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Copper Price Fluctuations and the Stock Market

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COPPER PRICE FLUCTUATIONS AND THE STOCK MARKET

MASTER THESIS

By

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Abstract

The aim of this study is to investigate whether the fluctuations in the copper price can add predictive power to a model forecasting stock market returns. Our findings from the in-sample test are that past fluctuations in the copper price are related to current stock returns. Appreciations in the copper price during contraction periods forecasts positive stock returns, and counter wise, decreased stock prices during expansionary periods. From the out-of-sample experiment, using a rolling window regression, we find that copper price returns forecast directional returns in the S&P 500. The discussion of our findings backs up the idea that stock market return predictability is the logical response to varying business cycle conditions rather than stock market inefficiencies.

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1.0 Introduction

Predicting the stock markets in a turbulent world is as intriguing as it is challenging. The search for sufficient estimators that can contribute producing quality forecasts on where the stock markets are headed has therefore for long been an attractive topic. There have been conducted several studies exploring the relationship between macroeconomic variables and the stock market returns. The stock market returns has seemed to vary with the business cycle in the past decades. Ilan Cooper and Richard Priestley (2007) have proved that the output gap is a strong predictor of the US stock returns. Moreover, Fama and French (1988) have also proved that the spot and futures prices of industrial metals are closely related to fluctuations in the business cycles. Since the output gap is a strong predictor of the stock market and the copper price is strongly related to the business cycle, it is not unreasonable to believe that there is a relationship between copper and equity prices.

Both macroeconomic trends and financial markets are constantly changing, and the increasing relevance of copper makes it a highly interesting commodity to investigate. The demand for industrial metals, and especially copper, is expected to increase in the coming years as electricity as an energy source are becoming more dominant in mobility, renewable energy sources and energy storage. The green shift will demand a significant and continuous growth in battery manufacturing over the next decades (Nurmi, 2019). Since copper is one of the most efficient thermal electrical conductors there is, it’s likely that the commodity will play a vital part of our renewable energy future. In a scenario that meets the Paris Agreement goals, clean energy technologies’ share of total demand rises significantly over the next two decades, to over 40 percent for copper (IEA, 2021).

Figure 1: *Historical prices of copper and the S&P 500 (Bloomberg). Shading indicates CFNAI defined contractionary periods.*

Due to this increased importance, copper has been recently called "the new oil" by Goldman Sachs (Saywell, 2021). The metal has for long been credited for having a Ph.D. in economics since the price of copper is considered as a leading indicator of turning points in the global economy. In a previous study conducted by Jacobsen et. al. (2018) it was proved strong predictability between industrial metals and stock market returns. In our thesis we aim to assess whether price fluctuations in the commodity copper is related to stock market returns. Our research questing is:

Can the fluctuations in the copper price improve the forecast of the stock market returns?

To answer our research question, we will conduct both in- and out-of-sample experiments. We will separate and study both contractionary and expansionary periods in the business cycle in order to investigate the dynamics between copper price fluctuations and the stock market. Our focus will be on the United States and S&P 500, as the US is the largest economy. However, we will also study several of the world's major stock indices in the analysis. Based on previous studies, we expect to find a negative relationship between past copper price fluctuations and stock market returns during expansionary periods, and otherwise in contractionary periods.

Our motivation to delve deeper into this topic of exploring the relationship between the copper price and other financial variables stems from that the previous research on similar topics are somewhat divided with respect to focus and empirical findings. Our findings will contribute to provide an understanding of the dynamics between the copper price and stock returns, as well as contribute with knowledge for further exploration on the subject. Our results may also confirm or refute the findings of Jacobsen et. al. (2018) with most recent data until 2021. We will also investigate the potential relationship on different stock markets. We are also interested in finding out whether the connection is stronger in copper exporting nations, as it has been proven that oil is a leading indicator for the Norwegian stock market returns (Bjørnland, 2008). Therefore, we include both Chile and Australia in our analysis. We will only discuss the economic reason for potential forecasting ability based on previous literature, and not conduct any empirical research on the matter.

Our thesis is structured in the following way: applied theory and literature will be presented and discussed in *chapter 2 Literature Review*. Here we explore existing literature on using commodities to predict the stock markets and its relation to the real economy. In *chapter 3 Methodology*, we present the hypotheses we have developed in line with our research question. Furthermore, we proceed by presenting and discussing the research methodology approach. We will also outline which variables we use and where they are retrieved from. In *chapter 4 Analysis*, we describe the analysis and our findings from our in- and out-of-sample tests Furthermore, in *chapter 5 Discussions*, we discuss reason for predictability, address the limitations of this thesis, and discuss opportunities for further research on the topic. At last, in *chapter 6 Conclusion*, we provide a final conclusion of our findings.

2.0 Literature Review

In financial economics, there have been done several studies exploring the relationship between commodities and the stock market. Results from these studies are inconclusive, but several works have uncovered existing causalities between macroeconomic variables and the stock market. While many studies have addressed the relationships between resource prices and economic variables, few have modeled the copper price's predictive power of economic or financial variables. In fact, there have been done in general limited research on any commodity's ability to forecast equity returns. In this chapter we will present relevant literature, empirical studies and theories which have tested and extended research on the topic.

Commodity prices have been shown to respond to changes in expected demand and supply, and have been shown to exhibit predictive power for future output growth (e.g. Bakshi, Panayotov, & Skoulakis, 2011; Jacobsen, Marshall, & Visaltanachoti, 2018). For this reason, changes in commodity prices may provide us timely information about the future economic conditions, which are also related to stock returns. This effect may be especially strong for energy commodities and industrial metals as these commodities are heavily used in the industrial production. As mentioned in the introduction, copper is the most applicable base metal there is, and it deserves therefore attention in the future exploration. This chapter will end with an explanation of why copper is such an important raw material.

2.1 Predicting the stock market

Predicting the stock market has for long been controversial and a popular topic of research. Despite the vast research on the topic, it is still a controversial subject. Under the efficient market hypothesis, the returns should not be predictable (Woolridge, 2018). If the market is fully efficient, all prices always reflect all relevant information. As soon as news comes out, prices immediately react to fully reflect the new information (Pedersen, L. H., 2015). If is this true, any effort to beat the market would be a wild-goose chase. However, if no investors would try to beat the market, the market would not be efficient, which is a paradox entailed by Grossman and Stiglitz (1980). They concluded that the stock markets must entail an “equilibrium level of disequilibrium”. However, some argue that risk factors must be the reason for predictability of stock market returns, since investors are rational, and market is always in equilibrium. Pricing errors are in this case impossible (Fama, 1970).

Many of the previous studies has delivered weak in-sample and out-of-sample results, and the reason for why the stock market is predictable is vague. Although, Fama and French (1988), Campbell and Shiller (1988), Lamont (1998) and Rangvid (2005) has documented that stock returns can be predicted using dividends, earnings, or GDP. Furthermore, Jacobsen et al. (2018) have proved that industrial metals can be used as a predictive indicator to predict stock returns, using a state-switching model depending on the state of the economy. However, many of the well-known anomalies in finance do not hold up in different sample periods. The size- and value effect, explored by Fama and French, seem to have disappeared after their results were published. The famous *weekend effect* and the *dividend yield effect* also seem to lose their predictive power after the theories were published. Similarly, the predictive power of inflation and dividend yield also seem to fade away after the papers that documented these findings were published (Schwert, 2003).

2.2 The link between industrial metal prices and the business cycle

Commodities, as raw materials for industrial production activities as well as necessary consumption goods for our daily life, play an essential role in the economy. Over the past decade, the trading volume of the commodity market increased from 800 million in 2005 to 4.6 billion in 2015 (Acworth, 2016). The commodity market differs from the traditional stock and bond markets in relation to GDP growth in the way that it combines the properties of both the goods market and the financial market, which relates finance to real economy (Ge & Tang, 2020).

The empirical relation between commodity prices and growth to economic output has long been an important topic, and over the long run, commodity booms and busts correspond well with the economic cycles. What is more, using factor analysis, Labys, Achouch and Terraza found that there is a strong relationship between international business cycles and the prices of industrial metals (Labys et al., 1999). More specific, Fama and French found that the spot- and futures prices of industrial metals, as aluminum, lead and copper, are closely related to the business cycles and that a rapid increase in metal prices occurs before the economy reaches its peak and a drop then occurs after the peak. They suggest that the increase in price reflects near-term supply responses that are insufficient to absorb positive demand shocks around the business cycle peaks (Fama & French, 1988). Jacobsen et. Al (2018) finds similar patterns and that the price of industrial metals starts increasing just before the economy hits the through.

Papers such as Baumeister and Kilian (2012) and Alquist et al. (2013) show changes in industrial metals prices have both in- and out-of-sample predictive power for the price of oil, like that from measures of global real activity (e.g., Kilian and Park, 2009). Empirical studies, such as Barsky and Kilian (2002, 2004), also suggest that the prices of industrial commodities can provide a signal for the strength of the economy, similar to the oil price. The idea that the copper price changes may provide important information about the economy is widely documented in the financial press. For instance: *«Copper has a Ph.D. in economics. Because copper is used in everything from electrical wiring to water pipes, it is seen as a good measure of the economy. If demand for copper falls, then it's believed the economy is slowing. »* (Who crashed the economy, 2007). This quote assumes that copper price changes mainly are a result of changes in demand. However, this may not always be the case, and supply side shocks can be expected to have some impact on the price as well.

