity index with a 4/5th estimation period, display a negative difference in R^2. On a relative basis, the results are worst for the 10 year U.S Yield and best for the Commodity Index.

Since no structural changes are assumed and out of sample forecasting begins in September 2010 and ends in December 2019 without any economic recessions, it is considerably different than the estimation period. The estimation period contains business cycles and crisis's, among which the GFC. As such, an explanation for the poor performance of the out to sample test could be the structural differences in sample properties (see e.g. Inoue and Kilian 2005).

Table 3.9: Out of sample R^2, 1988:12-2020:01.

The table displays the results of the out of sample R^2 of the forecast performance of the 22 days SMA CoG regression on asset returns. The variables studied are shown in the first column. Column two and three display the R^2 for the two thirds and and four fifths model estimation period respectively. The third column displays the in sample R^2. The fourth and fifth column display the difference between out of sample and in sample R^2.

	Estimation period:				
Variable	2/3th	4/5th	In sample	$\Delta_{2/3th}$	$\Delta_{4/5th}$
10 year U.S Yield (%)	-1.131	-1.148	0.176	-1.289	-1.291
S&P 500	-0.296	-0.287	0.010	-0.306	-0.297
FTSE 100	-0.103	-0.107	0.007	-0.110	-0.114
Nikkei 225	-0.067	-0.078	0.002	-0.069	-0.098
Euro Stoxx 50	-0.092	-0.119	0.007	-0.099	-0.126
GSCI Commodity index	-0.044	0.014	0.006	-0.05	0.008
Global Investment Grade bonds	-0.081	-0.057	0.005	-0.086	-0.062
Global High Yield bonds	-0.902	-0.886	0.022	-0.924	-0.908

4 Trading Strategy

The main objective of this chapter is to investigate the profitability, performance and the risk of using the CoG in a portfolio trading strategy. For this analysis, monthly cumulative data on the CoG and the various assets is used. The CoG is used as a technical indicator to identify entry- and exit points in the market, and the return from the trading strategy is compared to a buy-and-hold strategy. For simplicity, transaction costs are assumed to be zero.

4.1 Methodology

The methodology of the trading strategy is formed around changes in the cumulative return of the CoG leading up until the second to last day of the month. At the last day of the month, the CoG serves as a trading sign for the following month. An increase in the cumulative return of the CoG compared to the previous month, indicates a positive trading signal. The main logic behind this is the positive relationship between asset returns and the CoG as set out in chapter 1. When the trading signal is positive, the underlying index will be bought once and held for a month. Earning the return of that month. When the trading signal is negative, i.e the cumulative return CoG is lower, the market will be exited for that month. Earning a return of zero. To evaluate the performance of the strategy, where returns are reinvested, the compounding return is calculated using equation 4.1.

$$R_i = (1 + R_{t=1})(1 + R_{t=2})\dots(1 + R_{t=T}) - 1 \quad \text{for} \quad t = 1, \dots, T \tag{4.1}$$

Where R_i is the total cumulative return of asset i over time T, and R_t is the return of the asset at time t.

4.2 Results

Table 4.1 and figures 4.1 to 4.8, present the results obtained for the different asset classes and reports various risk and performance based metrics. The studied metrics are the Sharpe Ratio[1], standard deviation, the CAPM[2] Beta and Alpha and mean returns. Com-

[1] $S = \frac{R_a - R_f}{\sigma_a}$

[2] $E(R_i) = R_f + \beta_i(E(R_m) - R_f)$

paring the results of the trading strategy against those of the naive strategy, it can be concluded that the strategy is of economic value to some but not all asset classes. On a risk adjusted basis, the trading strategy performs better than the naive strategy on the S&P 500, Nikkei 225 and GSCI commodity index. For the U.S Yield, FTSE 100, Euro Stoxx 50 and the bond indices, the naive strategy provides better risk-adjusted performance. For most indices, the systematic risk (beta) is decreased by about half. Figures 4.1 to 4.8 display the cumulative return over time. Figures 4.4 and 4.6 show the return for the Nikkei and GSCI index, where the cumulative return of the trading strategy is higher than the buy-and-hold return.

Table 4.1: Trading Strategy Performance and Risk, 1988:12-2020:01.

The table displays the results of the Trading Strategy against the buy-and-hold strategy. The variables studied are shown in the first column. Column two and three display the Capital Asset Pricing model Alpha and Beta (significance at the 5% level). The third to last column displays the Sharpe Ratio (the risk-free rate is assumed to be zero), mean monthly return and the standard deviation. Asterisks (*) denote the statistic for the Trading Strategy.

