

Correlation changes between commodities and equities during extreme conditions:

Has the gain from diversification played out its role?

Christina Cho^a

Cecilia Filipsson^b

Abstract

Commodities are often used for diversification purposes to reduce the portfolio risk without sacrificing the expected return. The lower the correlation between assets, the higher is the gain from diversification. Many models within portfolio optimization and risk management based on the mean-variance theory assume that the correlation is constant between different assets. However, changes in correlations between commodities and equities over time and during extreme conditions are not widely understood as research in this field is not very extensive and give ambiguous results. The objective of this thesis is to examine correlation changes between commodities and equities in times of extreme conditions, which are when the benefits of diversification are needed the most. Extreme conditions are defined as times of recession, extreme market returns and extreme market volatility. The hypothesis tests show that the correlation between commodities and equities is not stable over the time period studied. Further, the tests indicate that correlations increase during recession periods driven by financial turmoil in general and during the recent financial crisis in particular, while recessions driven by instable oil market seem to decrease correlations. There is also evidence of increased correlation during extreme market return levels and extreme high market volatility. Higher correlations are shown in bear markets than in bull markets. Similar results are given for all commodity indices although the β -values and significance levels differ slightly between different commodities and types of tests. Diversification is most valuable during extreme negative market conditions, and we therefore conclude that increased correlation is a problem if disregarded. New more dynamic models could mitigate the risks, however, anticipating correlation is a rather complex task and further research is necessary to make the models useful in practice.

^{a)} 20628@student.hhs.se

^{b)} 20705@student.hhs.se

Acknowledgement

We would like to express our gratitude to our tutor Paolo Sodini, Associate Professor, for his valuable guidance. We are also grateful to Per-Olov Edlund, Associate Professor, and Jan Schnitzler and Christian Heyerdahl-Larsen at SIFR for their input.

Table of Contents

1. Introduction	3
1.1 Purpose	4
1.2 Contribution	5
2. Theoretical Background	5
2.1 Mean-Variance Theory.....	6
3. Previous Research	8
3.1 Simple Correlation Research	8
3.2 Conditional Correlation Research	9
4. Hypotheses	13
5. Methodology.....	13
5.1 Testing Correlation Stability through Time.....	13
5.2 Testing Correlation Increases during Extreme Conditions	14
6. Data.....	17
6.1 S&P 500 Composite Index.....	17
6.2 S&P Goldman Sachs Commodity Index	18
6.3 Ten Sub-Indices	19
6.4 Other Commodity Indices.....	20
7. Results	21
7.1 Results for Hypothesis 1	21
7.2 Results for Hypothesis 2a	25
7.3 Results for Hypothesis 2b	28
7.4 Results for Hypothesis 2c	32
7.5 Result Summary.....	35
8. Analysis	37
8.1 Result Analysis.....	37
8.2 Implication for Investment Management	40
9. Conclusion	43
9.1 Suggestions for Further Research	44
10. List of References	46
11. Appendix	48
11.1 Data.....	48
11.2 Results	49
11.3 Regression Results	50

1. Introduction

In times of financial turmoil, risk assessment becomes of increasing importance for investment management. The *mean-variance theory* (MVT) claims that an investor can reduce the portfolio risk without sacrificing the expected return by investing in a diversified portfolio. The risk of a diversified portfolio is always less than for the weighted average of the individual asset risks if the correlations between them are less than perfect. The MVT was developed by Markowitz, Tobin, Sharpe, and Lintner, among others in the 50's and 60's and is also known as the *modern portfolio theory* (MPT). Investment models based on the MPT rest on the assumption of constant correlation between different assets (Bodie, Kane and Marcus, 2008). Hence, an investment strategy based on the MPT can be devastating if possible correlation changes are not taken into consideration.

Commodities are physical goods which are often used as inputs in the manufacturing process. Examples of commodities are oil, wheat, copper, and sugar. Diversifying an investment portfolio using commodities is a common strategy that has been historically successful due to the low correlation between commodities and equities. Adding both asset classes to the portfolio would reduce the portfolio risk (volatility) while at the same time not lose the upside potential (Barclays, 2010). However, studies indicate that the correlation between commodities and equities increased during the recent financial crisis (Authers, 2009). If higher correlations can be shown to be a general pattern under extreme conditions, then the risk reduction benefit from diversification is smaller when it is needed the most, such as in times of financial crisis.

Initially, two articles inspired us to look closer into the subject of correlation changes. The first article is from Financial Times and discusses whether or not a new market model is needed to replace the *efficient market hypothesis* (EMH) after the recent financial crisis. In the article, Jeremy Siegel states that “*the most serious attack on efficient markets is the change in correlation of asset classes under extreme conditions*” (Authers, 2009), indicating a phenomena of increased correlations during financial turmoil. As an example, Siegel points out that oil and equities traditionally move in opposite directions, a higher oil price would damage the equity market. Investing in oil would therefore provide a hedge against declining equity prices since the correlation between the two asset classes is low. However, during the recent financial crisis, oil, as well as other commodities such as gold, showed increased correlations with the equity market. Consequently, adding commodities to an equity portfolio would result in making the same bet twice and the gain of diversification could be questioned.

Siegel believes that the models based on the EMH could be adopted to account for correlation changes during extreme conditions. However, those models would be rather complex and very different from what is used in practice and taught in finance classes today.

The other article published in *The Economist* (2009) also discusses what remains of the EMH after the financial crisis. The EMH has underpinned many of the financial industry's portfolio optimization and risk management models for years, e.g. the *value-at-risk* (VaR) models. VaR models are used to calculate how much capital institutions need to set aside as insurance against losses on risky assets. In the article, Michael Scholes criticizes the use of these models, which mistakenly assume constant volatility and correlations between prices. Like Siegel, Scholes claims that assets which are normally uncorrelated can suddenly become highly correlated in times of market distress, resulting in an inadequate capital buffer implied by VaR. However, neither Scholes nor Siegel question the EMH itself but rather the practitioners' usage of the theory and mean that they push the models too far.

1.1 Purpose

The purpose of this thesis is to contribute to increased knowledge on correlation changes between commodities and equities during extreme conditions and the implications for investment management. The objective of this thesis can be summarized as follows:

*Correlation changes between commodities and equities during extreme conditions:
Has the gain from diversification played out its role?*

In order to answer this question, correlation changes during extreme conditions need to be examined. The abovementioned articles claim that the correlation between commodities and equities increased during the recent financial crisis. The articles do not present any data or sources regarding this statement, and therefore tests need to be conducted to see if there are in fact correlation changes during this period. However, this thesis is not only concerned with correlation changes between commodities and equities during the recent financial crisis, but rather during extreme conditions in general. Using different approaches, we examine whether increased correlation is evident during extreme conditions, defined as periods of recession, extreme market returns and extreme market volatility, where the market is defined as the S&P 500. The differences in correlation changes between various commodity classes are also addressed. Finally, we discuss the implications of the findings for investment management and seek to answer whether or not portfolio diversification has played out its role.

1.2 Contribution

Constant correlations are assumed for many risk management models, portfolio optimization, hedging and diversification. However, changes in correlations over time and during extreme conditions are not widely understood. Most research on correlation changes concerns international equity markets with the purpose of examining the benefits of international diversification. The research on correlation changes between commodities and equities is not very extensive and mainly concerns changes in correlation between different time periods in general rather than during extreme conditions. The findings are also somewhat contradictory when it comes to the size and the direction of correlation changes during extreme conditions why this is of interest for further study. The methodology from any previous research cannot be applied straight off since a broader data set is used in this thesis, both in terms of time period and number of commodity indices, and most studies in the field are conducted on international equity markets. Instead, methodologies inspired by different papers are applied to examine correlation increases during the three different types of extreme conditions identified; periods defined as recessions, times of extreme market returns, and times of extreme market volatility.

We hope to contribute to the research on the correlation between equities and commodities for investment management purposes during extreme conditions since the existing research is ambiguous. Compared to previous studies on commodity and equity correlation a broader data set of commodities and a longer time span, including the recent financial crisis, is used. Also, different methodologies are applied to examine the correlation changes between the equity and the commodity market. By analyzing the results and their implications for investment management, we can either conclude that existing models for portfolio optimization and risk management are efficient or that new, more dynamic models need to be developed.

2. Theoretical Background

The main theoretical framework of this thesis is the *mean-variance theory* (MVT), and the *value-at-risk theory* (VaR) will also be touched upon. As presented in the introduction, the MVT was developed by Markowitz, Tobin, Sharpe, and Lintner, among others in the 50's and 60's and is also known as the *modern portfolio theory* (MPT). This section provides basic insight into these theories and models.

2.1 Mean-Variance Theory

Within portfolio management, there are three decision levels of investment; *capital allocation* between the risky portfolio and the risk-free asset; *asset allocation* across a broad set of asset classes and individual *security selection* (Bodie, Kane and Marcus, 2008). The capital allocation is determined by the investor's risk aversion as well as the expected risk-return trade-off of the optimal risky portfolio, and decides the total risk exposure. Both asset allocation and security selection aim to identify the optimal risky portfolio, also called the *mean-variance portfolio*. A fundamental concept of MVT is that the individual asset selection for the portfolio cannot be done on the assets' own merits; rather the correlation between the different assets needs to be considered. The goal is to create a portfolio with the highest expected return given a certain risk level. The expected rate of return for a portfolio is the weighted average of the expected returns of each individual security with the portfolio proportion as weights:

$$E(r_p) = \sum_{i=1}^n w_i E(r_i) \quad (2.1.1)$$

The risk, measured as the volatility of the portfolio, is not only determined by the volatility of the different assets but also by how they move relative to each other, which is measured by the correlation coefficient. Therefore, the portfolio volatility, or standard deviation (σ), is not calculated as the weighted average of the individual asset volatilities (Haugen, 1999). The portfolio volatility is instead a function of the asset correlations within the portfolio and as opposed to the portfolio return, the portfolio volatility is non-linear as the assets weights change. The portfolio variance is expressed as follows:

$$\sigma_p = \sqrt{\sum_{j=1}^n \sum_{i=1}^n w_j w_i \text{Cov}(r_j, r_i)} \quad (2.1.2)$$

The covariance (Cov) is computed from the correlation coefficient (ρ) and the standard deviations:

$$\text{Cov}(r_j, r_i) = \sigma_j \sigma_i \rho_{ji} \quad \text{where} \quad \rho_{j,i} = \frac{\text{cov}(j,i)}{\sigma_j \sigma_i} = \frac{E[(X - \mu_j)(Y - \mu_i)]}{\sigma_j \sigma_i} \quad (2.1.3)$$

If the individual assets in the portfolio are not all perfectly positively correlated, the standard deviation of the portfolio is less than the weighted average of the individual assets' standard deviations. Since the expected portfolio return is the weighted average of its individual assets, a portfolio with less than perfect correlation always offers a better return than the individual securities on their own, given the risk level. Therefore, by holding a diversified portfolio,

investors can reduce their exposure to individual asset risk without sacrificing the expected return. The lower the correlation between assets, the higher is the gain from *diversification* (Siegel, 2008).