2.3 The link between the business cycle and the stock market

The connection between macroeconomic variables and financial market has for long been an objective of financial economics, mainly since expected returns on stocks appears to vary with the business cycle, according to Lettau & Ludvigson (2001). They have studied the role of fluctuations in the aggregate consumption-wealth ratio for predicting the stock returns. This study was important in order to establish a more direct link between economic fundamentals and stock return predictability. By using the US quarterly stock market data, they found that the fluctuations in the consumption-wealth ratio is a strong predictor of real stock returns. Ilan Cooper and Richard Priestley (2007) have also proved in one of their studies that the output gap, which is a measure of actual output related to the potential output in the economy, is a strong predictor of the international stock excess returns. Furthermore, they also proved that it is a predictor of the US bond excess returns. Their results were robust in both their in-sample and out-of-sample tests.

2.4 The link between commodity prices and financial variables

There have been conducted several studies on the dynamics between commodity prices and the stock market. Sadorsky (1999) uses an unrestricted VAR on American monthly observation from 1947 to 1996. He concludes that oil price changes and oil price have a significantly negative impact on real stock returns on S&P 500. Moreover, a study conducted by Hilde Bjørnland (2008) provides evidence that following a 10 percent increase in oil prices, the Norwegian stock market returns increase by 2.5 percent, after which the effect eventually dies out. The results are robust, both OSEBX and OSEAX responds significantly to a shock in the oil price. The effects on the other variables; inflation, GDP, unemployment, and exchange rate, are more modest. However, all variables indicate that the Norwegian economy responds to higher oil prices by increasing aggregate wealth and demand. The results also emphasize the role of other shocks; monetary policy shocks in particular, as important driving forces behind stock price variability in the short term (Bjørnland, 2008).

While the oil price has been frequently used as explanatory variables in order to explain stock market fluctuations, very few have however explored the relationship between industrial metals and stock returns. Jacobsen et. al. (2018) conducted a study, using linear regression methods, whether price movements in base metals such as copper and aluminium predict stock returns. Using a state switching model based on two specifications of the business cycle states, they found that increasing industrial metal prices are bad news for equity markets in expansion periods, but good news in contraction periods. As noted by Kilian and Park (2009), the impact of commodity price changes, in their case oil, on stock returns differs depending on whether the changing price of oil is driven by demand or supply shocks. It is important for us to emphasize that this may have an impact on our discoveries and the quality of copper as a leading indicator for the stock market return. Especially in the future as it is expected that the supply of copper may be reduced. In our analysis, we will however assume that the price fluctuations are mainly driven by aggregate demand. Sadorsky (2014) performed a study of correlations between emerging market stock prices and the prices of copper, oil, and wheat. This study showed that the squared returns in emerging markets correlated highest with copper, compared to oil and wheat. The paper also shows that the dynamic conditional correlations between the prices of emerging market stocks, oil, copper, and wheat increased after 2008.

2.5 Economic regime shifts and predication

The study conducted by Jacobsen B. et al. (2018) proved significant evidence that price movements in industrial metals such as copper and aluminum indeed predict stock returns. They focused on historical futures metal prices rather than historical spot prices because futures are more liquid and receive more attention in the media. Their analysis proved that increasing industrial metal prices indicate increasing inflation and economic activity in both recessions and expansions. The fact that these increases coincide with increases in the stock market in recessions and decreases in expansions is consistent with Boyd et al. (2005). A one-standard-deviation increase in industrial metal returns predicts a price drop of one and a half percent in monthly stock market returns in expansions and an increase of around a half percent during recessions. This fits with the findings of Pesaran and Timmermann (1995) who showed that different variables are better at predicting U.S. stock returns at different times because of "economic regime switches" (p. 1224). Timmermann and Pesaran examined the robustness of the evidence on predictability of U.S. stock returns and addressed the issue of whether this predictability could have been historically exploited by investors to earn profits in excess of a buy-and-hold strategy in the market index. They found that the predictive power of various economic factors over stock returns changes through time and tends to vary with the volatility of returns. The degree to which stock returns were predictable seemed quite low during the relatively calm markets in the 1960s, but increased to a level where, net of transaction costs, it could have been exploited by investors in the volatile markets of the 1970s (Pesaran and Timmermann, 1995). Similarly, Boyed et al. (2005) found in a study that on average, an announcement of rising unemployment is good news for stocks during economic expansions and bad news during economic contractions. Several other studies find that many predictors tend to give stronger signals in economic recessions than in expansions (e.g., Dangl and Halling 2012, Henkel et al. 2011, Rapach et al. 2013).

2.6 The relevance of copper

The modern history of copper consumption is as briefly mentioned closely linked to the emergence of electricity. During the hundred years that followed, we have witnessed waves of electrification that have covered practically the entire globe in the most recent decades. Since high conductivity of electricity is one of the distinctive features of copper, this course of industrialization led to a vast increase in demand for this red metal. In the 20th century, copper's versatility has spread its use very widely among industrial and service activities that dominates every prosperous society. About half of the total usage has remained in applications related to electricity. Copper cables and wires have been carrying electric current for power, light and telecommunications across long distances as well as in buildings, cars, aircraft and devices like refrigerators, televisions and computers (Radetzki, 2009).

The relevance of the base metal copper is likely to increases in the future as it plays a vital role in the decarbonization of our society. The metal is a required material in almost all sectors and industries, which may indicate that this is not an unfounded thesis. Barsky and Kilian (2002, 2004) back this theory and also suggests that the prices of industrial commodities like oil or copper may provide a signal for the strength of the economy. Modern copper mining often requires the extraction and treatment of large volumes of low-grade copper ore. Such mines require investments of billions of dollars to develop new resources that are often many years in the planning and approval process. A sudden increase in demand for copper will likely lead to a significant increase in the price of the commodity and stimulate the large investments in new mines or mine expansions necessary to bring on new supplies of copper (Golding, 2017).

Copper is a base metal that has versatile applications across utilities — heavy industry, transport, and communication. It is the wide range of applications that makes copper prices a bellwether indicator of the booms and busts in the economic cycle (ICSG, 2018). The International Copper Study Group (ICSG) estimates the key user industries for copper to be equipment (31 percent), construction (29 percent), industry (11 percent), transport (13 percent) and infrastructure (16 percent). The reasons why copper is so desirable is its properties when it comes to electric resistivity, thermal conductivity, hardness, and its ultimate tensile strength. Electric resistivity is the most reported measure of the electrical properties for metals. It is the reciprocal of the material's ability to conduct electricity and so, the lower the value the better the electrical conductivity. Pure copper is twice as good as the aluminum alloy and several times better than steel in its ability to conduct electricity. (Golding, 2017).

3.0 Empirical Methodology

As shown above, there are some literatures on the subject and a certain interest in using commodities as explanatory variables to gain a better understanding of the equity market. This chapter provides the methodical framework we will use to examine the potential forecasting ability of the stock market using copper returns. We start by formulating our regression models, followed by building our hypothesis based on the previous literature presented above. Secondly, we describe the data used in our analysis. Finally, we will explain how we will check for violation of the classical linear regression model (CLRM) assumptions.

3.1 Models

To get an understanding of the significance of copper price in forecasting stock prices, we will first regress a simple ordinary least squares (OLS) model with lagged dependent variables. The reason for the time lag between the dependent and the independent variables is that we are curious to discover whether current copper price might be able to construct stock return forecasts one month ahead. Using a similar model design as Jacobsen et al. (2018), our state switching regression specification are given as follows:

(1) $$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper_{t-1} + \beta_2 C_{t-1} Copper_{t-1} + \beta_3 Control_{t-1} + \varepsilon_t$$

We will also test a model where we adjust for economic state in both copper price and the control variable.

(2) $$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper_{t-1} + \beta_2 C_{t-1} Copper_{t-1} + \beta_3 E_{t-1} Control_{t-1} + \beta_4 C_{t-1} Control_{t-1} + \varepsilon_t$$

Furthermore, we will test a model with non-state-switching copper price return, and non-state-switching control variable, for comparison.

$$(3)\ Stock\ r_t = \alpha + \beta_1 Copper_{t-1} + \beta_2 Control_{t-1} + \varepsilon_t$$

Where:

Stock r	*Monthly stock return on given index*
E	*Dummy variable for expansion*
C	*Dummy variable for contraction*
Copper	*Monthly return in copper spot price*
Control	*Some control variable in the model*

Expansions and recessions can be defined by setting E_{t-1} as a dummy variable that equals one if the economy is expanding and zero if it is contracting (in $t-1$). Similarly, R_{t-1} as a dummy that equals one if the economy is contracting and zero if it is expanding (in $t-1$) (Jacobsen et al., 2018). There are several alternatives to determine the state of the business cycle. Previous work uses the monthly published Chicago Fed National Activity Index 3-month moving average (CFNAI-MA3) US business cycle data, or the National Bureau of Economic Research (NBER) defined recessions as a proxy for the business cycle in all countries included in the analysis. Developments in the US economy, by far the world's largest, have a significant impact across the globe. An increase in US growth could provide a significant boost to the global economy both directly through increased import demand, and indirectly through productivity spillovers. Tightening US financial conditions, whether due to contractionary monetary policy or other reasons could cause negative impacts across the global financial markets. This may also cause detrimental effects on some developing economies that rely heavily on external financing. Given its sizable role in global commodity markets, an acceleration in US economic activity tends to significantly lift global commodity demand and raise prices (Kose et al., 2017). We find therefore the US data suitable as a proxy for the business cycle among all countries in our analysis.