Variable	CAPM α	CAPM β	Sharpe	Sharpe*	Mean	Mean*	SD	SD*
10 year U.S Yield (%)	-0.003	0.296	1.498	0.765	0.019	0.011	0.128	0.014
S&P 500	0.001	0.502	0.159	0.207	0.678	0.452	4.267	3.040
FTSE 100	0.000	0.499	0.099	0.070	0.412	0.206	4.178	2.957
Nikkei 225	0.002	0.487	0.029	0.062	0.182	0.305	6.303	4.396
Euro Stoxx 50	0.001	0.482	0.100	0.097	0.516	0.347	5.141	3.578
GSCI Comm.	0.003	0.462	0.059	0.117	0.357	0.481	6.055	4.110
Investment Grade bonds	0.000	0.558	0.346	0.245	0.579	0.374	1.673	1.282
High Yield bonds	0.000	0.630	0.289	0.227	0.919	0.580	3.174	2.558

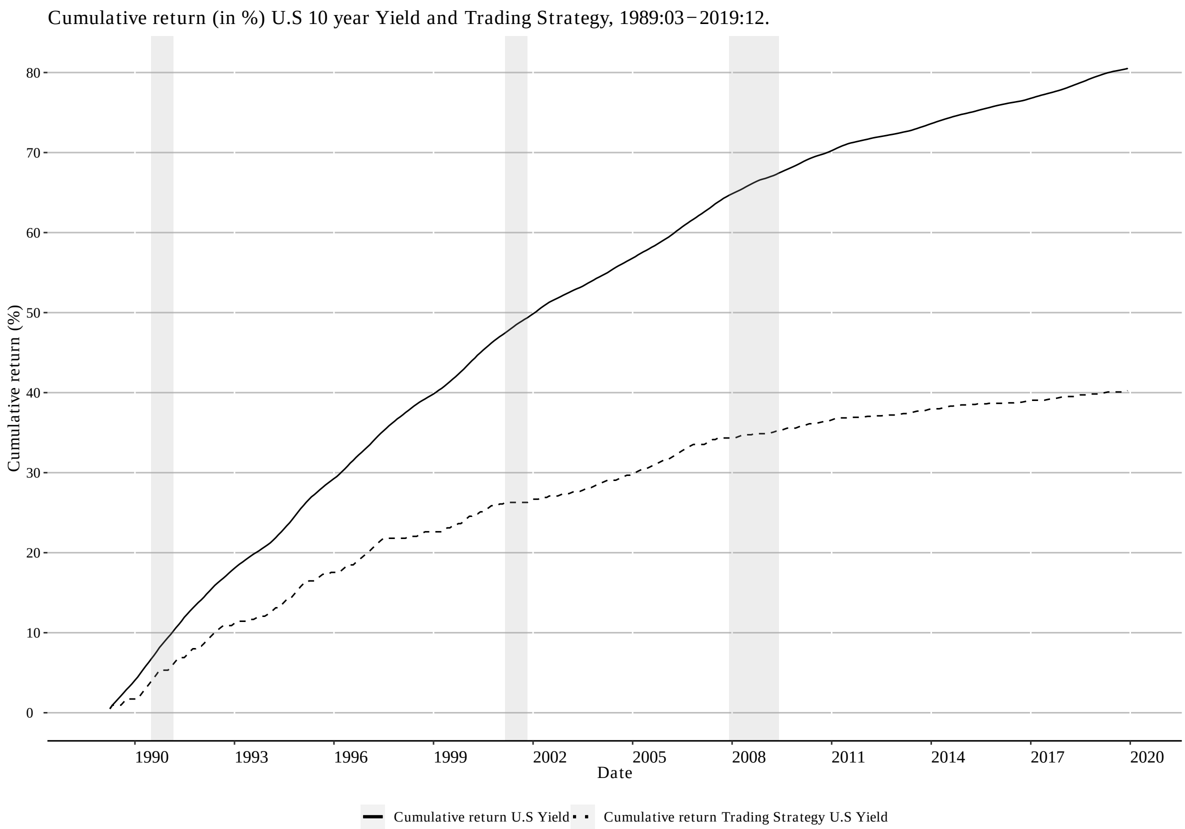

Figure 4.1: U.S Yield cumulative return Trading Strategy against buy-and-hold strategy 1989:03-2019:12. The solid line delineates the buy-and-hold strategy and the dotted line the Trading Strategy. Vertical grey bars display recessions as dated by the National Bureau of Economic Research (NBER).