The *efficient frontier* is the convex frontier above the *minimal variance portfolio* illustrated in *Figure 2.1.1*. The efficient frontier represents a set of risky portfolios with minimum variance and maximum returns, that is, a set of portfolios where both risk and return cannot be improved simultaneously. Portfolios above the frontier are not achievable by risky assets alone and portfolios below the frontier are suboptimal, hence rational investors would only hold portfolios on the efficient frontier. The *capital allocation line* (CAL) is the line of expected return against risk, which connects the risk free asset and the risky portfolio and has the following equation:

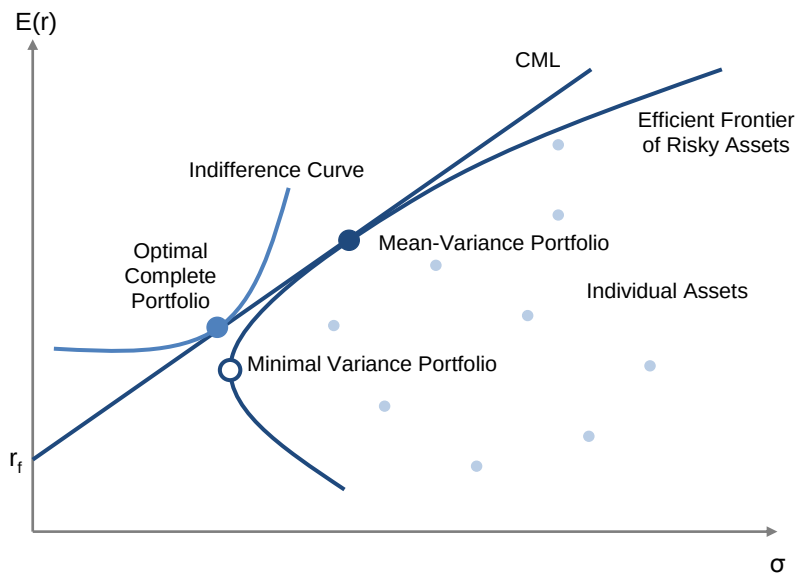
$$CAL: E(r_c) = r_f + \sigma_c \frac{E(r_p) - r_f}{\sigma_p} \quad (2.1.4)$$

The CAL, which is tangent to the efficient frontier, is called the *capital market line* (CML) as it goes through the mean-variance portfolio, see *Figure 2.1.1*. All points along the CML provide a higher return for any given risk level than any risky portfolios on the efficient frontier. The CML represents the CAL with the highest slope equal to the *Sharpe ratio* of the mean-variance portfolio (Bodie, Kane and Marcus, 2008). The Sharp ratio is defined as:

$$Sharpe \text{ Ratio} = \frac{\text{Risk premium}}{\text{Standard excess return}} S_p = \frac{E(r_p) - r_f}{\sigma_p} \quad (2.1.5)$$

The capital allocation between the risky portfolio and the risk free asset is determined by the investor's indifference curve, which in turn is determined by his risk aversion. Hence, the optimal combination is given by the *optimal complete portfolio* on the CML.

Figure 2.1.1 Efficient frontier, mean-variance portfolio and capital market line



Within risk management, VaR is widely used to measure the risk of loss on a specific portfolio of financial assets. It measures the worst expected loss under normal market conditions during a specific time interval. VaR is defined as a threshold value such that the probability that the mark-to-market loss on the portfolio over the given time horizon exceeds this value. Another way of expressing this is that VaR is the lowest quantile of the potential losses that can occur for a given portfolio during a specified time period. Since the threshold value is dependent on the volatility of the portfolio and the volatility in turn depends on the correlation, VaR is of interest in this thesis. VaR can be calculated by different methods, the most common is using a mean-variance covariance matrix (Benninga and Wiener, 1998).

3. Previous Research

There are a number of academic articles discussing the issue of correlation changes in general and during extreme conditions in particular. However, most papers focus on international equity markets while the research on correlation changes between commodities and equities is not as extensive. Previous research is rather contradictory and data from the recent financial crisis is not included. In this section, the conclusions and the methodologies from various articles on the subject are presented.

3.1 Simple Correlation Research

Several studies use *simple correlations*, such as rolling or moving historical correlations. Büyüksahin, Haig, and Robe (2008) use this method along with a dynamic conditional correlation (DCC) methodology to examine the correlation between the commodity index S&P GSCI and the equity index S&P 500 in the period January 1991 to May 2008. However, their main purpose is not to test for extreme conditions, but rather to focus on three sub-periods with different characteristics, such as different trading volumes and economic conditions. The sub-periods are (1) June 1992 to May 1997, (2) June 1997 to May 2003, and (3) June 2003 to June 2008. Both the simple rolling correlations and the DCC show that there has been no significant change in the correlation between the returns in the three sub-periods. Furthermore, they apply the simple rolling correlation methodology to test for extreme events when the values of returns on the S&P 500 deviate one or two standard deviations above or below its sample mean. The authors find no evidence of an increase in the correlation between the two investment options during extreme events, which leads to the conclusion that commodities are still useful investment options for portfolio diversification.

Coaker (2006) studies the volatility of correlation and its implications for asset allocation decision by analyzing the simple rolling correlation of 15 different asset classes against the S&P 500 in one-, three-, five-, and ten-year time series over a 35-year period (1970-2004). He also analyzes if these asset classes have been beneficial for diversification purposes in years when the equity market declined. The study shows that the correlation between natural resources and the S&P 500 varies vastly over the time period, but is less than 0.49 for all five-year periods and negative for 17 out of the 35 years studied. Coaker also concludes that equities and natural resources have different bull and bear market cycles.

3.2 Conditional Correlation Research

Various studies use *conditional correlation measures* to examine correlation changes between different time periods or during extreme returns. Chong and Miffre (2007) study the conditional risk premia and correlations in commodity futures markets from 1979 to 2004. They study weekly returns of the S&P 500, U.S. Treasury-bond index and 21 commodity futures contracts. By using the diagonal VEC¹ model, which is very similar to the univariate GARCH² (1,1) model, the authors find that investors in commodity futures markets earned a significant risk premia during the time period of study. What is more relevant for this thesis is the result showing that the conditional correlations between commodity futures and equity returns fell over time, and also in periods of above average market volatility. This result is obtained by using a bivariate GARCH (1,1) model to estimate the conditional correlation between equity and commodity futures returns, and performing a simple regression on a constant and a time trend.

The abovementioned findings of a falling conditional correlation between commodity futures and equity returns over time are in line with the results of a research conducted by the same authors a year later, Chong and Miffre (2008). In this paper, the focus is on temporal variations in the conditional return correlations between commodity futures and traditional asset classes, such as global stock indices and treasury bonds. Unlike the previous paper which uses a GARCH (1,1) model, the DCC³ (1,1) model is used to estimate the conditional correlation. The dataset is also different and consists of weekly returns of 25 commodities and 13 traditional asset classes from December 12th 1980 to December 27th 2006. However,

¹ For more information on the VEC model, see Chong and Miffre (2007).

² For more information on the GARCH model, see Engle (2009).

³ For more information on the DCC model, see Chong and Miffre (2008).

the same type of regression is used as in Chong and Miffre's paper from 2007. They find that the conditional correlations between commodity futures and the S&P 500 fell over time, and in periods of above average volatility in equity markets. Furthermore, the results show that the average conditional correlation between commodity futures and the S&P 500 is of the same magnitude as the average unconditional correlation, and that the conditional correlations are for the most part insignificant at a 5% level.

Longin and Solnik (2001) study *international equity market* correlations using monthly equity index returns for five countries from January 1959 to December 1996. The extreme value theory⁴ (EVT) is used to study the dependence structure of international markets, and the findings suggest that the correlation between different equity markets is not related to market volatility per se but to the market trend. Also, the correlation increases in bear markets, but not in bull markets. To study correlations of extreme returns, the return exceedances are defined with various threshold levels given by $\pm X$ percentage points away from the empirical mean of each country. By applying a bivariate framework, the correlation between the U.S. market and each of the other four markets is studied separately. The correlation of large negative returns tends to increase with the threshold level while the correlation of large positive returns tends to decrease and converge to zero as the threshold level increases. In contrast to these findings, Campbell, Koedijk, and Kofman (2000), which are discussed in more detail further down, find evidence of a general increase in the correlation between international financial assets in both the lower and upper outermost tail sections of a bivariate distribution.

Extreme co-movements between financial assets are also investigated by Mashal and Zeevi (2002). They test the underlying dependence structure using a t-dependence structure as a proxy to test for extremal behavior using data from international equity markets, as well as foreign exchange and commodity markets. They provide empirical evidence that extreme co-movements are more significant as the number of underlying assets of a basket increases. The focus of this study is similar to Longin and Solnik (2001) as both papers study the underlying dependence structure of joint asset returns. However, Longin and Solnik (2001) only provide empirical evidence of bivariate extreme co-movements between assets whereas Mashal and Zeevi (2002) test for any number of given assets.

⁴ For more information on the EVT model, see Longin and Solnik (2001).

Campbell, Koedijk, and Kofman (2000) look at correlation changes between international financial assets and the focus is on whether extreme movements are more correlated than usual returns. The benefits from portfolio diversification would then rapidly vanish since extreme returns are expected to occur with greater simultaneity. They use two different conditional correlation measures of non-overlapping quantiles of the joint return distributions on daily data from different countries' stock indices; a truncated measure, which looks at spurious correlation, and a quantile approach, which is closely linked to portfolio management use of correlation and hence more appealing from a practical point of view. The truncated approach shows that the correlation is greater in the outermost tail section of the bivariate distribution than in the center. Using the quantile approach, the data appear to violate the assumption of normality, and the correlation and covariance structure change when looking at the tails of the distribution. Up until 95% level, the null hypothesis of constant correlation cannot be rejected. However, the increased correlation in the tails suggests that a tail-adjusted variance-covariance matrix should be used for mean-variance portfolio analysis. Campbell, Koedijk, and Kofman (2002) show similar results using only the quantile approach and conclude that the correlation is increasing more in bear markets than in bull markets.

In summary, the simple correlation analysis performed by Büyüksahin, Haig and Robe (2008) show no significant change in the correlation, neither between the three sub-periods nor during extreme events. These findings are contradictory to those of Coaker (2006). He finds that for 17 out of 35 years studied, the correlation between the S&P 500 and natural resources is negative, implying changes in the correlation.

Conditional correlation studies also give diverse results. Chong and Miffre (2007 and 2008), find that the correlation between equities and commodities fell over time, while Longin and Solnik's (2001) study on international equity markets suggest that the correlation increases in bear markets but not in bull markets. Mashal and Zeevi (2002) show that extreme co-movements are more significant as the number of underlying assets in a portfolio increases. Finally, studies show a general increase in the correlation between international financial assets in both the upper and lower outermost tail sections of a bivariate return distribution (Campbell, Koedijk and Kofman, 2000). However, higher correlations are evident in bear markets than in bull markets (Campbell, Koedijk and Kofman, 2002).