Expansions last on average about four to five years but have been known to go on anywhere from 10 months to more than 10 years. NBER subsequently determines the dates for business cycles in the United States. We will use the CFNAI-MA3 business cycle data when determining the business cycle dummy variables. This index is a weighted average extracted from 85 separate economic series describing the real economy. It is normalized to zero on average, so positive values denote economic activity above its trend rate of growth, whereas negative values indicate growth rate below the trend. When the CFNAI-MA3 is below -0.70, we classify the month as "*Contraction*". The reason why we prefer the CFNAI before NBER is due to its real time properties. It makes it more suitable when performing a real time prediction. For the out-of-sample experiment using the NBER data would cause hindsight bias since the figures aren't released until the quarter has finished. To ensure that hindsight bias is not driving the results, we will therefore also use the CFNAI in our out-of-sample tests. In this way this section uses only data that would have been available to investors in real time.

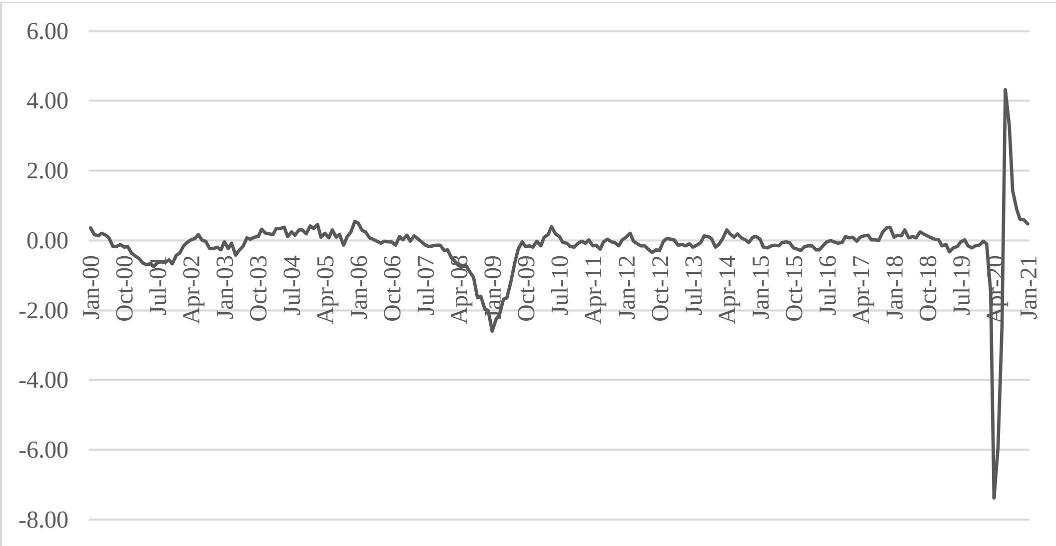

Figure 2: *Historical data of the Chicago Fed National Activity Index, 3 month moving average (CFNAI-MA3). A positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend.*

3.2 Hypothesis

When formulating our model for the in-sample test, we find inspiration from the article of Jacobsen et al. (2018), as they have already performed a similar study with the industrial metal index. We will differentiate ourselves from them by using the copper spot price to predict the different stock markets and using more up-to-date data. The different timeframe enables us to test whether the findings provided by Jacobsen et al. are still valid for more recent data. Based on previous findings, we expect to find a positive relationship between the copper price in periods classified as contraction, but otherwise in expansion periods.

We will regress a model and investigate whether it results in a significant movement in the world's largest stock market indices. Based on the research question stated in the introduction, we have formed the following two hypotheses.

Hypothesis 1: In-sample
Is there a relationship between copper price return and future stock returns?

> *H_0: Copper price return coefficients are zero.*
> *H_1: Copper price return coefficients are statistically different from zero.*

Hypothesis 2: Out-of-sample
Can the fluctuations in the copper price forecast the direction of the stock market returns?

> *H_0: Copper price return coefficients forecasts no direction.*
> *H_1: Copper price return coefficients forecast a direction.*

3.3 Data collection

The time series data for the analysis will be collected using Bloomberg and Macrobond. We will include monthly time series data, priced denominated in US dollars and dated back to year 1977. The data will first be implemented as a data frame in Excel before we implement it into Matlab for analysis. We have included major national stock indices as: US, Chile, China, India, South Korea, Canada, Australia, Norway, UK, Japan, France, and Germany. This will enable us to observe the potential relationship in both copper exporting- and importing countries. Furthermore, we will use copper's settlement price traded at LME as the international copper price in dollars per ton. We evaluate Bloomberg and Macrobond as reliable data sources.

For each data series, continuously compounded monthly returns are calculated as $100 \cdot \ln{(p_t/p_{t-1})}$ where p_t is monthly closing or settlement price. The CFNAI-MA3 historical data for the state-switching model is retrieved from the homepage of the Federal Reserve Bank of Chicago (Chicagofed, 2021).

Country	**Stock Index**
US	S&P 500
Norway	OBX
Japan	Nikkei 225
Germany	DAX
UK	FTSE 100
Canada	S&P/TSX Composite Index
China	SSE Composite Index
India	BSE 500
Chile	IPSA
France	CAC 40
Australia	ASX 200
South Korea	KOSPI

Table 1: *The countries and their respective stock indices.*

3.4 Control variables and multicollinearity

We will try our model with several different control variables. Following Goyal and Welch (2008), and like Jacobsen et al (2018), we include Agriculture, Livestock, Precious Metals, US Industrial Production Index, GSCI Spot Index, US CPI Urban, and US 10y Yield.

Variable	Name	Database
Agriculture	S&P GSCI Agriculture Total return Index	Bloomberg
Livestock	S&P GSCI Livestock Spot Index	Bloomberg
Precious Metals	S&P GSCI Precious Metal Index	Bloomberg
Industrial Prod US	US, Industrial Production Index	Macrobond
GSCI Spot	S&P GSCI Index Spot Index	Bloomberg
US CPI	US CPI Urban Consumers NSA	Bloomberg
US 10Y	US Gov. Federal Reserve, 10 Year, Yield	Macrobond
Copper	LME Copper Spot	Bloomberg

Table 2: *Control variables, full title, and source.*

As we have covered in the introduction, the price of copper is related to the industrial production, as an important commodity. The industrial production index focuses on sectors that include manufacturing, mining, gas, and the electric industries. Overall, these sectors represent approximately 20 precent of the economy (Davig, 2008). CPI is one of the indicators used to measure inflation rate. Including this in the regression model may be a way to control for that the effect we see in the stock market isn’t simply a result of aggregate price increases. The GSCI Spot index determines the most important commodities in the global economy.

When using OLS estimation methods, an implicit assumption is that the explanatory variables are not highly correlated with each other (Brooks, 2019). When the explanatory variables are highly correlated with one another, the problem of multicollinearity arises. The consequences are that the regression becomes sensitive to small changes in the specification and confidence intervals wide, resulting in an inappropriate conclusion (Brooks, 2019). The way we will test for multicollinearity is to check for high correlation between the copper returns and the control variables before we include them to our dataset. The highest correlation we find among our control variables is the "*contraction GSCI spot index return*" with "*contraction Copper return*", with a correlation with the copper price returns equals 0.79. We also find a correlation of 0.57 between "contraction Agriculture return" and "contraction Copper return". This may cause an issue regarding multicollinearity in the models with state-switching control variables. On the other hand, among the variables used in the models with non-state-switching control variables, we find no high correlations.

	Copper LME	**Copper LME C**	**Copper LME E**
Agriculture	0.27	0.27	0.19
Livestock	0.11	0.11	0.07
Precious Metals	0.30	0.15	0.26
Industrial Prod US	0.17	0.31	0.03
GSCI Spot	0.49	0.43	0.33
US CPI	0.21	0.20	0.07
US 10Y	0.26	0.15	0.22
Copper LME C		1	0.00
Agriculture C		**0.57**	0.00
Livestock C		0.43	0.00
Precious Metals C		0.37	0.01
Industrial Prod US C		0.36	0.02
GSCI Spot C		**0.79**	0.00
US CPI C		0.57	0.03
US 10Y C		0.32	-0.00
Copper LME E		0.00	1
Agriculture E		0.00	0.2
Livestock E		0.00	0.07
Precious Metals E		0.01	0.28
Industrial Prod US E		0.02	0.05
GSCI Spot E		0.00	0.39
US CPI E		0.03	0.08
US 10Y E		-0.00	0.24

Table 3: *Correlation between explanatory variables. C = control variable in contractionary periods, while E = control variable in expansionary periods.*

3.5 CLRM assumptions

3.5.1 Assumption 1: The mean of the disturbance is zero

The first classic linear regression model assumption is that the error terms have an average value equal to zero.

$$E(u_t) = 0$$

If a constant term is included in the regression model this assumption will never be violated. Not including a constant would lead to forcing the regression line through the origin. This could lead to severe biases in the estimation of the slope coefficients, and it would allow the R^2 to be negative (Brooks, 2019). With this in mind, an intersect is included in all the regression equations used in our analysis.