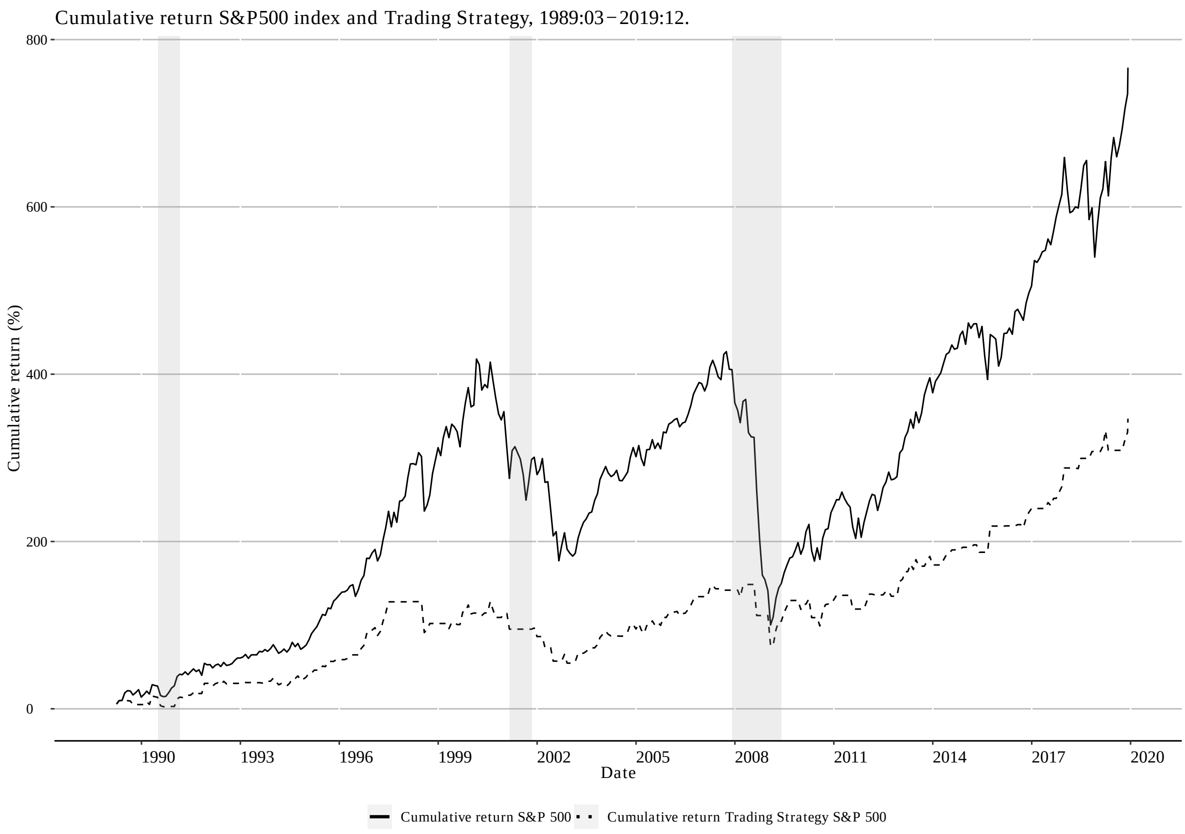

Figure 4.2: S&P 500 cumulative return Trading Strategy against buy-and-hold strategy 1989:03-2019:12. The solid line delineates the buy-and-hold strategy and the dotted line the Trading Strategy. Vertical grey bars display recessions as dated by the National Bureau of Economic Research (NBER).