Table 3.2.1 A summary of previous research on correlation changes over time and during extreme conditions

	Büyükşahin, Haig and Robe (2008)	Coaker (2006)	Chong and Miffre (2007)	Chong and Miffre (2008)	Longin and Solnik (2001)	Mashal and Zeevi (2002)	Campbell, Koedijk and Kofman (2000)
Type of correlation	Simple (time and size)	Simple (time)	Conditional (time)	Conditional (time)	Conditional (size)	Conditional (joint returns)	Conditional (time and size, joint returns)
Data	S&P 500 and S&P GSCI	S&P 500 and 15 different asset classes (e.g. natural resources)	S&P 500, US Treasury-bond index and 21 commodity futures contracts	25 commodities and 13 traditional asset classes (e.g. S&P 500)	Equity index returns for five countries (U.S, Germany, France, Japan, U.K)	International equity markets, foreign exchange and commodities	Equity index returns for five countries (U.S, Germany, France, Japan, U.K)
Time period	1991 - 2008	1970 - 2004	1979 - 2004	1980 - 2006	1959 - 1996	1989 – 2002	1990 - 1999
Method	Rolling correlation, DCC	Rolling correlation	Bivariate GARCH (1,1) model	DCC (1,1) model	Bivariate framework	t-dependence structure, likelihood ratio-based methods	Truncated measure and quantile approach
Characteristics	Study three sub-periods and extreme events	Use one-, three-, five-, and ten-year time series			Study correlations of extreme returns using various threshold levels	Similar to Longin and Solnik (2001)	Use the VaR methodology
Findings	No significant change in the correlation between the returns in the three sub-periods, no evidence of an increase in co-movement between the two investment options during extreme events.	Different bull and bear market cycles, the correlation between natural resources and S&P 500 varies vastly over the time period, but is negative for 17 out of the 35 years studied.	The conditional correlations between commodity futures and equity returns fell over time, also in periods of above average market volatility.	Correlations between commodity futures and S&P 500 fell over time, also in periods of above average volatility in equity markets. The average conditional correlation is of the same magnitude as the average unconditional correlation.	The correlation between equity markets is related to the market trend. As the threshold level increases, the correlation of large negative returns increase, while the correlation of large positive returns decreases and converges to zero.	Extreme co-movements are more significant as the number of underlying assets in a basket increases.	The correlation is greater for bear markets than for bull markets. Up until the 95% level, the null of constant correlation cannot be rejected. However, the correlation appears to increase further out into the tails of the distribution.

4. Hypotheses

Firstly, the correlation stability between commodities and equities is studied over time. This is to conclude if the correlations are in fact fluctuating, but also to study the correlation distributions and the existence of trends or regime shifts (*Hypothesis 1*).

Hypothesis 1: The correlation in returns between the commodity indices and the S&P 500 is constant between 1970 and 2009.

If the hypothesis of constant correlation can be rejected, the next step would be to see if the correlation increases during extreme conditions, that is, when diversification is needed the most. Three types of extreme conditions are identified and correlation increases are tested in periods of recession (*Hypothesis 2a*), times of extreme market returns (*Hypothesis 2b*) and times of extreme market volatility (*Hypothesis 2c*). To test each of the hypotheses, three different types of approaches are applied. The methodologies used are explained in detail in *Section 5*.

Hypothesis 2a: The correlation in returns between the commodity indices and the S&P 500 is constant between times of *recession and expansion* as defined by NBER.⁵

Hypothesis 2b: The correlation in returns between the commodity indices and the S&P 500 is constant and does not depend on *extreme return levels* of the S&P 500.

Hypothesis 2c: The correlation in returns between the commodity indices and the S&P 500 is constant and does not depend on *extreme volatility levels* of the S&P 500.

5. Methodology

5.1 Testing Correlation Stability through Time

One key assumption when analyzing financial time series data using a statistical model is that the parameters of the model are stable over time. If the estimated parameters of a rolling window analysis do not differ from each other greatly, one can conclude that the parameters are fairly constant over the whole sample (Wang and Zivot, 2002).

⁵ The National Bureau of Economic Research.

In *Hypothesis 1*, non-overlapping one-year rolling correlation windows as well as one-year moving correlation windows used to estimate daily correlations are graphed in order to study whether or not the correlation between assets are constant over time. Rolling correlations are also used by Coaker (2006) to study correlation volatility through time. When performing either a rolling- or moving correlation analysis, the choice of the window length is of great importance. The window should be short enough to give a good picture of the contemporaneous correlation, but long enough to smooth out erratic time series of sample correlations (Jia and Adland, 2002). We believe that a one-year window meets the criteria mentioned above and will therefore use this for both non-overlapping data and to estimate daily data. The one-year moving window consists of 252 observations, which is the average number of trading days per year for the dataset. All tests are conducted in STATA and the Pearson's correlation is used in the analyses:

$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \quad (5.1.1)$$

A study of the one-year rolling correlation windows percentage distribution between the different commodity indices and the S&P 500 is also performed (*Table 7.1.3*). This shows in which value range most of the correlations can be found. When all the one-year rolling correlation windows are calculated, they are assigned to different correlation ranges depending on their correlations. The total number of observations in each value range divided by the number of observations of each commodity index gives the percentage distribution.

5.2 Testing Correlation Increases during Extreme Conditions

After studying the correlation stability and distribution through time, *Hypothesis 2a, b and c* test whether or not the correlation is in fact increasing during extreme conditions using three different approaches: graphical illustrations, regressions and conditional correlations.

Firstly, the relationship between the S&P GSCI and the S&P 500 correlations and the defined extreme conditions tested in *Hypothesis 2a, b and c* is *graphed*; one-year correlations versus recession periods, one-year correlations versus one-year market return, and one-year correlations versus market volatility. The graphs could give a first indication of the co-movements between equities and commodities.

Secondly, different types of *regressions* are performed to see if correlations can be explained by the extreme conditions: recessions, extreme market returns and extreme market volatility. When running the regressions, both yearly and daily data are used depending on

the characteristics of the tests performed. Similar to the tests described in *Section 5.1*, yearly data is estimated by rolling correlation windows consisting of non-overlapping data, while daily correlations and standard deviations are estimated by one-year moving windows. The basic ordinary least squares (OLS) regression model used is the following:

$$\rho_{S\&P\ 500, Commodity\ index} = \alpha + \beta \times Extreme\ Condition + \varepsilon \quad (5.2.1)$$

Dummies are used to perform even more specific tests, depending on the type of the explanatory variable.

$$\rho_{S\&P\ 500, Commodity\ index} = \alpha + \beta_1 \times Dummy\ 1 + \beta_2 \times Dummy\ 2 + \beta_3 \times Dummy\ 3 + \dots + \varepsilon \quad (5.2.2)$$

The first regression run in *Hypothesis 2a* tests whether the correlations between equities and commodities are higher in times defined as recessions with significant decline in economic activity. The test is conducted by creating one dummy variable for these years and then running the regression for each of the commodity indices. Most recessions do not perfectly match full calendar years, e.g. one of the recessions start in July 1990 and end in March 1991. In this case, both 1990 and 1991 are identified as recession periods. The same methodology is applied to test for correlation increases during the recent financial crisis. In addition, a regression is performed to determine if there are any differences between various types of recessions for which different dummies are assigned for; the recent financial crisis, oil recessions and all other recessions (*Equation 5.2.2*). Unlike the previous regressions, daily data is used in order to be more specific with the time periods and to include more observations per recession. Dummies are assigned for all days within each of the different recession types, see *Table 5.1.1*.

Table 5.1.1 NBER defined periods of recession

Peak	Through
December 1969	November 1970
November 1973	March 1975
January 1980	July 1980
July 1981	November 1982
July 1990	March 1991
March 2001	November 2001
December 2007	*

* The full year of 2009 is defined as recession

Similar types of regressions are performed in *Hypothesis 2b* based on the return levels of the S&P 500. We expect the correlation to increase when market returns are extreme, that is, a u-shaped relationship between the correlation and market returns. Therefore, the squared

market returns is added to *Equation 5.2.1* for the first regression. A second regression is also performed using two dummies representing extreme returns. Daily return levels are sorted according to their size and dummies are assigned to observations in the 95th percentile and above as well as to the 5th percentile and below. The 5th percentile is defined as the value of which 5% of the data falls below. The p-value of the β -values will tell if the correlation increases are of statistical significance and the size of the latter determines which of the two ends of the return distribution is more sensitive to correlation changes. Daily correlations are estimated by one-year moving correlations.

To test *Hypothesis 2c*, a regression is run for correlation over the volatility level of the S&P 500 to see if the correlation is dependent on the market volatility level, an approach similar to Büyüksahin, Haig and Robe (2008). Estimated daily standard deviations and correlations are used. As in *Hypothesis 2b*, a second regression is run using two dummies representing extreme volatility; one for volatility levels in the 5th percentile and below, and one for the 95th percentile and above. Daily standard deviations are estimated by one-year moving windows and sorted according to their size. By studying the β -values and their significance from the different regressions, the hypothesis can either be rejected or not.

Finally, the correlation conditional on different sub-sets of the sample is studied to conclude whether the correlation is higher during extreme conditions. In *Hypothesis 2a*, all days which are defined as recession periods are identified, thus being more exact than when limiting recessions to one-year periods. The correlation is compared for; days in recession versus expansion, and days within the recent financial crisis versus excluding the recent financial crisis. The correlation is also tested when excluding the days during oil recessions. In *Hypothesis 2b*, days are also sorted on the return level of the S&P 500 and divided into different percentiles. Correlations are estimated conditional on these percentiles and this methodology is similar to the one used by Longin and Solnik (2001). However, they look at joint returns of international equity markets while we test for correlation changes solely based on the S&P 500 returns. By doing this we can examine if the correlation increases further out in the tails and also address potential differences in correlation between extreme negative and positive returns in the S&P 500. For diversification purposes, the correlation when market returns are negative is of greater interest. Similarly for *Hypothesis 2c*, all days are sorted by the volatility level, estimating daily volatility with one-year overlapping moving windows. The correlation is estimated in the different percentiles of the volatility distribution to study the correlation conditional of market volatility.

6. Data

In this section, the data used for the hypothesis tests is presented as well a discussion about the choice of data used.

To analyze the correlation changes in returns between equities and commodities, total return data for the S&P 500 Composite Index and the S&P Goldman Sachs Commodity Index (S&P GSCI) are used, as well as ten sub-indices of the S&P GSCI. The chosen individual commodity indices are presented in *Table 6.1.1* and are the ten largest components of the S&P GSCI. The data covers a 40 year period from 1970 to 2009 and captures both economic expansions and contractions. However, not all indices are available from 1970, and this will be addressed in *Section 6.2*.