3.5.2 Assumption 2: Homoskedasticity

Heteroskedasticity refers to the absence of homoskedasticity, in which the variance of the residuals is unequal over a range of measured values (Woolridge, 2018). While it doesn't cause bias in the coefficient estimates, it does make them less precise. We will therefore conduct a White's test to detect any signs of heteroskedasticity in our models. White's test is one of the best approaches because it makes few assumptions about the form of the heteroskedasticity (Brooks, 2019). This is done by estimating the model using OLS to obtain the estimated residuals, $\hat{u}_t$, and run the auxiliary regression:

$$\hat{u}_t^2 = \alpha_1 + \alpha_2 x_{2_t} + \alpha_3 x_{3_t} + \alpha_4 x_{2\,t}^2 + \alpha_5 x_{3\,t}^2 + \alpha_6 x_{2_t} x_{3_t} + v_t$$

We then obtain the R^2 from this regression and multiply it with the number of observations. The null and alternative hypothesis are:

H_0: The variance of the errors is constant

$$\alpha_2 = 0 \ and \ \alpha_3 = 0 \ and \ldots and \ \alpha_k = 0$$

H_1: The variance of the errors is not constant

$$\alpha_2 \neq 0 \ and \ \alpha_3 \neq 0 \ and \ldots and \ \alpha_k \neq 0$$

We find the critical value, $\chi^2(m)$, where m is the total number of parameters in the model. If the p-value is greater than the chosen alpha, we keep the null hypothesis.

Dealing with this issue we use White's heteroskedasticity consistent standard errors. The effect of using White's correction is that in general the standard errors for the slope coefficients are increased relative to the OLS standard errors (Brooks, 2019). In both finance and economics, using robust standard errors has become common practice. Should the residuals turn out to be homoscedastic, the robust standard errors should be close to estimates of the normal standard errors since the theoretical standard errors then would be identical. However, if the residuals in fact are heteroskedastic, estimates of the standard errors generally prove a more accurate measure of sampling variance (Angrist & Pischke, 2015).

3.5.3 Assumption 3: No Autocorrelation

The third CLM assumption assumes that the covariance between the error terms is zero over time. In other words, that the error term is not autocorrelated (Brooks, 2019). A way to test for autocorrelation is to use the Breusch-Godfrey test. We will use this approach because it is a general test for r^{th} order autocorrelation, which makes it mor preferable than the Durbin-Watson test (Brooks, 2019). In order to conduct the Breusch-Godfrey test, we first estimate the regression using OLS and the residual, $\hat{u}$. Furthermore, we regress $\hat{u}$ on the same model, but this time we will add lagged variables of the error term to the model. We will use ten lags.

$$\hat{u}_t = \beta_1 + \beta_2 x_2 + \beta_3 x_3 + \hat{u}_{t-1} + \hat{u}_{t-2} + .. + \hat{u}_{t-10} + v_t$$

The null and alternative hypothesis are:

H_0: The current error is not related to any of its r previous values.

$$\rho_1 = 0 \text{ } and \text{ } \rho_2 = 0 \text{ } and \dots and \text{ } \rho_r = 0$$

H_1: The current error is related to any of its r previous values.

$$\rho_1 \neq 0 \text{ } and \text{ } \rho_2 \neq 0 \text{ } and \dots and \text{ } \rho_r \neq 0$$

We obtain the R^2 from the auxiliary regression and calculate the test statistics by:

$$(T - r)R^2 \sim \chi_r^2$$

If the p-value is greater that the chosen alpha, we will keep the null hypothesis and conclude that there is no sign of autocorrelation in the residual.

3.5.4 Assumption 4: The regressors are non-stochastic

This assumption is based on the independence of the error terms. If one or more of the explanatory variables is contemporaneously correlated with the error term, the OLS estimator won't be consistent. The reason for this is that the estimator assigning explanatory power to the variables where it is arising from the correlation between y_t and the error term. This would result in both biased and inconsistent parameter estimates, and a fitted regression line that would appear to capture the features of the data much better than it did (Brooks, 2019).

3.5.5 Assumption 5: The error terms are normally distributed

The disturbances need to be normally distributed to conduct single or joint hypothesis tests about the parameters. A case with non-normal distribution indicates skewness or kurtosis. Skewness measures the extent to which the distribution is not symmetric about its mean value and kurtosis measures how fat the tails of the distribution are (Brooks, 2019).

Skewedness:

$$E(Z^3) = E[(X - \mu)^3]/\sigma^3$$

Kurtosis:

$$E(Z^4) = E[(X - \mu)^4]/\sigma^4$$

We will use the test by Bera and Jarque (1981) to check for normality, with the hypothesis formulated as:

H_0: The error term is normally distributed.

$$\rho_1 = 0 \; and \; \rho_2 = 0 \; and \ldots and \; \rho_r = 0$$

H_1: The error term is not normally distributed.

$$\rho_1 \neq 0 \; and \; \rho_2 \neq 0 \; and \ldots and \; \rho_r \neq 0$$

A high level of kurtosis indicates heavy tails in the distribution or outliers. However, linear regression models with residuals deviating from a normal distribution often still produce valid results, without performing arbitrary outcome transformations, especially in large sample size settings (Schmidt & Finan, 2018).

Despite that the residuals are not normally distributed, we can use the central limit theorem to conclude that the OLS estimators satisfy asymptotic normality, which means they are approximately normally distributed in large enough sample sizes (Wooldridge, 2018).

4.0 Analysis

We start testing our first hypothesis, by performing an in-sample analysis for all the major stock indices. Thereafter, we run an out-of-sample analysis with no control variables. The main focus in our analysis will be to examine whether copper price movements may be used as an estimator for the future stock market return.

4.1 In-Sample Analysis

In the in-sample analysis, we have various length of data series available. We want to use as long data series as possible since we already have few contraction periods after 1990. The first historical dataset containing the S&P 500 (*US*), DAX Index (*Germany*), NIKKEI (*Japan*) and S&P TSX Composite Index (*Canada*) is from 1977-2021. The second dataset containing ASX200 (*Australia*), IPSA (Chile), KOSPI (*South Korea*), FTSE100 (*UK*) and SSE COMP (*China*) is from 1992-2021. The last dataset containing OBX (*Norway*), CAC40 (*France*) and BSE500 (*India*) is from 1999-2021. Datasets 1, 2 and 3 contain 42, 20 and 20 contraction periods respectively. The endpoint of our analysis is end of January 2021.

4.1.1 CLRM assumptions

White's test tells us that there is evidence of heteroscedasticity in our models. After performing the test on the S&P 500, we discovered signs of heteroskedasticity, and the null hypothesis is rejected. Moreover, after conducting the Breusch-Godfrey test for autocorrelation, we find no patterns in the residuals. Going further in our analysis, ignoring the heteroskedasticity, will not affect our estimators, but might cause us to draw wrong conclusions regarding statistical significance. We therefore choose to go further using White's robust standard errors. After conducting the Jarque-Bera test for normality, we find that the residuals are not normally distributed. We know that the normality assumption is important to unbiasedly estimate standard errors, and hence confidence intervals and t-statistics. However, we know by the central limit theorem that this is not a problem when conducting analysis with large sample size.

4.1.2 In-sample evidence

We find that, when using monthly returns, the copper coefficient is consistently positive in periods classified as contraction, but otherwise in expansion periods. This implies that a positive movement in the copper price, this month, forecasts a fall in the stock price next month during expansion periods. On the other hand, a positive return in the copper price during contraction periods forecasts higher stock prices the upcoming month. This is in accordance with our expectations and previous literature. The significance of the results varies among the stock indices under the scope. The estimators are heteroscedasticity- and autocorrelation consistent. We find the most significant results on the S&P500 and DAX Index, where we find significant estimators both in expansion periods and contraction periods. We can therefore reject the null hypothesis and conclude that the copper return coefficients are statistically different from zero.

The coefficients in contraction periods are higher, in absolute terms, than the coefficients from expansion periods. They are also more consistently significant. Our results from the US stock market, S&P500, are presented underneath in three different tables. The results in *table 4* are based on the non-state switching control variables, while the results in *table 5* are based on the state-switching control variable treatment. Furthermore, the results in *table 6* are based on a non-state-switching treatment for both the control variables and the copper price. The two different states of the economy are presented with either C for contraction, of E for expansion. The estimates for the control variables are presented under the heading CV, control variables. See *exhibit 2* for results from all countries.

	Copper		Control	
Model	**Contraction**	**Expansion**		R^2_{adj}
No CV	0.28***	-0.06**		0.038
Agriculture	0.27***	-0.06**	0.01	0.036
Livestock	0.27***	-0.06**	0.03	0.037
Precious Metals	0.28***	-0.05*	-0.02	0.037
Industrial Prod US	0.32***	-0.05**	-0.46	0.046
GSCI Spot	0.34***	-0.03	-0.08*	0.045
US CPI	0.30***	-0.06**	-0.79	0.040
US 10Y	0.29***	-0.04*	-0.05	0.042

Table 4: *Normal control variable, S&P 500 (1977-2021).*

Note: The copper price is state switching, but not the control variable.

The stars indicate different significant level, where:

* $\alpha = 0.1.$ ** $\alpha = 0.05$ *** $\alpha = 0.01$

	Copper		Control		
Model	**Contraction**	**Expansion**	**Contraction**	**Expansion**	R^2_{adj}
No CV	0.28***	-0.06**			0.038
Agriculture	0.30***	-0.06**	-0.07	-0.02	0.035
Livestock	0.30***	-0.06**	-0.17	0.04	0.038
Precious Metals	0.28**	-0.03*	-0.03	-0.02	0.035
Industrial Prod US	0.34***	-0.06**	-0.76**	0.02	0.050
GSCI Spot	0.22**	-0.04	-0.15	-0.04	0.018
US CPI	0.13	-0.05*	-0.58	-0.45	0.010
US 10Y	0.16**	-0.04	-0.10	-0.02	0.019

Table 5: *State switching control variables, S&P 500 (1977-2021).*

Note: Both the copper price and the control variables are state switching.