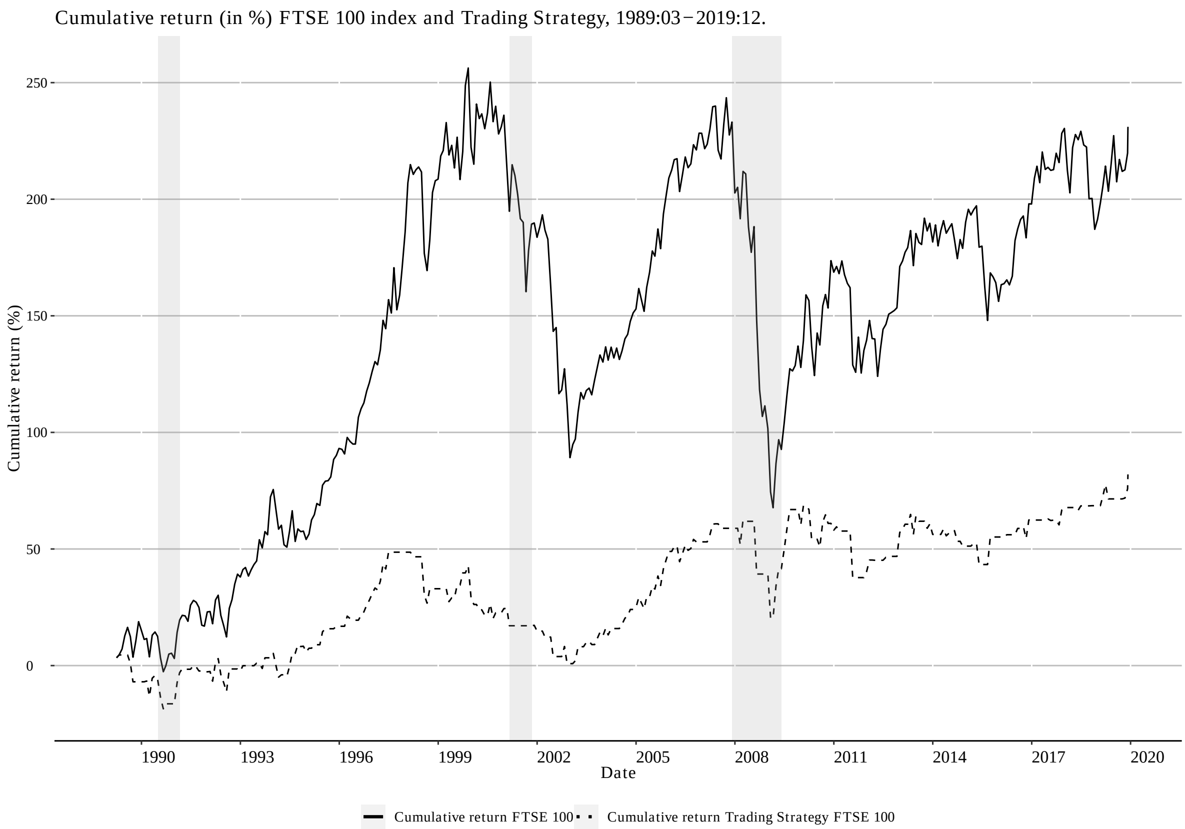

Figure 4.3: FTSE 100 cumulative return Trading Strategy against buy-and-hold strategy 1989:03-2019:12. The solid line delineates the buy-and-hold strategy and the dotted line the Trading Strategy. Vertical grey bars display recessions as dated by the National Bureau of Economic Research (NBER).