Table 6.1.1 Index names, acronyms and available time periods

Index	Acronym	Available from
S&P 500 Composite	S&P	12/31/1963
S&P GSCI	GSCI	01/02/1970
Crude oil	Cru Oil	01/07/1987
Brent crude oil	BrCrOil	01/08/1999
Gas oil	Gas Oil	01/06/1999
Natural gas	Nat Gas	01/07/1994
RBOB gas	RBOB	01/07/1988
Heating oil	Heat Oil	12/31/1982
Copper	Copper	01/07/1979
Corn	Corn	12/31/1969
Wheat	Wheat	12/31/1969
Sugar	Sugar	01/01/1973

The daily total return data for the indices are downloaded from DataStream and Wharton Research Data Services. The data is re-calculated to show the percentage returns which are used in the various tests. Holidays and other dates when the equity market is closed are omitted from the dataset. The most important statistics for the indices are shown in *Table 11.1.1* in the appendix.

6.1 S&P 500 Composite Index

The S&P 500, first published in 1957, focuses on the large cap sector of the U.S. equity markets. 500 leading American companies from a diverse range of industries are included in the index which captures 75% of the U.S. equities coverage. The S&P 500 is a market value weighted index, meaning that each stock's weight is proportionate to its market value (Standard & Poor's, 2009).

The U.S equity market is the largest one in the world (WFE, 2010). It is therefore chosen to represent the market in this study. The Dow Jones Industrial Average is also frequently used as a benchmark index for the U.S. equity market. However, it only comprises 30 companies and therefore reflects a poorer picture of the market compared to the S&P 500. The S&P 500 is also often used in research as a proxy of the market portfolio as illustrated in the articles presented in *Section 3*.

This thesis concerns correlation changes and its implication on investment management, and the investor perspective is therefore important. A total return index includes all dividends and thus offers a better picture of an investor's returns from investing in an index. Previous studies have also used total return data or excess return data.

Both the S&P 500 and the S&P GSCI publish excess return indices which, just like the total return indices, provide a good representation of returns available to investors from investing in the indices. However, the two excess return indices are not comparable to each other. The S&P 500 excess return index is the return above the risk-free rate while the S&P GSCI excess return index is not (Standard & Poor's, 2007). The total return index is therefore chosen for both the S&P 500 and S&P GSCI for comparability reasons.

6.2 S&P Goldman Sachs Commodity Index

The S&P GSCI is chosen to represent the commodities market. The index consists of 24 production-weighted commodities representing various commodity sectors, as illustrated in *Table 6.2* below. The commodities included in the hypothesis tests are in italic in the table.

Table 6.2.1 *The S&P GSCI components and dollar weights (%) as of January 29, 2010*

Energy	69.26 %	Industrial Metals	8.26 %	Precious Metals	3.24 %	Agriculture	14.54 %	Livestock	4.69 %
<i>Crude Oil</i>	35.88	Aluminum	2.63	Gold	2.90	<i>Wheat</i>	2.92	Live Cattle	2.72
<i>Brent Crude Oil</i>	14.16	<i>Copper</i>	3.64	Silver	0.34	Red Wheat	0.58	Feeder Cattle	0.44
<i>RBOB Gas</i>	4.38	Lead	0.49			<i>Corn</i>	3.18	Lean Hogs	1.53
<i>Heating Oil</i>	4.44	Nickel	0.78			Soybeans	2.27		
<i>Gas Oil</i>	5.51	Zinc	0.72			Cotton	1.11		
<i>Natural Gas</i>	4.89					<i>Sugar</i>	3.34		
						Coffee	0.73		
						Cocoa	0.41		

The quantity of each commodity in the index is determined by a five year moving average of world production data. The index is therefore a useful economic indicator since the actual production is reflected in the index. For example, the economic consequences of doubling the

price of wheat on inflation and economic growth, is directly dependent on the production of wheat in the economy (Standard & Poor's, 2007). In addition, averaging five years of data decreases the chances of large changes in the weights from year to year since four of the five years averaged will be the same. This method increases the reliability of the component weights as it captures market trends which are persistent while at the same time prevents the index from overreacting to temporal or random phenomena.

Although the S&P GSCI is first published in 1991, the index data is available from January 2, 1970. The historical value of the index is calculated based on the selection criteria, methodology and procedures adopted in 1991. The S&P GSCI is normalized to a value of 100 on January 2, 1970, which makes it possible to compare the value of the index over time (Standard & Poor's, 2010). Since the actual values of the components are used, the calculated historical values do not undermine the data's credibility. The index is a tool used to track the commodities' performance and its value is not influenced by the trading value. Therefore, the correlation between the S&P GSCI and the S&P 500 is not affected by the fact that the S&P GSCI is not publicly traded between 1970 and 1991.

The S&P GSCI total return index data measures *"returns accrued from investing in fully-collateralized nearby commodity futures ... (it) is the measure of commodity returns that is completely comparable to returns from a regular investment in the S&P 500 (with dividend reinvestment) or a government bond"* (Standard & Poor's, 2007. p.3). This index is used since it represents the return available to investors by investing in the S&P GSCI, and the investor's perspective is of interest in this thesis.

6.3 Ten Sub-Indices

The sub-indices chosen for complementary testing are the ten largest components of the S&P GSCI. They are chosen based on the dollar weights as of January 29th 2010 and are meant to provide a broader picture of the commodity market. It is more interesting to look at dollar weights than production weights for investment purposes since commodities like oil, gas and corn are of greater importance for the commodities market compared to for instance feeder cattle and silver. This is reflected in the trading volumes in which the volume of crude oil futures is more than 130 times higher than those of feeder cattle (CME, 2010). The component weights shift frequently as they are based on dollar-weights and therefore, the S&P GSCI should not be seen as a representation of the ten chosen sub-indices.

6.4 Other Commodity Indices

In this thesis, the S&P GSCI is chosen to represent the commodities market. However, there are other commodity indices which potentially could have been used. Here, two other commodity indices are presented along with a discussion of the different indices' advantages and disadvantages.

When the CRB index was first launched in 1957 by the Commodity Research Bureau, it comprised 28 commodities such as eggs, rye, and lard but not a single energy component. Since then, the index has undergone revisions to better reflect the prevailing market environment and consists today of 19 components, see *Table 11.1.3* in the appendix (Thomson Reuters/Jefferies, 2010a). In 2005, there was a radical weighting revision and the index is now rebalanced monthly and not all of the components are equally weighted. An arithmetic averaging technique is also used instead of a geometric averaging technique (Thomson Reuters/Jefferies, 2010a and 2010b), which means that the comparability of the data is very low.

Dow Jones-UBS Commodity Index (DJ-UBSCI), introduced in 1998, is a dollar-weighted index comprising 19 components. In order to avoid concentrations in one commodity or a specific sector, the index does not assign more than 33% of the index to one group, and one single commodity is not allowed to comprise more than 15% of the index (*Table 11.1.2* in the appendix). DJ-UBSCI is reweighted and rebalanced annually on a price-percentage basis (Dow Jones & Company Inc., 2009a). The component weights are calculated by a 2:1 ratio of five year average liquidity and production data. Since using production data alone could underestimate the economic significance of storable commodities, such as gold, at the expense of less storable commodities, e.g. live cattle (Dow Jones & Company Inc., 2009b), the component weight calculations of the DJ-UBSCI may present a better picture of the market conditions than those of the S&P GSCI. However, the data is only available for 12 years and this is not sufficient for the tests performed in this study. The S&P GSCI is a motivated choice since it provides comparable data over a long time period and a good picture of the current commodities market and is also used in previous research.

7. Results

In this section, the results from the different hypothesis tests are presented and discussed in separate subsections. In *Section 8*, a more comprehensive discussion on the findings and the implication for portfolio and risk management follows.

7.1 Results for Hypothesis 1

Hypothesis 1: The correlation in returns between the commodity indices and the S&P 500 is constant between 1970 and 2009.

Firstly, the correlations for all indices are calculated over the whole sample as a baseline for further comparison. The correlation used throughout the thesis is Pearson's correlation (*Equation 5.1.1*). The correlation between the S&P GSCI and the S&P 500 is fairly low over the period; 0.066, and most of the other commodity indices range from about 0.031 to 0.067, see *Table 7.1.1*. The exceptions are Brent Crude Oil and Copper, which are higher than the other indices, 0.137 and 0.158 respectively. All correlations are significant at a 5%-level except for Gas Oil and Natural Gas, whereof Gas Oil is significant at a 10% level while Natural Gas is not. The correlations are of similar magnitude as the unconditional correlation estimated by Chong and Miffre (2008), 0.014 but different from the findings of Büyüksahin, Haig, and Robe (2008) which was -0.035. This deviation is not of great concern since both the time period and the composition of the indices differ between the studies.

Table 7.1.1 Correlations between the commodity indices and the S&P 500 over the whole sample period, daily data

	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
Correlation	0.0661*	0.0437*	0.1367*	0.0347	0.0224	0.0550*	0.0308*	0.1578*	0.0674*	0.0640*	0.0415*
p-value	0.0000	0.0009	0.0000	0.0685	0.1563	0.0000	0.0110	0.0000	0.0000	0.0000	0.0001
# of obs	10096	5797	2762	2762	4025	5544	6807	8323	10096	10096	9335

* Significant at a 5%-level

Figures 7.1.1 and *7.1.2* show the correlation between the S&P GSCI and the S&P 500 using one-year rolling and moving windows, respectively. The correlation is shown to fluctuate vastly between different years, following a similar pattern for both the rolling- and moving correlation windows; a great decline in 1990, and a major increase in the recent years.

Figure 7.1.1 Correlations between the S&P GSCI and the S&P 500, one-year rolling windows