Model	**Copper**	**CV**	R^2_{adj}
No CV	-0.00		-0.002
Agriculture	-0.01	0.03	-0.003
Livestock	0.01	-0.04	-0.002
Precious Metals	0.00	-0.03	-0.003
Industrial Prod US	0.00	-0.24	-0.001
GSCI Spot	0.01	-0.04	-0.002
US CPI	-0.00	-0.33	-0.003
US 10Y	0.01	-0.05	0.002

Table 6: *Non-state-switching model, S&P 500 (1977-2021).*

Note: None of the variables are state switching.

The average copper contraction and expansion coefficients of 0.29 and -0.05 in the normal control variable models compare to contraction and expansion coefficients of 0.25 and -0,05 in the “state switching” control variable specification. This implies that, for example, if the copper price increases with 5 percent in February in a contraction period, the stock market will increase with 1.45 percent in March. This is statistically significant with a 99 percent confidence interval. The $\bar{R}^2$ from the S&P 500 model, obtained from the OLS regressions are 3.8% with no control variable, but is as high as 4.6% when including the *industrial production* variable.

We can see that the copper coefficients vary more in *table 4* than in *table 5*, depending on which control variables that are included. If the explanatory variables were orthogonal to one another, adding or removing a variable from a regression equation would not cause the values of the coefficients on the other variables to change (Brooks, 2019). This may indicate that there is a problem with *near multicollinearity* in some of the control-state-switching models. The coefficients in the non-state switching models, presented in *table 6*, are not statistically significant. This implies that there is no relationship between past copper price fluctuations and future stock returns when we don’t control for the economic cycle. Moreover, most of the control variables are not statistically significant in any of the models. The copper price is therefore a superior indicator compared to the control variables. We find the poorest results on the SSE COMP index and IPSA, where there are very few of the coefficients that are statistically significant in any of the models.

4.1.3 Indicating the turning points

As mentioned above, we only find significant coefficients for the copper price return, for both contraction and expansion periods, in US and Germany. However, we find strong relations during contraction periods in all countries, except for China, Japan, and Chile. In Norway for instance, we find coefficients above 0.5 with a 99 percent confidence interval and $\bar{R}^2$ above 6 percent. The findings are the same in France, India, Australia, UK, and Canada. These observations implies that the copper price may be a valuable indicator to indicate the turning point from the stock market busts.

From an economics point of view, as the activity declines, an attempt to stimulate the economy with monetary policy actions or government spending may have a positive impact on the price of copper. In New Keynesian theory an expansionary monetary policy shock would lead to an increase in aggregate demand and consumption. In a case with price rigidities, the profit maximizing firms will therefore increase their production to meet this new level of demand, and hence potentially cause an increase in the price of raw materials. Normally if the government tries to stimulate the economy through government spending, the central bank will counteract it by increasing the interest rate. If the central bank doesn't respond, for instance if the economy was in a deep recession, there would be a rise in both prices and economic activity (Romer, 2019).

4.1.4 Commodity exporting countries

Considering the study concerning an oil-price fluctuations and stock market returns in an oil-exporting country, conducted by Bjørnland (2008), it would be reasonable to suggest that positive shocks to the price of copper would lead to increased stock market returns in both Chile and Australia. These two countries are the most important copper-exporters included in our analysis. According to Trading Economics (2021) 48 percent of Chile's total exports relies on copper. However, according to our findings from the in-sample analysis there are no such relationship between the price of copper and the Chilean stock market returns. We find this puzzling, as Chile has the worst statistical results in the analysis. We will therefore suggest, for further research, to look further into the macroeconomic transition channels from copper price shocks in Chile.

4.2 Out-of-Sample Analysis

The last part of our analysis, the out of sample test, is performed to answer our second hypothesis. With our second hypothesis, our aim is to examine whether the copper price return have any forecast ability on the stock markets. Performing an out-of-sample test enable us to assess the forecast quality of our estimators. To avoid hindsight bias, we only use data that was available at the time period in real time of the prediction. Similarly, as we did in the in-sample analysis, the monthly published CFNAI-MA3 is therefore used to define the state of the economy in favor of NBER definitions. For the experiment we use a rolling regression methodology. That is, the models are first estimated using data until the first forecasting period. In the next step, the estimation period is rolled forward by one month, keeping the total length of the estimation period constant. We will use the first 13 years, (2006-2018), as initial estimation period, which leaves us with a forecast period of approximately two years, (2019-2021). We choose an out-of-sample period of 15 years because we want to use recent data, but still include the financial crisis of 2008-2009 as these years contains valuable contraction periods.

To generate the beta coefficients, for each month we regress stock return in month t with the Copper LME return in month $t-1$. This enables us to use the latest published CFNAI-MA3 announcement in month $t-2$ to define the economic state dummies in month $t-1$.

$$Stock\ r_t = \alpha + \beta_1 E_{t-2} Copper\ LME_{t-1} + \beta_2 C_{t-2} Copper\ LME_{t-1} + \varepsilon_{t-1}$$

This leaves us with $\hat{\beta}_1\ and\ \hat{\beta}_2$, one estimator for each state of the economy. Furthermore, we multiply the estimators with the copper price in $t-1$ in order to find the estimated return for the stock market in month t. The state of the economy is determined from month $t-2$. If we have come to the end of May and are to estimate the *S&P 500* return in June, we use the copper return from May, and the CFNAI results from April.

4.2.1 Forecast error variance

For an unbiased predictor, the mean squared error (MSE) is the forecast error variance which is useful in setting up interval forecasts. The MSE is derived based on the forecast errors, that is the difference the actual and the predicted value of a time series. The most used evaluation method for forecast accuracy is the root mean squared error (RMSE). This is a measure of the size of the forecast error and is simply the square root of the MSE (Bjørnland and Thorsrud, 2015).

$$\sqrt{E[(e_{T+h})^2]} = \sqrt{E[(e_{T+h} - \hat{y}_{T+h})^2]}$$

An estimate of the of the RMSE can be derived from the vector of out-of-sample forecast errors:

$$\widehat{RMSE}_h = \sqrt{(P)^{-1} \sum_{i=0}^{P-1} e_{T+h+i}^2}$$

The RMSE for each of the stock indices are listed in table 7.

4.2.2 Directional Accuracy

A measure closely correlated with profitability of a forecast model is the "percentage correct sign" predictions, or *directional accuracy*. We will create a dummy variable for each period the estimator successfully predicts the direction of the stock return. If the predictor manages to predict the correct direction of the stock market return, we set the dummy variable equal to one, and zero if it predicts wrong direction. By summing the dummy vector and divide it on total predictions we will determine the accuracy ratio. A null hypothesis of no directional accuracy implies forecast accuracy of copper returns for stock markets of 0.5. This will imply complete random directional accuracy.

Our hypothesis is formulated as follows:

H_0: Copper price return forecast accuracy is 0.5.

H_1: Copper price return forecast accuracy is > 0.5.

We test this null hypothesis using the test of Pesaran and Timmermann (2009).

Out-of-Sample results

1-month forecast evaluation

Country	Bias	RMSE	DSR	PT test p-value
US	1.06	5.85	0.70**	0.039
Norway	-0.17	9.64	0.65*	0.094
Japan	1.33	5.55	0.70**	0.037
Germany	0.27	6.87	0.55	0.422
UK	-0.63	6.98	0.65*	0.094
Canada	0.17	7.52	0.60	0.189
China	1.29	4.62	0.55	0.422
India	-0.25	9.25	0.50	0.518
Chile	-1.2	9.94	0.60	0.126
France	0.06	7.67	0.65*	0.094
Australia	-0.01	9.32	0.65*	0.095
South Korea	1.58	7.39	0.50	0.500

***Table 7**: Out of sample results.*

Notes: Bias, root-mean -square error (RMSE), directional success ratio (DSR), Pesaran Timmermann (PT) test statistics. The stars indicate significance level.

As shown in the table above, the copper price predicts 70 percent correct direction on the S&P 500 index, which is statistically significant with a 95 percent confidence interval. We find the same result on the Nikkei; however, we do not have evidence from the in-sample test for predictability in both contraction and expansion periods. We do have evidence for predictability in both periods on the DAX index, but the out of sample results fails to pass the Pesaran Timmermann test, with only a directional success ratio of 55 percent. The bias can be described as the tendency to either over- or under-forecast the stock market returns, which leads to systematic forecasting errors. For US we observe that the bias is equal to 1.06. This means that the S&P 500 returns are slightly over-forecasted.

In order to further evaluate the out of sample results, we run a simple AR(1) model with one month lag on the S&P 500 index in the same period, for a comparison. The AR(1) model predicted the direction of next period returns with an accuracy of 60 percent. In the Pesaran Timmerman test we cannot reject the null hypothesis at significance level of 0.05. This shows that our state-switching model is favorable in forecasting future stock market returns.

5.0 Discussion

In this chapter we will discuss the reason for the copper price predictability of the stock market. We will further discuss some of the limitations of our thesis, and finally propose recommendations for further research.