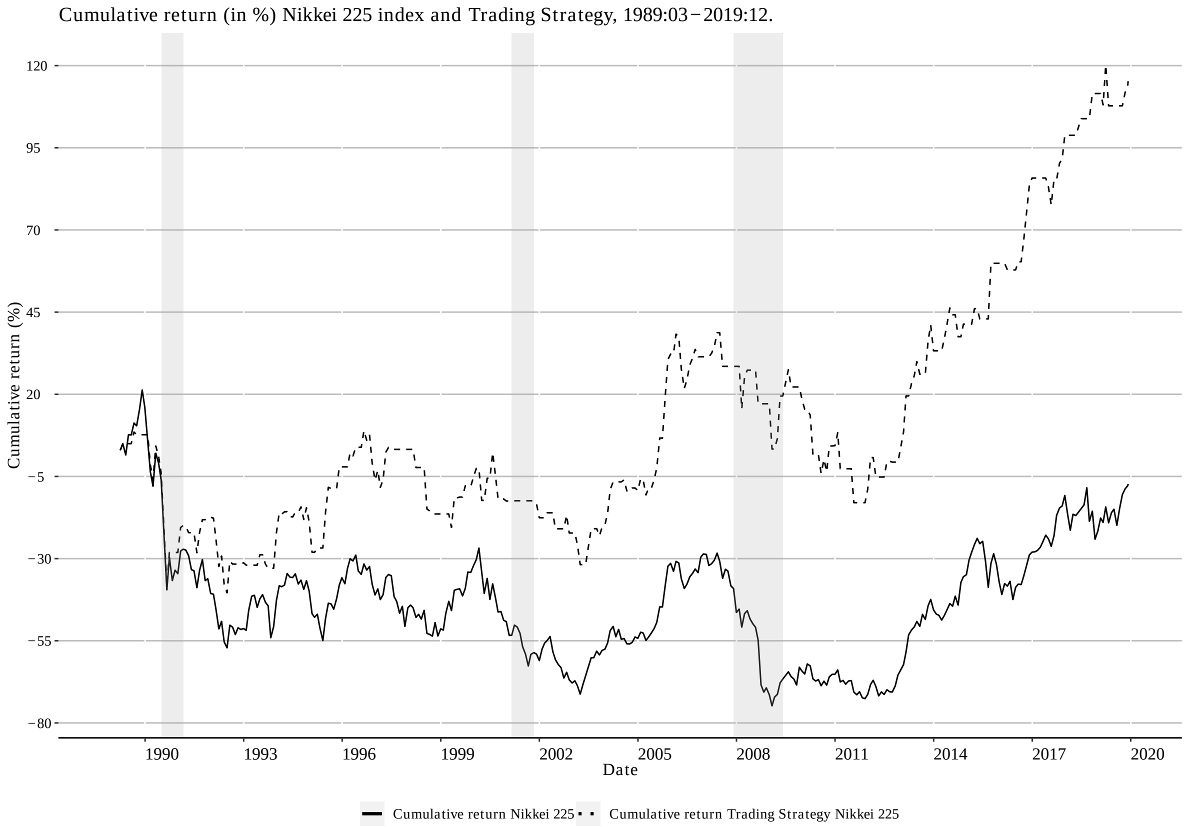

Figure 4.4: Nikkei 225 cumulative return Trading Strategy against buy-and-hold strategy 1989:03-2019:12. The solid line delineates the buy-and-hold strategy and the dotted line the Trading Strategy. Vertical grey bars display recessions as dated by the National Bureau of Economic Research (NBER).