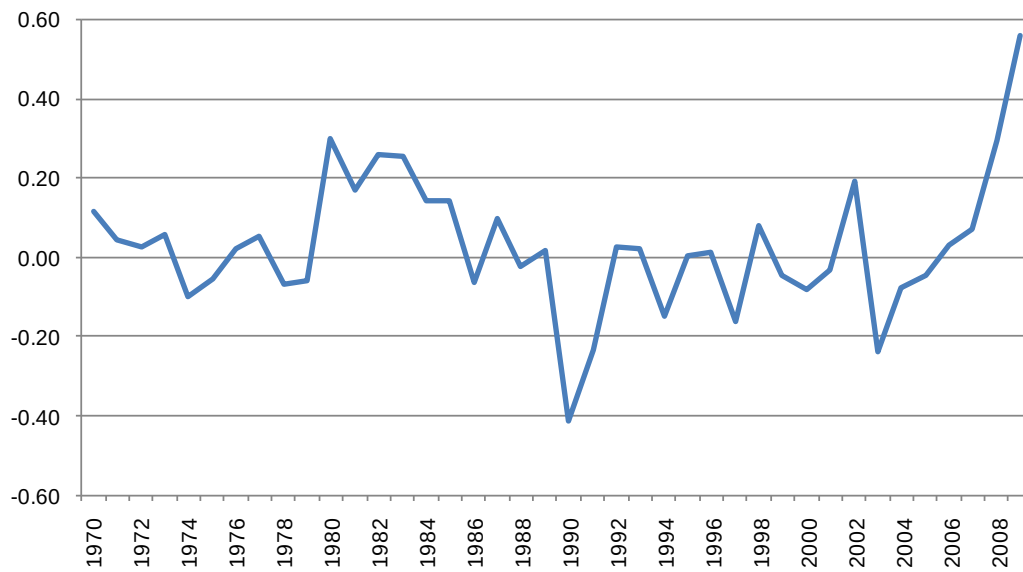
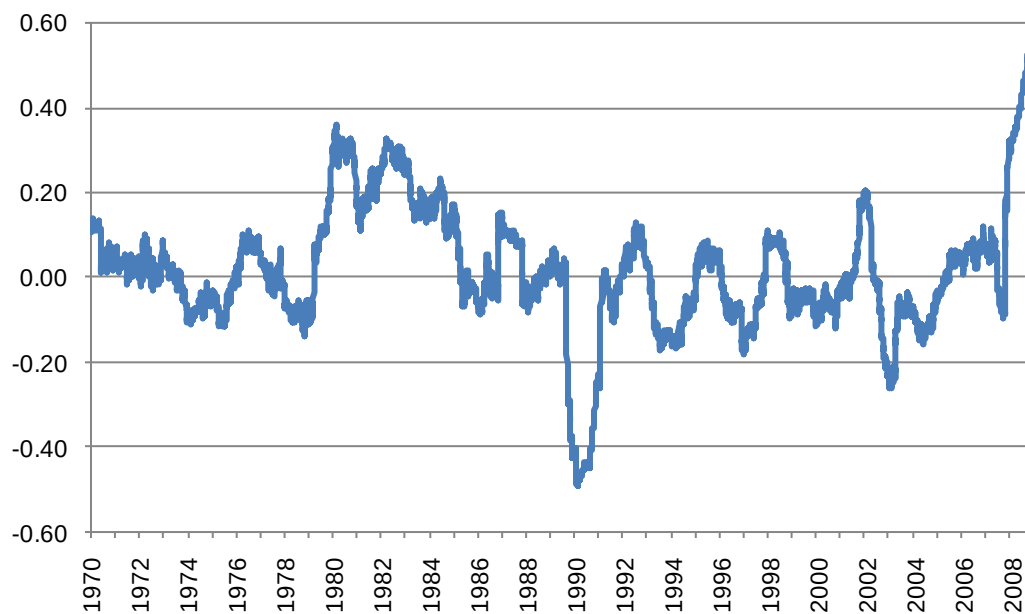


Figure 7.1.2 Correlations between the S&P GSCI and the S&P 500, one-year moving windows



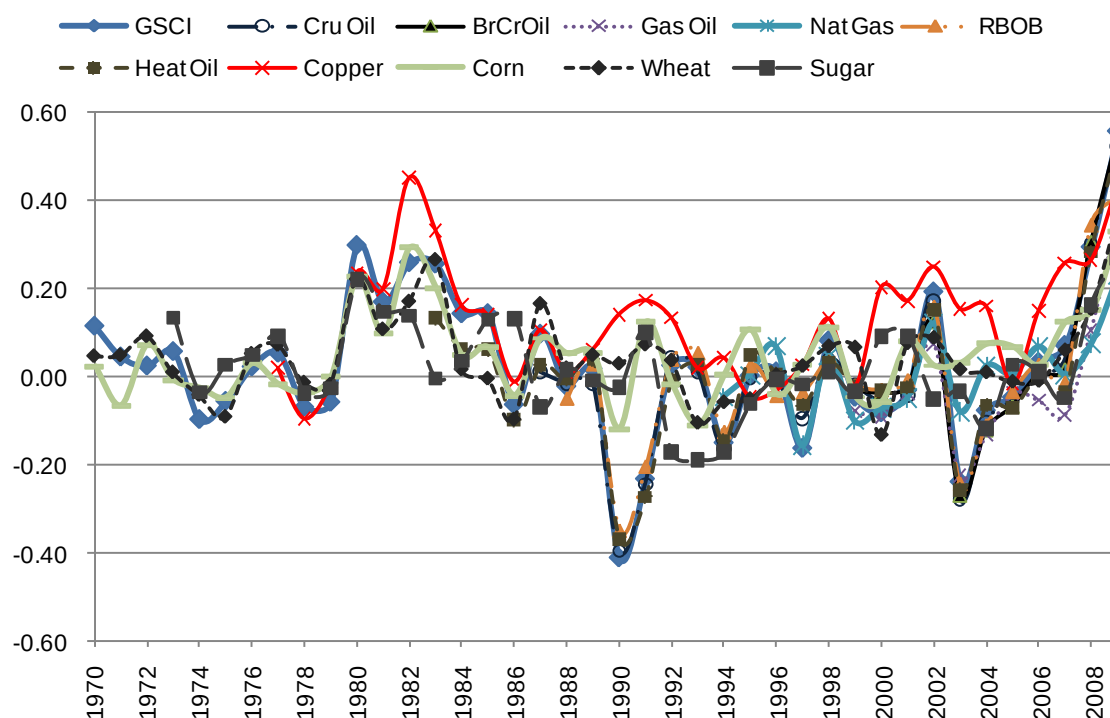
In Table 7.1.2, no great differences can be detected when comparing the minimum and maximum values for rolling- and moving correlation windows of the S&P GSCI and the S&P 500. The sub-indices show similar results. However, the standard deviations as well as the mean values are somewhat greater for the rolling window analysis. This could be due to great autocorrelation when applying the moving window measure.

Table 7.1.2 Mean, standard deviation, and min/max for one-year rolling versus moving correlation windows between the commodity indices and the S&P 500

Roll Corr	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
Mean	0.0286	-0.0153	0.0414	-0.0186	0.0090	-0.0064	-0.0029	0.1275	0.0477	0.0435	0.0211
Std. Dev.	0.1691	0.1840	0.2205	0.1541	0.0949	0.1658	0.1683	0.1333	0.0981	0.0987	0.1048
Min	-0.4120	-0.3961	-0.2698	-0.2249	-0.1565	-0.3505	-0.3693	-0.0949	-0.1183	-0.1337	-0.1886
Max	0.5582	0.5228	0.5479	0.3588	0.2306	0.4060	0.5246	0.4518	0.3310	0.3626	0.2679
Mov Corr	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
Mean	0.0190	-0.0303	0.0092	-0.0451	0.0039	-0.0165	-0.0212	0.1232	0.0420	0.0394	0.0184
Std. Dev.	0.1514	0.1551	0.1699	0.1169	0.0795	0.1482	0.1441	0.1237	0.0949	0.0966	0.0999
Min	-0.4952	-0.4822	-0.2896	-0.2711	-0.1887	-0.4584	-0.4730	-0.1788	-0.1809	-0.1615	-0.2310
Max	0.5582	0.5228	0.5479	0.3658	0.2306	0.4723	0.5246	0.4556	0.3506	0.4125	0.3205
# of obs	10096	5797	2762	2762	4025	5544	6807	8323	10096	10096	9335

Figure 7.1.3 shows that many of the index correlations have similar patterns. However, there are some indices which deviate from the general pattern in certain years, such as Copper and Sugar in the early 1990s and 2000s. In the last three years, all the indices seem to have experienced a strong increase in their correlations with the S&P 500.

Figure 7.1.3 Correlations between the commodity indices and the S&P 500, yearly data



Most of the index correlations follow the same pattern and are within a close range. However, Copper has generally higher correlation compared to other indices, as mentioned above. This is illustrated in Table 11.2.1 in the appendix and Figure 7.1.3. In 1990, indices such as the S&P GSCI, Crude Oil, RBOB Gas and Heating Oil were negatively correlated to the S&P

500 with values ranging from -0.351 to -0.412 while Copper's correlation value was 0.142. Brent Crude Oil has also higher correlation than other indices over the whole sample period but does not have any extremely deviating values on a yearly basis.

In certain years, the S&P GSCI's one-year correlations are shown to be significantly higher than the whole sample period, that is, in 1980-1983, 2002, 2008 and 2009. The rest of the indices also show high correlations in these years. There are also years when the S&P GSCI's correlation is extremely negative, 1990-1991, and 2003. From 2003 and onward, the correlations of the S&P GSCI and indices like Crude Oil, increase steadily and are around 0.3 in 2008 before reaching extreme levels above 0.5 in 2009, respectively. *Figure 7.1.1* supports the claim of increased correlation during the recent financial crisis, which was presented in the two articles in the introduction of this thesis. In *Section 7.2*, formal tests are conducted to show if this increase is statistically significant. When disregarding the past three years, the correlation between the S&P GSCI and the S&P 500 range from -0.2 to 0.2. Including all years, the lowest and the highest yearly correlations are in 1990 and 2009, respectively

Table 7.1.3 shows the distribution of all the correlation values from a one-year rolling window analysis. The percentage distribution shows that most of the values are clustered around a correlation of zero, with the highest concentration of values ranging from -0.1 to 0.1. As we move further out in the tails, both upper and lower, the number of observations decreases. The distribution reminds of a normal distribution, which has most of the observations gathered around the center of the distribution and flattens out in the tails. A similar pattern is found in Coaker's (2006) data.

Table 7.1.3 *Percentage distribution of correlations between the commodity indices and the S&P 500, yearly data*

Correlation	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
0.5-0.6	3%	4%	9%	0%	0%	0%	4%	0%	0%	0%	0%
0.4-0.5	0%	0%	0%	0%	0%	5%	0%	6%	0%	0%	0%
0.3-0.4	0%	4%	9%	9%	0%	5%	0%	3%	3%	3%	0%
0.2-0.3	10%	0%	0%	0%	6%	0%	4%	15%	8%	5%	5%
0.1-0.2	13%	4%	9%	9%	6%	0%	7%	36%	13%	10%	19%
0.0-0.1	35%	22%	18%	9%	50%	27%	30%	18%	43%	53%	27%
-0.1-0.0	28%	43%	36%	55%	25%	36%	41%	21%	30%	25%	38%
-0.1-(-0.2)	5%	9%	9%	9%	13%	14%	4%	0%	5%	5%	11%
-0.3-(-0.2)	5%	9%	9%	9%	0%	9%	7%	0%	0%	0%	0%
-0.4-(-0.3)	0%	4%	0%	0%	0%	5%	4%	0%	0%	0%	0%
-0.5-(-0.4)	3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
-0.6-(-0.5)	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
# of obs	40	23	11	11	16	22	27	33	40	40	37

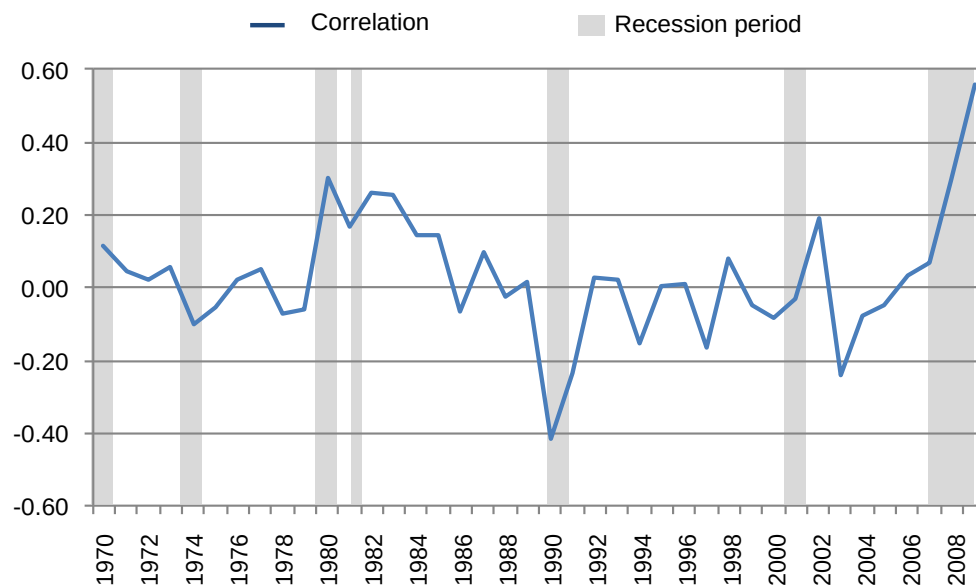
Given these results, it is hard to claim that the correlation between the equity and the commodity market is constant over the time period studied. Had the correlation been constant, there would not have been any differences in the correlations between the different data points in the rolling- and moving window analysis. Hence, we can reject *Hypothesis 1* and conclude that correlations in returns between the commodity indices and the S&P 500 are not constant between 1970 and 2009.