5.1 Reason for forecasting ability

We will not conduct any empirical analysis to explain the reason for the forecasting ability. We will however explain a possible economic reason, based on previous research on the topic. It is obvious to question whether our findings are evidence of market inefficiency, or evidence of time-varying equilibrium expected returns. In Jacobsen et. al's (2018) study on whether the industrial metals predict the stock market, they found it unlikely that the predictability results are due to time-varying risk premia. Their rationale is that industrial metal prices predicted negative excess returns, and negative excess return can, by definition, not be a compensation for risk (Schwert, 2003). In their study they found that an average of 36-56 percent of information in industrial metal prices is reflected in equity prices contemporaneously in expansions, and 76-77 percent is reflected contemporaneously in recessions. This indicates a relatively slow information diffusion in expansions. Studies have shown that there may be severe information frictions regarding the global supply and demand for industrial metals, such as copper, and that this may prevent investors from instantly and correctly inferring the implications of price changes for equities (Sockin and Wong, 2015). The lack of arbitrageurs can therefore be a result of the imperfection of information and uncertainty related to the economic nature of the apparent mispricing. On the other hand, proposing that the market is inefficient is somewhat controversial. This is, as mentioned in our literature review, due to the assumption of rational agents and market clearing. If arbitrage opportunities arise, any rational investor would trade on it and the opportunity would quickly disappear. Mispricing in the stock market is in this case not possible (Fama, 1970). We have earlier argued, backed by several studies, that the copper price may indicate the health of the economy. An appreciation in the copper price during contractionary periods might indicate a recovering economy and lower market risk. Therefore, a more realistic rationale would be that the predictability of the stock market is due to the varying business cycle conditions rather than mispricing in the stock market. Hence, the underlying reason for predictability is related to time varying risk premia rather than market inefficiency.

5.2 Limitations

Using the CFNAI-MA3 index and the -0.7 threshold gives us less observations classified as contractionary periods in comparison to the NBER definitions, which is identified only in retrospect. However, in some of the previous recessions, as in 2001-02 and 2007-09, the index was quite accurate both for the beginning and end of the recessions. A major advantage of using CFNAI is due to the monthly publishment which we regard as a predominant argument in light of eliminating hindsight bias in the analysis. Due to few contraction periods in the last 50 years, we wanted to use as much data as possible for each country. The sample sizes are therefore not consistent among the stock indices, due to limitations in data available. This makes it difficult to compare the results among the stock indices. We justify this by that we have valued maximized amount of data for each country, rather than ideal conditions for comparing the different countries against each other.

Supply side shocks may also have some effect on the price of copper. In our analysis we have not made any attempt to separate supply- and demand-side shocks to the copper price. This is due to the scope of the thesis. In Kilian and Park's (2009) study of the oil-price and stock returns, they found that the response of real stock returns differs depending on the underlying cause of the oil-price fluctuations. However, they found that the supply side shocks are substantially less important than the oil-price shocks caused by aggregate demand for understanding changes in stock prices.

5.3 Opportunity for further research

As the phasing out of petroleum activities intensifies minerals used in generating electricity, copper may take over the position as the most important of the industrial commodities. An interesting topic for further research would therefore be examining whether copper price returns forecasting ability increases in the future as the green shift continues. On the contrary, we recommend conducting a study on whether the predictive effect gradually fades away similar as we have seen with other significant predictive variables in the past. The theory that the copper price indicates the health of the economy and the equity markets has gained more attention in the media recently. It is therefore likely that it's predictive power will decrease in the future. Moreover, it would be interesting to do a further study on whether the copper price predicts some asset classes better than others. We therefore recommend further research experimenting with several asset classes as response variables. Furthermore, a useful contribution to our findings could be to do a similar analysis but using a structural vector autoregressive model approach to investigate simulated shocks to the price of copper. This could provide valuable insight about the transition channels of a price shock and the dynamics in several economic variables, especially in copper-exporting countries. Lastly, it would be interesting to look at alternative ways to define the economic state-dummy variables E_{t-1} and C_{t-1}. It would for example be even more convenient to find a real-time variable with no reporting delay.

6.0 Conclusion

In this thesis, our main objective has been to test whether the price fluctuations in the industrial metal copper are associated with the future return of the stock markets, both in- and out-of-sample, using monthly returns. Our findings are that an appreciation in the copper price is associated with increasing stock prices during contraction periods, and counter wise, depreciation in the stock prices during expansion periods. This agrees well with our expectations and previous findings conducted by Jacobsen et. al. We find no evidence for using the copper price to provide forecasts for the stock market without adjusting for the state of the economy. We find the strongest predictability in the US and the German stock market. In these markets, the copper price coefficients are statistically significant in both expansion and contraction periods. Although, the copper price returns are a stronger predictor for the next month's stock return during contraction periods. In these periods, the coefficients are larger in absolute terms, and they are consistently more statistically significant among our models. We also find evidence that contraction estimators are statistically significant in several countries, compared to the expansion estimators. This implies that the copper price may have a particular capability to provide an indication of the turning point from stock market busts. The out of sample test, using a rolling window regression approach shows that the copper price also serves as a predictor to the stock market return. We find that the copper price returns forecast the S&P 500 directional returns with 70 percent accuracy, statistically significant with 95 percent confidence interval.

In Chile, one of the world's most important copper-exporters, we find no statically significant results in neither expansionary nor contractionary periods. This was not in line with our prior expectations, and we recommend a specific study on this matter for further research.

As for explaining the reason for the predictability we have not conducted any empirical research. However, our discussion of the findings backs up the idea that stock market return predictability is the rational response to varying business cycle conditions rather than stock market inefficiencies.

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Appendices

Exhibit 1. Regressions for the In-Sample analysis

State-switching control variables:

Regression I	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 E_{t-1} Agriculture_{t-1} + \beta_4 R_{t-1} Agriculture_{t-1} + \varepsilon_t$
Regression II	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 E_{t-1} Livestock_{t-1} + \beta_4 R_{t-1} Livestock_{t-1} + \varepsilon_t$
Regression III	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 E_{t-1} Precious\ metals_{t-1} + \beta_4 R_{t-1} Precious\ metals_{t-1} + \varepsilon_t$
Regression IV	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 E_{t-1} Industrial\ Production\ US_{t-1} + \beta_4 R_{t-1} Industrial\ Production\ US_{t-1} + \varepsilon_t$
Regression V	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 E_{t-1} GSCI\ Spot_{t-1} + \beta_4 R_{t-1} GSCI\ Spot_{t-1} + \varepsilon_t$
Regression VI	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 E_{t-1} US\ CPI_{t-1} + \beta_4 R_{t-1} US\ CPI_{t-1} + \varepsilon_t$
Regression VII	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 E_{t-1} US\ 10y_{t-1} + \beta_4 R_{t-1} US\ 10y_{t-1} + \varepsilon_t$

Normal Control Variables:

Regression I	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 Agriculture_{t-1} + \varepsilon_t$
Regression II	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 Livestock_{t-1} + \varepsilon_t$
Regression III	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 Precious\ Metals_{t-1} + \varepsilon_t$
Regression IV	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 Industrial\ Production_{t-1} + \varepsilon_t$
Regression V	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 GSCI\ Spot_{t-1} + \varepsilon_t$
Regression VI	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 US\ CPI_{t-1} + \varepsilon_t$
Regression VII	$Stock\ r_t = \alpha + \beta_1 E_{t-1} Copper\ LME_{t-1} + \beta_2 R_{t-1} Copper\ LME_{t-1} + \beta_3 US\ 10Y_{t-1} + \varepsilon_t$

Non-state-switching models:

Regression I	$Stock\ r_t = \alpha + \beta_1 Copper\ LME_{t-1} + \beta_2 Agriculture_{t-1} + \varepsilon_t$
Regression II	$Stock\ r_t = \alpha + \beta_1 Copper\ LME_{t-1} + \beta_2 Livestock_{t-1} + \varepsilon_t$
Regression III	$Stock\ r_t = \alpha + \beta_1 Copper\ LME_{t-1} + \beta_2 Precious\ metals_{t-1} + \varepsilon_t$
Regression IV	$Stock\ r_t = \alpha + \beta_1 Copper\ LME_{t-1} +$ $\beta_2 Industrial\ Production\ US_{t-1} + \varepsilon_t$
Regression V	$Stock\ r_t = \alpha + \beta_1 Copper\ LME_{t-1} + \beta_2 GSCI\ Spot_{t-1} + \varepsilon_t$
Regression VI	$Stock\ r_t = \alpha + \beta_1 Copper\ LME_{t-1} + \beta_2 US\ CPI_{t-1} + \varepsilon_t$
Regression VII	$Stock\ r_t = \alpha + \beta_1 Copper\ LME_{t-1} + \beta_2 US\ 10y_{t-1} + \varepsilon_t$

Exhibit 2. In-Sample results

*   P-value < 0.1
**   P-value < 0.05
*** P-value < 0.01

$C = Contraction\ periods$
$E = Expansion\ periods$
$\bar{R}^2 = Adjusted\ R^2$

State-switching model

		Copper		Control		
Country	**Model**	**C**	**E**	**C**	**E**	$\bar{R}^2$
USA	No CV	0.28***	-0.06**			0.038
	Agriculture	0.30***	-0.06**	-0.07	-0.02	0.035
	Livestock	0.30***	-0.06**	-0.17	0.04	0.038
	Precious Metals	0.28**	-0.03*	-0.03	-0.02	0.035
	Ind. Prod. US	0.34***	-0.06**	-0.76**	0.02	0.050
	GSCI Spot	0.22**	-0.04	-0.15	-0.04	0.018
	US CPI	0.13	-0.05*	-0.58	-0.45	0.010
	US 10Y	0.16**	-0.04	-0.10	-0.02	0.019
Japan	No CV	0.22	0.01			0.007
	Agriculture	0.19	0.01	0.09	-0.01	0.004
	Livestock	0.26*	0.00	-0.31	0.05	0.009
	Precious Metals	0.26*	0.01	-0.18	0.01	0.007
	Ind. Prod. US	0.27	0.01	-0.62*	-0.32	0.016
	GSCI Spot	0.05	0.04	0.00	0.01	-0.005
	US CPI	0.07	0.04	-1.40	-1.22	0.001
	US 10Y	0.07	0.04	-0.09	-0.02	-0.001
Germany	No CV	0.26**	-0.08**			0.021
	Agriculture	0.28**	-0.08**	-0.04	0.04	0.019
	Livestock	0.26**	-0.08**	0.02	0.08	0.022
	Precious Metals	0.29***	-0.07*	-0.12	-0.02	0.019
	Ind. Prod. US	0.30***	-0.08**	-0.43	0.10	0.020
	GSCI Spot	0.23*	-0.06	-0.15	-0.06	0.013
	US CPI	0.15	-0.07**	-1.29	-0.73	0.010
	US 10Y	0.15*	-0.07*	-0.04	-0.02	0.008
Canada	No CV	0.38**	-0.03			0.035
	Agriculture	0.36**	-0.04	-0.04	0.06	0.033
	Livestock	0.40***	-0.03	-0.17	0.06	0.035
	Precious Metals	0.40**	-0.04	-0.10	0.04	0.033
	Ind. Prod. US	0.45**	-0.03	-0.88*	0.28	0.045