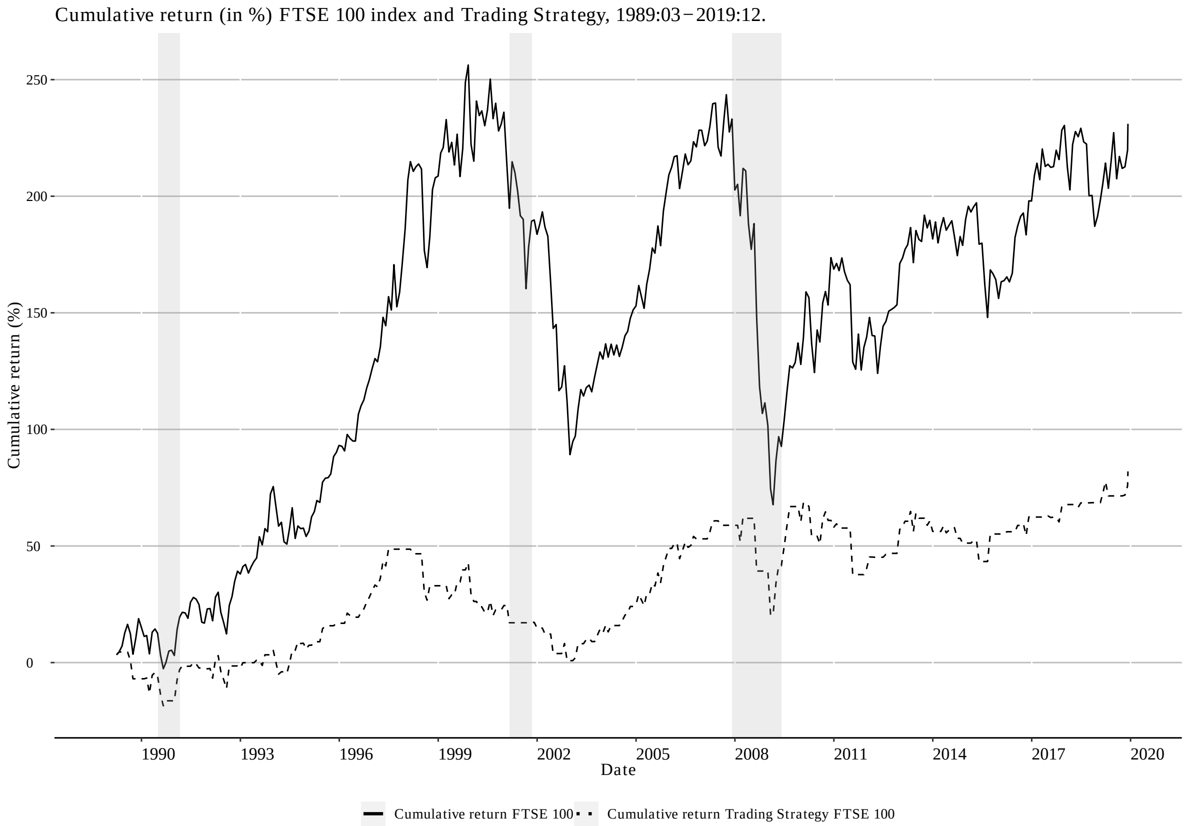

Figure 4.5: Euro Stoxx 50 cumulative return Trading Strategy against buy-and-hold strategy 1989:03-2019:12. The solid line delineates the buy-and-hold strategy and the dotted line the Trading Strategy. Vertical grey bars display recessions as dated by the National Bureau of Economic Research (NBER).

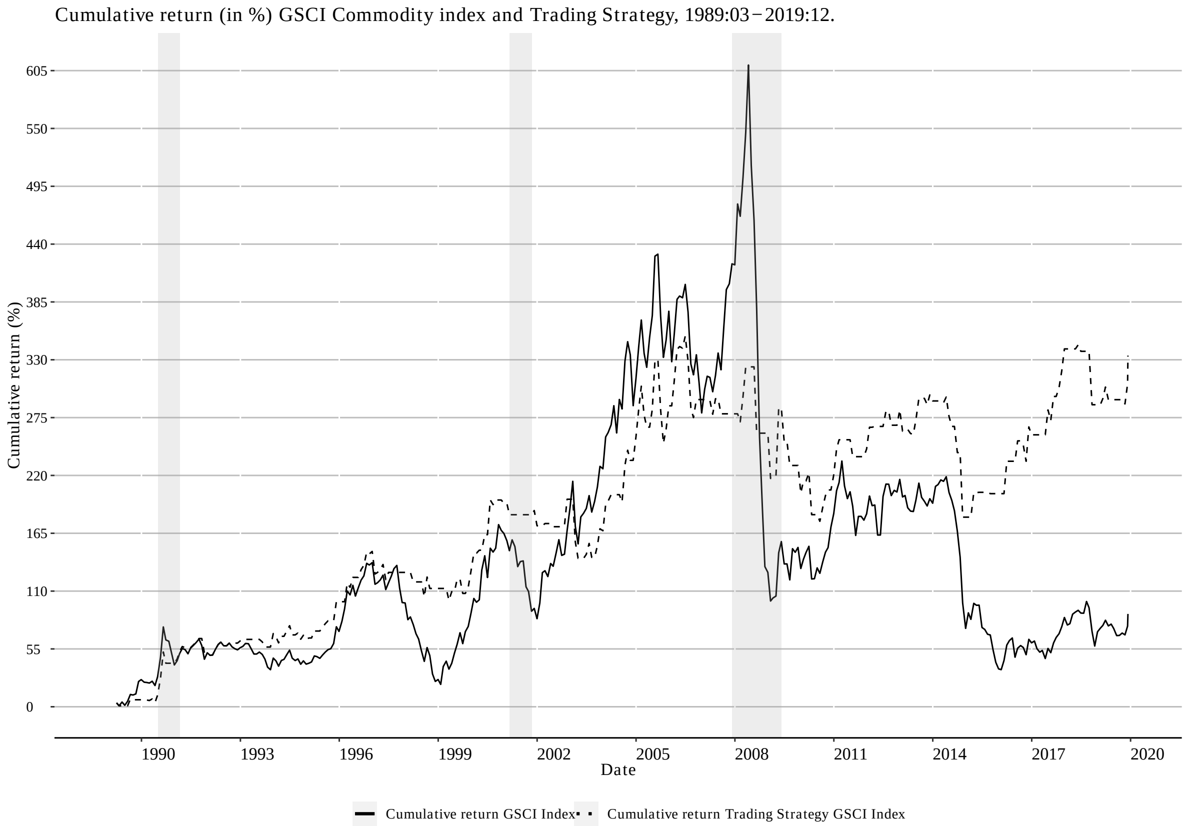

Figure 4.6: GSCI Commodity index cumulative return Trading Strategy against buy-and-hold strategy 1989:03-2019:12. The solid line delineates the buy-and-hold strategy and the dotted line the Trading Strategy. Vertical grey bars display recessions as dated by the National Bureau of Economic Research (NBER).