7.2 Results for Hypothesis 2a

Hypothesis 2a: The correlation in returns between the commodity indices and the S&P 500 is constant between times of *recession and expansion* as defined by NBER.

The yearly correlations between the S&P GSCI and the S&P 500 are graphed together with recession periods as defined by NBER (2010) in *Figure 7.2.1*. In general, the correlation seems to increase during recession periods. However, there are two recession with clear decreasing correlation, in 1974 and 1990. These two recessions differ from the others as they were driven by highly distressed oil markets. In 1973, OPEC members proclaimed an oil embargo targeting countries supporting Israel in the Yom Kippur War and in 1990, Iraq invaded Kuwait which led to increased oil prices (BBC, 2008). These two periods will be referred to as oil recessions in the hypothesis tests further down.

Figure 7.2.1 Recession periods and yearly correlations between the S&P GSCI and the S&P 500



In order to see if recessions in general can explain correlation increases, the following regression is performed using yearly data:

$$\rho_{\text{S\&P 500, Commodity index}} = \alpha + \beta \times \text{Recession period} + \varepsilon \quad (7.2.1)$$

The β -values for the regression on recession periods are positive for all indices, see *Table 7.2.1*. This indicates that recession periods identified by the NBER in *Table 5.1.1* have higher correlations than times of expansion. However, not all β -values are significant at a 5%-level, which is not too surprising as the correlation between the S&P GSCI and the S&P 500 in *Figure 7.2.1* show different patterns for different types of recessions. It can also be explained by a mismatch between the recessions and full years as well as a low number of observations since there is not data on all indices for all the periods defined as recession. Brent Crude Oil and Copper are however significant and have the highest β -values, and are thus more sensitive to periods of recession. They also have the highest R-square values, which explain how many percent of the changes in the correlation values can be explained by recession. All tables from the regression can be found in *Table 11.3.1* in the appendix.

Table 7.2.1 Results from the regression on recession periods for all commodity indices, yearly data

	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
β -value	0.0597	0.0616	0.2691*	0.1626	0.0760	0.0494	0.0263	0.1420*	0.0718*	0.0860*	0.1021*
p-value	0.3400	0.4940	0.0440	0.0920	0.1730	0.5470	0.7430	0.0070	0.0440	0.0150	0.0090
R-square	0.0240	0.0226	0.3793	0.2835	0.1282	0.0184	0.0044	0.2151	0.1028	0.1460	0.1796
# of obs	40	23	11	11	16	22	27	33	40	40	37

* Significant at a 5%-level

The same method is used for studying correlation changes during the recent financial crisis:

$$\rho_{\text{S\&P 500, Commodity index}} = \alpha + \beta \times \text{Recent financial crisis} + \varepsilon \quad (7.2.2)$$

Instead of creating a dummy variable for all recession periods, only years covering the recent financial crisis are identified. Yearly correlations are regressed on this variable, yielding β -values found in *Table 7.2.2*. More β -values from the regression on the recent financial crisis are significant at a 5%- level compared to the regression on all recession periods. The S&P GSCI, which is significant at a 5%-level, has a correlation value which is 0.302 times higher during the recent financial crisis compared to the rest of the time period studied.

Table 7.2.2 Results from the regression on the recent financial crisis for all commodity indices, yearly data

	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
β -value	0.3020*	0.3490*	0.3425*	0.1980	0.1170*	0.2927*	0.2931*	0.2105	0.1671*	0.1600*	0.1155
p-value	0.0020	0.0010	0.0110	0.0510	0.0500	0.0020	0.0030	0.0070	0.0030	0.0050	0.0660
R-square	0.2271	0.4268	0.5266	0.3603	0.2471	0.3845	0.3111	0.2125	0.2064	0.1868	0.0931
# of obs	40	23	11	11	16	22	27	33	40	40	37

* Significant at a 5%-level

Results for the recent financial crisis in *Table 7.2.2* also show that the S&P GSCI, Crude Oil, and Brent Crude Oil have the highest β -values. Crude Oil and Brent Crude Oil have the highest R-square values as well, along with RBOB Gas. Both the β - and R-square values are considerably lower when the regressions are performed on all recession periods than only on the recent financial crisis.

An additional regression is performed using three dummies:

$$\rho_{S\&P\ 500, \text{Commodity index}} =$$

$$\alpha + \beta_1 \times \text{Recent financial crisis} + \beta_2 \times \text{Oil recessions} + \beta_3 \times \text{Other recessions} + \varepsilon \quad (7.2.3)$$

Three explanatory variables are tested at the same time to see which of them has the greatest impact on correlation changes. They are defined as the recent financial crisis, oil recessions, and all other recessions. To reduce the mismatch between the recession periods and the yearly correlations and also to include more observations, daily data is used. Dummies are assigned to days within the different types of recession periods and are regressed with the estimated one-year moving correlation windows. The results are presented in *Table 7.2.3*.

Table 7.2.3 β -values and number of observations from the regression using three explanatory variables for all commodity indices and one-year moving correlation windows, daily data

β -values	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
Recent fin. crisis	0.2372*	0.2799*	0.2851*	0.1624*	0.0785*	0.2590*	0.2392*	0.1765*	0.1216*	0.1300*	0.1344*
Oil recessions	-0.1210*	-0.2677*	-	-	-	-0.2538*	-0.2259*	0.0381*	-0.0874*	-0.0409*	0.0251*
Other recessions	0.0962*	0.0204*	0.0538*	0.0069	-0.0973*	-0.0073	0.0167	0.1387*	0.0561*	0.0472*	0.1032*
# of obs	9845	5546	2511	2511	3774	5293	6556	8072	9845	9845	9084

* Significant at a 5%-level

All β -values for the recent financial crisis are positive and significant at a 5%-level. They also show the highest values in absolute terms, indicating that the recent financial crisis has the greatest impact on correlations among the three explanatory variables. For Brent Crude Oil, Gas Oil and Natural Gas, there are no β -values available on oil recessions as the explanatory variable since there are no data for these indices during this time. However, the majority of the other indices have negative β -values, indicating that the correlations decrease during oil recessions. Not surprisingly, oil related products have the highest negative relationship with the equity market while the sensitivity of industrial metal and agricultural products seems to be closer to zero during oil recessions. For all other recession periods, the β -values are for the most part positive and significant at a 5%-level.

Another approach is to compare the correlation for days in recession to days in expansion. *Table 7.2.4* shows that the correlation between the S&P GSCI and the S&P 500 is higher in days defined as recession compared to days of expansion. This coincides with our initial findings using regressions on one-year rolling correlation windows. As the β -values from *Equations 7.2.1* and *7.2.2* suggest, the correlations are much higher during the recent financial crisis compared to all recession periods. Correlations excluding the recent financial crisis have lower values than those excluding the oil recessions, indicating that correlations increase when a recession is driven by financial turmoil while recessions driven by oil crisis tend to decrease the correlations.

Table 7.2.4 Correlation between the commodity indices and the S&P 500 in days of different recessions, expansion, and days excluding different recession days

Correlation	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
Recession	0.1655*	0.1517*	0.3340*	0.1778*	0.1091*	0.1780*	0.1489	0.2931*	0.1317*	0.1293*	0.1094*
Expansion	0.0054	-0.0194	-0.0326	-0.0715*	-0.0146	-0.0164	-0.0194	0.0959*	0.0366*	0.0313*	0.0134
Recent fin. crisis	0.3849*	0.3792*	0.3868*	0.2097*	0.1390*	0.3648*	0.3678*	0.3269*	0.2110*	0.2203*	0.1980*
Excl. recent fin. crisis	-0.0149	-0.0622*	-0.0331	-0.0642*	-0.0139	-0.0513*	-0.0490*	0.1160*	0.0358*	0.0297*	0.0227*
Excl. oil recessions	0.1000*	0.0839*	0.1367*	0.0347	0.0224	0.0886*	0.0601*	0.1577*	0.0754*	0.0731*	0.0463*

* Significant at a 5%-level

In summary, the tests for *Hypothesis 2a* show that correlations increase in periods of economic recession. The explanatory power and the increase in the correlations are greater during the recent financial crisis than during other recession periods. However, recessions driven by financial turmoil in general tend to increase the correlation while recessions driven by oil crisis decrease the correlation. Overall, our expectation of increased correlations in times of recession is supported, hence *Hypothesis 2a* can be rejected.

7.3 Results for Hypothesis 2b

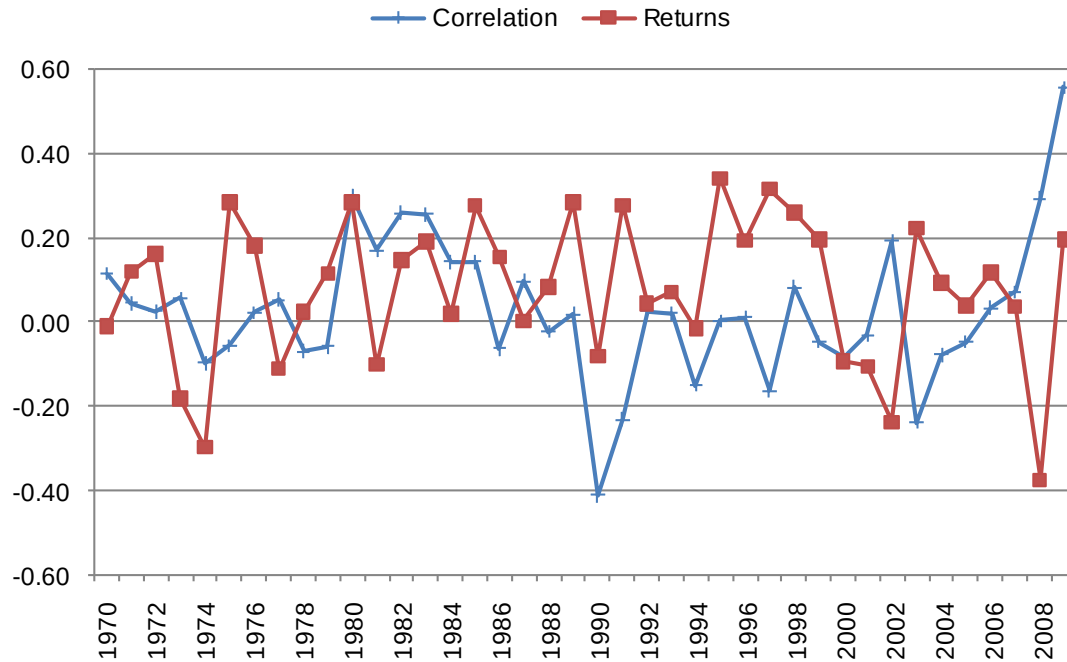
Hypothesis 2b: The correlation in returns between the commodity indices and the S&P 500 is constant and does not depend on *extreme return levels* of the S&P 500.