	GSCI Spot	0.37**	-0.05	-0.19	0.05	0.029
	US CPI	0.26**	-0.03	-0.96	-0.04	0.022
	US 10Y	0.27**	-0.02	-0.05	-0.06	0.026
Australia	No CV	0.44**	-0.05			0.055
	Agriculture	0.50***	-0.04	-0.16	-0.02	0.051
	Livestock	0.47**	-0.05	-0.21	0.09	0.055
	Precious Metals	0.47**	-0.04	-0.14	-0.00	0.051
	Ind. Prod. US	0.53**	-0.05	-0.95	0.99	0.074
	GSCI Spot	0.57**	-0.05	-0.29	0.05	0.045
	US CPI	0.44**	-0.03	-3.25	-1.23	0.041
	US 10Y	0.35**	-0.04	-0.01	-0.01	0.031
South Korea	No CV	0.50**	-0.07			0.027
	Agriculture	0.48**	-0.06	0.04	-0.02	0.022
	Livestock	0.54**	-0.06	0.28	-0.03	0.023
	Precious Metals	0.53*	-0.07	-0.16	0.04	0.023
	Ind. Prod. US	0.60**	-0.06	-1.05*	-0.17	0.031
	GSCI Spot	0.70***	-0.04	-0.37	-0.09	0.027
	US CPI	0.64***	-0.06	-7.90**	-2.91**	0.040
	US 10Y	0.47**	-0.06	-0.19	-0.01	0.026
Chile	No CV	0.25	-0.05			0.010
	Agriculture	0.06	-0.05	0.53*	0.04	0.022
	Livestock	0.35**	-0.05	-0.64	0.11	0.019
	Precious Metals	0.26	-0.06	-0.04	0.06	0.005
	Ind. Prod. US	0.35	-0.05	-0.98*	0.30	0.019
	GSCI Spot	0.37	-0.05	-0.17	-0.00	0.008
	US CPI	0.39**	-0.05	-5.27**	-1.05	0.020
	US 10Y	0.24	-0.04	-0.02	-0.04	0.006
UK	No CV	0.34**	-0.02			0.052
	Agriculture	0.34***	-0.01	-0.02	-0.02	0.047
	Livestock	0.36***	-0.02	-0.14	0.12**	0.061
	Precious Metals	0.39***	-0.01	-0.30	-0.01	0.059
	Ind. Prod. US	0.37**	-0.02	-0.37	0.76	0.060
	GSCI Spot	0.42**	-0.01	0.18	-0.01	0.045
	US CPI	0.35***	-0.01	2.44	-0.27	0.043
	US 10Y	0.28**	-0.01	0.02	-0.03	0.038
China	No CV	0.24	-0.01			-0.001
	Agriculture	0.14	-0.01	0.26	0.01	-0.005
	Livestock	0.40*	-0.02	-1.04**	0.26**	0.016
	Precious Metals	0.29	-0.00	-0.27	-0.03	-0.005

	Ind. Prod. US	0.26	-0.01	-0.29	-0.23	-0.006
	GSCI Spot	0.29	-0.02	-0.18	0.07	-0.007
	US CPI	0.28	0.00	-4.24	0.31	-0.005
	US 10Y	0.16	0.03	-0.01	-0.07	-0.007
Norway	No CV	0.54**	0.004			0.064
	Agriculture	0.52**	0.02	0.06	-0.06	0.059
	Livestock	0.55***	-0.00	-0.03	0.10	0.060
	Precious Metals	0.56**	0.03	-0.07	-0.12	0.060
	Ind. Prod. US	0.62**	-0.00	-0.73	1.34	0.075
	GSCI Spot	0.88***	-0.01	-0.46**	-0.02	0.086
	US CPI	0.64***	-0.02	-4.35	-0.78	0.072
	US 10Y	0.53***	-0.01	-0.06	-0.02	0.063
France	No CV	0.38**	-0.01			0.048
	Agriculture	0.45***	-0.00	-0.19	-0.05	0.046
	Livestock	0.38**	-0.02	-0.01	0.14	0.051
	Precious Metals	0.44**	-0.01	-0.30	-0.03	0.050
	Ind. Prod. US	0.41**	-0.02	-0.32	1.42	0.060
	GSCI Spot	0.55***	-0.01	-0.28	-0.03	0.050
	US CPI	0.46***	-0.01	4.38*	-0.99	0.052
	US 10Y	0.33**	0.00	0.00	-0.05	0.037
India	No CV	0.54**	0.04			0.050
	Agriculture	0.45*	0.06	0.24	-0.08	0.048
	Livestock	0.67**	0.04	-0.83	0.05	0.058
	Precious Metals	0.58**	0.05	-0.22	-0.02	0.045
	Ind. Prod. US	0.65**	0.03	-1.17*	2.44*	0.084
	GSCI Spot	0.82**	0.12	-0.49	-0.15*	0.060
	US CPI	0.64**	0.07	-7.31**	-2.83*	0.060
	US 10Y	0.44**	0.10	-0.05	-0.09	0.035

Normal Control variable

		Copper		Control	
Country	**Model**	**C**	**E**		R^2
USA	No CV	0.28***	-0.06**		0.038
	Agriculture	0.27***	-0.06**	0.01	0.036
	Livestock	0.27***	-0.06**	0.03	0.037
	Precious Metals	0.28***	-0.05*	-0.02	0.037
	Ind. Prod. US	0.32***	-0.05**	-0.46	0.046
	GSCI Spot	0.34***	-0.03	-0.08*	0.045
	US CPI	0.30***	-0.06**	-0.79	0.040
	US 10Y	0.29***	-0.04*	-0.05	0.042
Japan	No CV	0.22	0.01		0.007
	Agriculture	0.26	0.01	0.00	0.005
	Livestock	0.21	0.01	0.02	0.006
	Precious Metals	0.22	0.01	-0.02	0.006
	Ind. Prod. US	0.26	0.01	-0.50*	0.011
	GSCI Spot	0.23	0.01	-0.02	0.005
	US CPI	0.26*	0.01	-1.58**	0.014
	US 10Y	0.23	0.02	-0.04	0.008
Germany	No CV	0.26**	-0.08**		0.021
	Agriculture	0.25**	-0.08**	0.03	0.020
	Livestock	0.25**	-0.08**	0.08	0.024
	Precious Metals	0.27***	-0.07*	-0.03	0.020
	Ind. Prod. US	0.28***	-0.07**	-0.23	0.021
	GSCI Spot	0.34***	-0.05	-0.10	0.027
	US CPI	0.29***	-0.07**	-1.21*	0.025
	US 10Y	0.27***	-0.07*	-0.03	0.021
Canada	No CV	0.38**	-0.03		0.035
	Agriculture	0.36**	-0.03	0.06	0.035
	Livestock	0.37**	-0.03	0.04	0.034
	Precious Metals	0.37**	-0.03	0.02	0.033
	Ind. Prod. US	0.41**	-0.02	-0.44	0.038
	GSCI Spot	0.39**	-0.02	-0.02	0.033
	US CPI	0.39**	-0.03	-0.63	0.034
	US 10Y	0.39**	-0.01	-0.06	0.038
Australia	No CV	0.44**	-0.05		0.055
	Agriculture	0.46**	-0.04	-0.04	0.053
	Livestock	0.43**	-0.05	0.07	0.055
	Precious Metals	0.45**	-0.04	-0.02	0.052
	Ind. Prod. US	0.48**	-0.05	-0.36	0.055