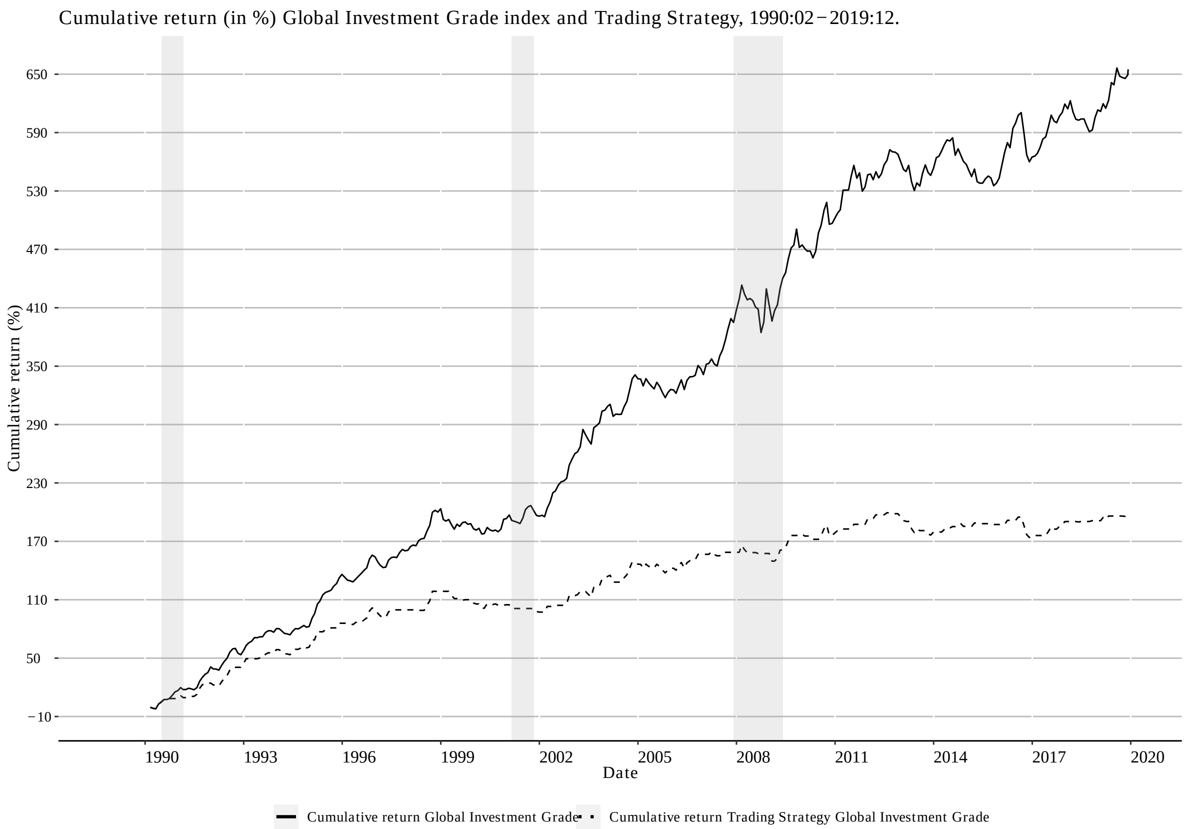

Figure 4.7: Global Investment Grade bonds cumulative return Trading Strategy against buy-and-hold strategy 1989:03-2019:12. The solid line delineates the buy-and-hold strategy and the dotted line the Trading Strategy. Vertical grey bars display recessions as dated by the National Bureau of Economic Research (NBER).