In the previous section, we conclude that the correlations increase when the market is in distress. Here, we elaborate on this further by studying the relationship between the correlation and the size of market returns. It is also of interest to study any differences in the correlations between bear and bull markets.

It is difficult to detect a clear pattern in the co-movements of the correlation and the market return by studying *Figure 7.3.1*. For some periods, the correlation and the market

returns move in opposite directions, i.e. when the returns are high, the correlation is low. This is particularly evident in 2002-2004 and 2007-2008. However, there are also years when they move in the same direction, such as 1989-1990 and in 2009.

Figure 7.3.1 Yearly returns of the S&P 500 and one-year rolling correlation windows between the S&P GSCI and the S&P 500



If increased correlation is expected during extreme conditions, i.e. when returns are extremely positive or extremely negative, a linear regression such as *Equation 7.3.1* is not anticipated to give significant results. *Table 11.3.4* and *11.3.5* in the appendix show that none of the β -values are significant at a 5%-level for regressions on both the one-year (rolling windows) and daily data (moving windows), which support the belief of a non-linear relationship.

$$\rho_{S\&P\ 500, Commodity\ index} = \alpha + \beta \times Return_{S\&P\ 500} + \varepsilon \quad (7.3.1)$$

To test whether the relationship between the correlation and market returns is indeed u-shaped, the following regression is run, where the squared market returns is added to the model:

$$\rho_{S\&P\ 500, Commodity\ index} = \alpha + \beta_1 \times (Returns_{S\&P\ 500})^2 + \beta_2 \times Returns_{S\&P\ 500} + \varepsilon \quad (7.3.2)$$

The regression results in *Table 7.3.1* on daily data of the S&P 500 returns show highly significant β_1 -values for all indices, which suggest that a u-shape relationship exists. At the same time, the β_2 -values are insignificant for all indices, which is in line with the results in *Table 11.3.4* and *11.3.5* of non-linear relationships.

Table 7.3.1 β -values from the regression on correlation between the commodity indices and the S&P 500 over the squared S&P 500 returns and S&P 500 returns using one-year moving correlation windows, daily data

β -value	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
Return (S&P 500) ²	16.0072*	49.7924*	44.6615*	28.7610*	5.7800*	53.0505*	19.2739*	14.2756*	5.5300*	9.5151*	9.1078*
Return (S&P 500)	0.0607	-0.0567	0.0857	0.0564	0.1396	-0.1021	0.1514	0.0253	0.0749	0.0396	0.0391
# of obs	9845	5546	2511	2511	3774	5293	6556	8072	9845	9845	9084

* Significant at a 5%-level

To further test the behavior of correlations during extreme conditions, another regression is run as a complement to the previous one above. Two dummies are created; one for the extreme positive returns, defined as the 95th percentile and above and one for extreme negative returns, defined as the 5th percentile and below.

$$\rho_{S\&P\ 500, \text{Commodity index}} =$$

$$\alpha + \beta_1 \times \text{Extreme positive Returns}_{S\&P\ 500} + \beta_2 \times \text{Extreme negative Returns}_{S\&P\ 500} + \varepsilon \quad (7.3.3)$$

The regression results in Table 7.3.2 show that all the β_1 - and β_2 -values are significant at a 5%-level, except for Corn. The values are also positive which means that correlations are higher when return levels are extreme, both in the upper and lower tails of the return distribution, and the sensitivity is fairly similar between the two extreme return levels. Brent Crude Oil has the highest β -values in both the upper- and lower percentiles while Natural Gas has the lowest values.

Table 7.3.2 β -values from regression on correlation between the commodity indices and the S&P 500 over the S&P 500 returns using dummies for extreme positive and negative market returns, daily data

β -value	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
Extr. positive Returns	0.0385*	0.0761*	0.1146*	0.0742*	0.0157*	0.0788*	0.0601*	0.0537*	0.0125*	0.0205*	0.0310*
Extr. negative Returns	0.0310*	0.0867*	0.1100*	0.0695*	0.0134*	0.0892*	0.0628*	0.0374*	0.0057	0.0123*	0.0340*
# of obs	9845	5546	2511	2511	3774	5293	6556	8072	9845	9845	9084

* Significant at a 5%-level

When looking at the correlation in different percentiles, Table 7.3.3 shows that the correlation is generally higher in the tails than over the whole sample, both in the upper and the lower tails. However, the correlation is higher when the S&P 500 has extreme negative returns (5th percentile and below) than when the returns are extremely positive. These results are similar to Longin and Solnik (2001)'s findings in which the correlation was higher for negative return exceedances defined with lower thresholds. Very few observations are significant at a

5%-level in the upper tail while all observations in the lower tail are significant at a 5%-level, indicating higher certainty of correlation increase in bear markets than in bull markets. This is also in line with the findings of Campbell, Koedijk and Kofman (2002).

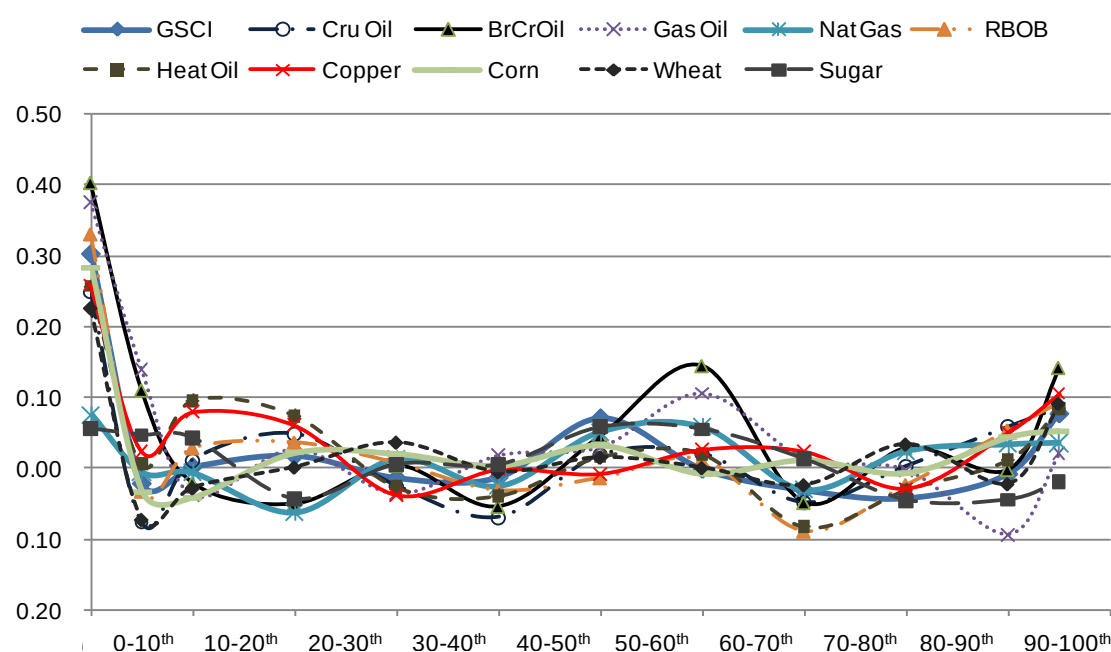
Table 7.3.3 Correlation between the commodity indices and the S&P 500 conditional on the different percentiles of the S&P 500 daily returns

%	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
0-5	0.3026*	0.2484*	0.4021*	0.3761*	0.0758	0.3305*	0.2573*	0.2585*	0.2838*	0.2258*	0.0559
5-10	-0.0210	-0.0772	0.1096	0.1395	-0.0053	-0.0317	0.0057	0.0243	-0.0331	-0.0720	0.0471
10-20	0.0024	0.0112	-0.0212	-0.0385	-0.0063	0.0293	0.0956*	0.0795*	-0.0410	-0.0275	0.0429
20-30	0.0182	0.0480	-0.0507	0.0269	-0.0614	0.0373	0.0744	0.0609	0.0218	0.0017	-0.0439
30-40	-0.0134	-0.0253	0.0034	-0.0362	0.0138	0.0080	-0.0266	-0.0375	0.0204	0.0367	0.0050
40-50	-0.0124	-0.0693	-0.0545	0.0177	-0.0246	-0.0305	-0.0386	-0.0015	0.0037	-0.0048	0.0046
50-60	0.0713*	0.0185	0.0454	0.0297	0.0512	-0.0128	0.0163	-0.0074	0.0323	0.0156	0.0580
60-70	-0.0007	0.0200	0.1439*	0.1055	0.0580	0.0129	0.0200	0.0267	-0.0077	0.0009	0.0552
70-80	-0.0306	-0.0489	-0.0490	0.0135	-0.0298	-0.0880*	-0.0823*	0.0239	0.0116	-0.0233	0.0125
80-90	-0.0420	0.0026	0.0281	-0.0027	0.0242	-0.0226	-0.0301	-0.0281	-0.0069	0.0341	-0.0457
90-95	-0.0076	0.0581	-0.0024	-0.0934	0.0338	0.0545	0.0123	0.0513	0.0436	-0.0218	-0.0448
95-100	0.0774	0.0845	0.1413	0.0210	0.0361	0.0941	0.0850	0.1055*	0.0531	0.0915*	-0.0192
# of obs	10096	5797	2762	2762	4025	5544	6807	8323	10096	10096	9335

* Significant at a 5%-level

Figure 7.3.2 illustrates the correlations graphically and a general increase in the correlations is detected in the lower percentiles. The u-shaped relationship discussed above is asymmetric, indicating high conditional correlation during extreme negative returns.