	GSCI Spot	0.46**	-0.04	-0.03	0.052
	US CPI	0.51**	-0.04	-2.00**	0.062
	US 10Y	0.45**	-0.04	-0.02	0.052
South Korea	No CV	0.49**	-0.07		0.027
	Agriculture	0.50**	-0.06	-0.01	0.025
	Livestock	0.50**	-0.06	-0.04	0.025
	Precious Metals	0.49**	-0.07	0.02	0.025
	Ind. Prod. US	0.57**	-0.06	-0.79	0.032
	GSCI Spot	0.61**	-0.02	-0.14	0.031
	US CPI	0.63***	-0.05	-4.3***	0.045
	US 10Y	0.53**	-0.04	-0.08	0.029
Chile	No CV	0.25	-0.05		0.010
	Agriculture	0.22	-0.06	0.09	0.012
	Livestock	0.24	-0.05	0.07	0.009
	Precious Metals	0.24	-0.05	0.04	0.008
	Ind. Prod. US	0.031	-0.04	-0.59	0.014
	GSCI Spot	0.28	-0.04	-0.03	0.008
	US CPI	0.32	-0.04	-2.08**	0.015
	US 10Y	0.27	-0.04	-0.04	0.009
UK	No CV	0.34**	-0.02		0.052
	Agriculture	0.34**	-0.01	-0.02	0.050
	Livestock	0.32**	-0.02	0.11**	0.061
	Precious Metals	0.35**	-0.01	-0.05	0.052
	Ind. Prod. US	0.34**	-0.02	-0.03	0.050
	GSCI Spot	0.37**	-0.00	-0.04	0.052
	US CPI	0.37**	-0.01	-0.93	0.053
	US 10Y	0.34**	-0.01	-0.02	0.050
China	No CV	0.24	-0.01		-0.001
	Agriculture	0.22	-0.01	0.03	-0.004
	Livestock	0.20	-0.02	0.19*	0.002
	Precious Metals	0.25	0.00	-0.06	-0.003
	Ind. Prod. US	0.26	-0.01	-0.27	-0.003
	GSCI Spot	0.23	-0.01	0.01	-0.004
	US CPI	0.27	-0.01	-1.01	-0.003
	US 10Y	0.26	0.01	-0.06	-0.002
Norway	No CV	0.55**	0.00		0.064
	Agriculture	0.56**	0.01	-0.05	0.062
	Livestock	0.53**	-0.00	0.09	0.064
	Precious Metals	0.57**	0.03	-0.12	0.066
	Ind. Prod. US	0.57**	0.01	-0.22	0.062

	GSCI Spot	0.64***	0.05	-0.12	0.068
	US CPI	0.60**	0.01	-1.71	0.066
	US 10Y	0.56**	0.02	-0.04	0.063
France	No CV	0.38**	-0.01		0.048
	Agriculture	0.40**	-0.00	-0.07	0.048
	Livestock	0.36**	-0.02	0.13*	0.054
	Precious Metals	0.39**	0.00	-0.07	0.047
	Ind. Prod. US	0.37**	-0.01	0.13	0.044
	GSCI Spot	0.45**	0.02	-0.09	0.051
	US CPI	0.44**	-0.00	-1.98*	0.056
	US 10Y	0.39**	-0.00	-0.03	0.046
India	No CV	0.54**	0.04		0.050
	Agriculture	0.55**	0.05	-0.04	0.047
	Livestock	0.54**	0.04	-0.01	0.046
	Precious Metals	0.55**	0.06	-0.05	0.047
	Ind. Prod. US	0.56**	0.04	-0.25	0.047
	GSCI Spot	0.74***	0.14	-0.24**	0.071
	US CPI	0.68**	0.06	-4.30***	0.075
	US 10Y	0.57**	0.07	-0.08	0.052

Non-state-switching model

Country	**Model**	**Copper**	**CV**	R^2
USA	No CV	-0.00		-0.002
	Agriculture	-0.01	0.03	-0.003
	Livestock	0.01	-0.04	-0.002
	Precious Metals	0.00	-0.03	-0.003
	Ind. Prod. US	0.00	-0.24	-0.001
	GSCI Spot	0.01	-0.04	-0.002
	US CPI	-0.00	-0.33	-0.003
	US 10Y	0.01	-0.05	0.002
Japan	No CV	0.04*		0.001
	Agriculture	0.04	0.01	-0.001
	Livestock	0.04	0.02	-0.001
	Precious Metals	0.05	-0.02	-0.001
	Ind. Prod. US	0.05	-0.35	0.002
	GSCI Spot	0.04	0.01	-0.001
	US CPI	0.05	-0.04	0.001
	US 10Y	0.05	-0.04	0.001
Germany	No CV	-0.02		-0.001
	Agriculture	-0.03	0.05	-0.001
	Livestock	-0.03	0.09*	0.002
	Precious Metals	-0.01	-0.04	-0.002
	Ind. Prod. US	-0.02	-0.01	-0.003
	GSCI Spot	-0.00	-0.05	-0.001
	US CPI	-0.02	-0.73	-0.001
	US 10Y	-0.02	-0.03	-0.002
Canada	No CV	0.04		0.000
	Agriculture	0.02	0.08	0.003
	Livestock	0.03	0.05	0.000
	Precious Metals	0.03	0.02	-0.001
	Ind. Prod. US	0.04	-0.18	-0.001
	GSCI Spot	0.03	0.03	-0.001
	US CPI	0.04	-0.09	-0.001
	US 10Y	0.05	-0.05	0.003
Australia	No CV	0.06		0.002
	Agriculture	0.06	-0.00	0.001
	Livestock	0.05	0.10	0.004
	Precious Metals	0.06	-0.02	0.001
	Ind. Prod. US	0.06	0.03	-0.001
	GSCI Spot	0.04	0.04	0.000

	US CPI	0.06	-0.64	0.000
	US 10Y	0.06	-0.01	0.001
South Korea	No CV	0.05		0.001
	Agriculture	0.05	0.03	-0.004
	Livestock	0.06	-0.02	-0.004
	Precious Metals	0.05	0.02	-0.004
	Ind. Prod. US	0.06	-0.31	-0.003
	GSCI Spot	0.08	-0.06	-0.003
	US CPI	0.08	-2.61*	0.004
	US 10Y	0.08	-0.07	0.000
Chile	No CV	0.02		-0.003
	Agriculture	-0.01	0.11	0.002
	Livestock	0.01	0.08	-0.003
	Precious Metals	0.01	0.05	-0.005
	Ind. Prod. US	0.03	-0.33	-0.003
	GSCI Spot	0.01	0.01	-0.005
	US CPI	0.03	-1.19	-0.003
	US 10Y	0.03	-0.03	-0.004
UK	No CV	0.06		0.006
	Agriculture	0.06	0.00	0.003
	Livestock	0.05	0.12**	0.017
	Precious Metals	0.07	-0.05	0.005
	Ind. Prod. US	0.05	0.23	0.006
	GSCI Spot	0.06	0.01	0.003
	US CPI	0.06	0.01	0.003
	US 10Y	0.06	-0.01	0.003
China	No CV	0.04		-0.002
	Agriculture	0.03	0.05	-0.005
	Livestock	0.03	0.20*	0.002
	Precious Metals	0.06	-0.06	-0.004
	Ind. Prod. US	0.05	-0.07	-0.005
	GSCI Spot	0.02	0.04	-0.005
	US CPI	0.05	-0.33	-0.005
	US 10Y	0.06	-0.05	-0.003
Norway	No CV	0.15*		0.017
	Agriculture	0.15*	-0.01	0.013
	Livestock	0.14*	0.11	0.017
	Precious Metals	0.18**	-0.12	0.018
	Ind. Prod. US	0.14	-0.19	0.014
	GSCI Spot	0.17*	-0.04	0.014

	US CPI	0.15*	-0.34	0.013
	US 10Y	0.17*	-0.04	0.015
France	No CV	0.09		0.008
	Agriculture	0.10*	-0.04	0.006
	Livestock	0.08	0.15*	0.018
	Precious Metals	0.11*	-0.08	0.008
	Ind. Prod. US	0.08	0.40	0.010
	GSCI Spot	0.11*	-0.03	0.006
	US CPI	0.10*	-0.93	0.008
	US 10Y	0.11*	-0.03	0.007
India	No CV	0.18*		0.019
	Agriculture	0.18**	-0.01	0.015
	Livestock	0.18*	0.01	0.015
	Precious Metals	0.19**	-0.06	0.016
	Ind. Prod. US	0.17*	0.13	0.015
	GSCI Spot	0.26**	-0.17*	0.027
	US CPI	0.21**	-2.86**	0.029
	US 10Y	0.21**	-0.08	0.022

Exhibit 3. Variables

This overview provides information on each variable that has been used in the analysis, and where the data is retrieved from.

Variable	**Name**	**Database**
Agriculture	S&P GSCI Agriculture Total return Index *This index has been designed to provide an exposure to the agriculture sector in commodity asset class on a total return basis.*	Bloomberg
Livestock	S&P GSCI Livestock Spot Index *This index provides investors with a reliable and publicly available benchmark for investment performance in the livestock commodity market.*	Bloomberg
Precious Metals	S&P GSCI Precious Metal Index *The S&P GSCI Precious Metals Index provides investors with a reliable and publicly available benchmark for investment performance in the precious metals market.*	Bloomberg
Industrial Prod US	US, Industrial Production Index *The Industrial Production Index is an economic indicator that measures real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities*	Macrobond
GSCI Spot	S&P GSCI Index Spot Index *The S&P GSCI is the first major investable commodity index. It is one of the most widely recognized benchmarks that is broad-based and production weighted to represent the global commodity market beta. The index is designed to be investable by including the most liquid commodity futures.*	Bloomberg

US CPI	US CPI Urban Consumers NSA *The consumer price index is a measure of the average change in the prices paid by urban consumers for a fixed market basket of goods and services.*	Bloomberg
US 10Y	US Gov. Federal Reserve, 10 Year, Yield *10 year nominal yields on US government bonds from the Federal Reserve. The 10 year government bond yield is considered a standard indicator of long-term interest rates.*	Macrobond
Copper	LME Copper Spot *Current and historical spot price of copper trading on the London Metals Exchange.*	Bloomberg
CFNAI	Chicago Fed National Activity Index *An index published by the Federal Reserve Bank of Chicago (FRBC) indicating national activity. This index is a weighted average extracted from 85 separate economic series describing the real economy.*	FRBC