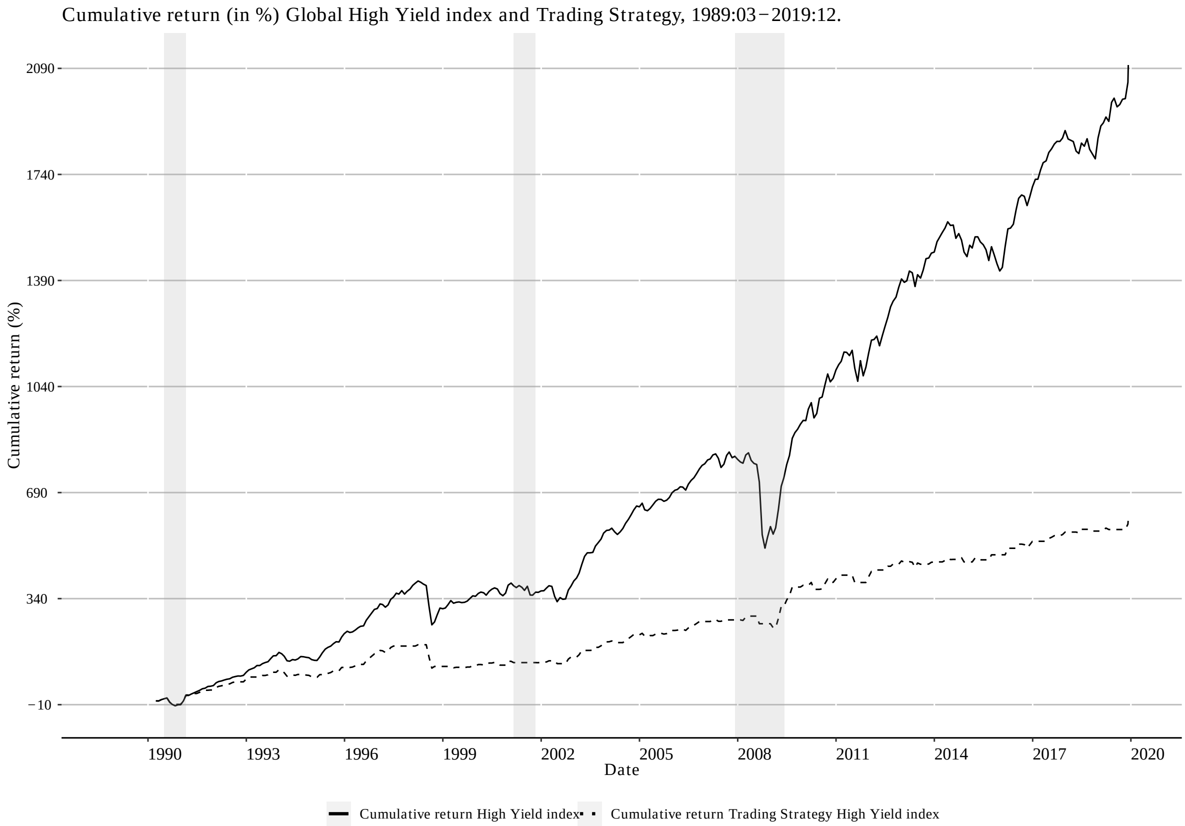

Figure 4.8: Global High Yield bonds cumulative return Trading Strategy against buy-and-hold strategy 1989:03-2019:12. The solid line delineates the buy-and-hold strategy and the dotted line the Trading Strategy. Vertical grey bars display recessions as dated by the National Bureau of Economic Research (NBER).

5 Discussion and Conclusion

In this study, we find that the CoG, when controlling for economic and financial variables, is a statistically and economically significant predictor of interest rates and of equity, commodity and high yield bond market returns. The significance has been found for our sample period covering 1988:12 until 2020:01. No significance of the CoG as a predictor for Investment Grade bond returns have been found, as possibly this asset class is less subject to the economic cycle. In out-of-sample forecasts on monthly returns over the same time frame, no statistically and economically significant predictive power was found. This could be due to structural changes in the data over time or due to the fact that in-sample results do not by definition match out-of-sample results.

The predictor is most significant for the 10 year U.S Yield, where its predictive power spans the period covering the entire time frame, as well as the pre- and post GFC period. The hypothesis that the relationship between the CoG and the U.S Yield weakened after the GFC is rejected. The predictive power is found to have increased significantly post GFC. Further research on the impact of monetary policy on our predictor variable is needed to find an explanation for this.

The hypothesis that the CoG is a predictor for equity market returns cannot be rejected based on our findings. However, a negative relationship was found instead of the hypothesised positive relationship. Given earlier literature which found a positive relationship, a practical implication for our study is that this is the result of our model specification.

The statistical and economical significance of moving average past returns of the CoG, has been found for the U.S Yield, all equity indices, the commodity index and High Yield bonds. For the U.S Yield, commodity and equity market returns, this effect is strongest for short to medium term past returns of the CoG. This indicates that short and medium term trends in the CoG are more relevant when predicting current returns than longer term trends. For the High Yield index, past returns are significant regardless of the time frame considered.

Our trading strategy, were changes in the return of the CoG are used as a trading sign, resulted in economic value for the S&P 500, the Nikkei 225 and GSCI Commodity Index. For these indices, higher risk adjusted returns were achieved than a naive strategy. Significantly lower risk adjusted returns were achieved when trading the U.S Yield. Given the significant predictive power of the CoG on the U.S Yield as found in this study, we believe that refining the trading strategy, by including more trading signals, could yield better results.

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