Figure 7.3.2 Correlation between the commodity indices and the S&P 500 conditional on the different percentiles of the S&P 500 daily returns



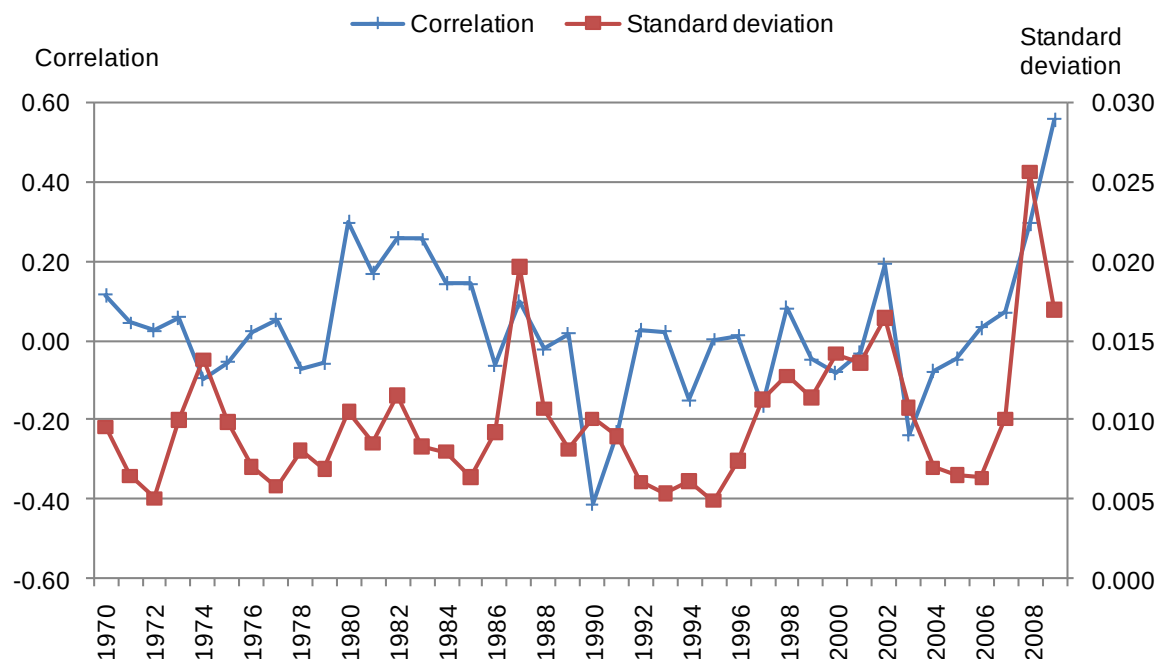
In summary, regression results show that the relationship between the correlations and the market returns is non-linear and rather u-shaped, indicating higher correlations during extreme conditions. This is confirmed by the regressions using dummies for the extremely positive- and negative return levels which yield significant results. Conditional correlations in the different percentiles on market return levels show greater values in bear markets relative to bull markets, since the u-shape is asymmetric as shown in *Figure 7.3.2*. Overall, *Hypothesis 2b* can be rejected based on the given results.

7.4 Results for Hypothesis 2c

Hypothesis 2c: The correlation in returns between the commodity indices and the S&P 500 is constant and does not depend on *extreme volatility levels* of the S&P 500.

By studying the graph in *Figure 7.4.1*, it is hard to determine a clear relationship between the correlation and the standard deviation just as it was between the correlation and return levels in *Figure 7.3.1*. It is however evident that the correlation is relatively higher in periods of extreme volatility, such as in 1987, the dot-com crisis in 2001, and the financial crisis in 2007-2009.

Figure 7.4.1 Yearly volatility of the S&P 500 and one-year rolling correlation windows between the S&P GSCI and the S&P 500



A regression (*Equation 7.4.1*) with the volatility as the independent variable and the correlation as the dependent variable gives only two significant β -values at a 5%-level, see

Table 7.4.1. Although this may seem surprising, the regression does not test for extreme market volatility and assumes a linear relationship, which Figure 7.4.2 shows is not the case.

$$\rho_{S\&P\ 500, \text{Commodity index}} = \alpha + \beta \times S\&P\ 500\ \text{Volatility level} + \varepsilon \quad (7.4.1)$$

Table 7.4.1 Results from the regression on the volatility of the S&P 500 for all commodity indices, yearly data

	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
β-value	0.1769	0.2784	0.7872	0.5137	0.2830	0.2305	0.2600	0.5028*	0.1707	0.1421	0.4258*
p-value	0.5010	0.4450	0.1290	0.1600	0.1700	0.4850	0.4210	0.0310	0.2600	0.3530	0.0070
R-square	0.0120	0.0280	0.2371	0.2068	0.1298	0.0247	0.0261	0.1410	0.0332	0.0227	0.1874
# of obs	40	23	11	11	16	22	27	33	40	40	37

* Significant at a 5%-level

Just like in *Hypothesis 2b*, a regression is performed using dummies for the upper- and lower 5% of the estimated S&P 500 volatility distribution, Table 7.4.2.

$$\rho_{S\&P\ 500, \text{Commodity index}} =$$

$$\alpha + \beta_1 \times \text{Extreme high volatility}_{S\&P\ 500} + \beta_2 \times \text{Extreme low volatility}_{S\&P\ 500} + \varepsilon \quad (7.4.2)$$

Almost all β-values are significant at a 5%-level in both tails and most of them are positive when the volatility is extremely high. Brent Crude Oil has the highest β-value. However, Natural Gas and Heating Oil show negative β-values, indicating that the correlations decrease when the S&P 500 returns are extremely volatile. Surprisingly, Heating Oil, along with RBOB Gas and Crude Oil also has a high positive β-value when the market returns have extreme low volatility. For most indices, the correlations are not expected to increase when the market is relatively stable.

Table 7.4.2 β-values from regression on correlation between the commodity indices and the S&P 500 using dummies for extreme high and low S&P 500 volatility, daily data

	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
Extreme high volatility	0.2535*	0.0206*	0.4515*	0.3026*	-0.0993*	0.2918*	-0.1597*	0.1260*	0.0848*	0.0583*	0.0994*
Extreme low volatility	-0.0553*	0.0790*	0.0245	-0.0205*	-0.0199*	0.1253*	0.1021*	-0.0619*	0.0187*	0.0136*	-0.0088
# of obs	9845	5546	2511	2511	3774	5293	6556	8072	9845	9845	9084

* Significant at a 5%-level

Using the second method, we test the correlation conditional on the size of the S&P 500 volatility levels. Daily one-year moving standard deviation for the S&P 500 is estimated. As in *Hypothesis 2b*, the data is then sorted according to the daily standard deviations and the correlations for different percentiles are estimated using varying threshold values, Table 7.4.3.

Correlations indicate that the greater the volatility, the greater the correlation between the indices. This is in line with the results from the regressions which showed that volatility has explanatory power on correlation values. The correlations in the upper percentiles are both higher in absolute values and yield more significant results at a 5%-level. The many insignificant correlations in the lower percentiles make it difficult to draw any strong conclusions concerning the correlations when the volatility is extremely low.

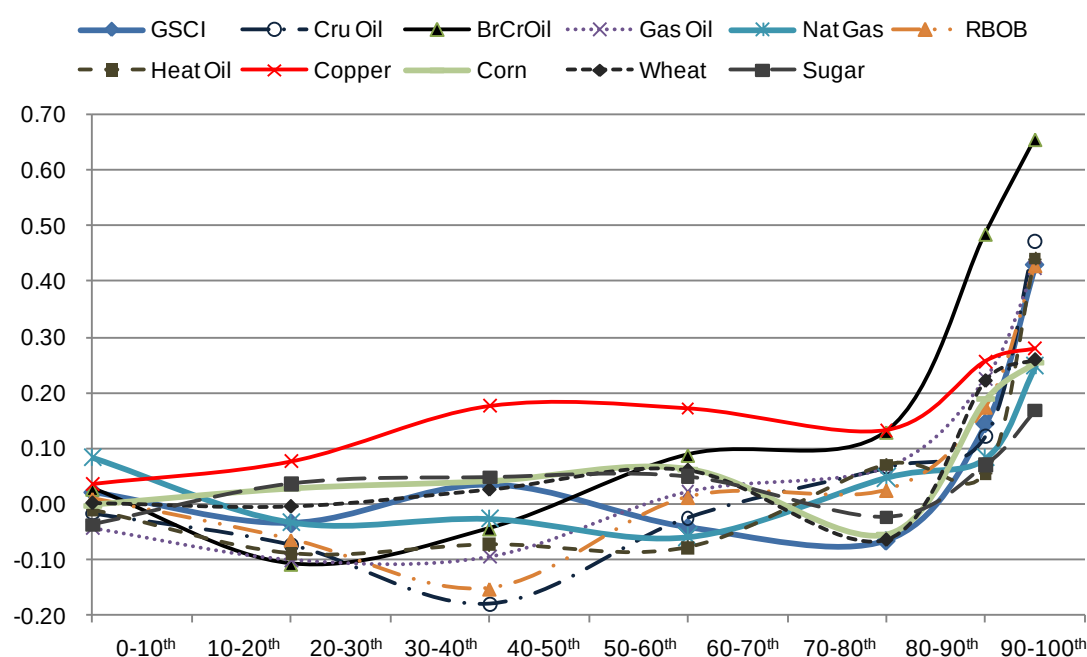
Table 7.4.3 Correlations between the commodity indices and the S&P 500 conditional on different percentiles of the S&P 500 daily returns volatility level

%	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
0-20	0.0214	-0.0180	0.0268	-0.0446	0.0840*	0.0090	-0.0115	0.0349	-0.0031	0.0022	-0.0383
20-40	-0.0343	-0.0747*	-0.1083*	-0.1016*	-0.0328	-0.0651*	-0.0898*	0.0754*	0.0261	-0.0040	0.0358
40-60	0.0347	-0.1805*	-0.0447	-0.0960*	-0.0267	-0.1530*	-0.0738*	0.1752*	0.0394	0.0262	0.0475*
60-80	-0.0420	-0.0257	0.0878*	0.0211	-0.0595	0.0116	-0.0788*	0.1711*	0.0615*	0.0607*	0.0485*
80-90	-0.0656*	0.0643	0.1294*	0.0650	0.0476	0.0243	0.0700	0.1320*	-0.0567	-0.0636*	-0.0250
90-95	0.1447*	0.1202*	0.4860*	0.2253*	0.0827	0.1739*	0.0552	0.2562*	0.1872*	0.2209*	0.0697
95-100	0.4298*	0.4722*	0.6565*	0.4245*	0.2480*	0.4283*	0.4408*	0.2791*	0.2531*	0.2586*	0.1675*
# of obs	9845	5546	2511	2511	3774	5293	6556	8072	9845	9845	9084

* Significant at a 5%-level

Figure 7.4.2 illustrates the abovementioned findings graphically. It is evident that the correlations increase at extreme high levels of volatility. Brent Crude Oil has the highest correlation while Sugar has the lowest.

Figure 7.4.2 Correlations between the commodity indices and the S&P 500 conditional on the different percentiles of the S&P 500 daily returns volatility level



In summary, the β -values from the regression on the S&P 500 volatility level are different from zero at a 5%-level for only two indices, Corn and Sugar. The regression is however not a test of extreme conditions and the results are therefore not of great concern. The second regression shows that correlations tend to increase when the volatility is extremely high. This is confirmed by the actual correlation estimations conditional on different percentiles of the S&P 500 volatility distribution. Hence, *Hypothesis 2c* can be rejected.

7.5 Result Summary

The focus has been to examine correlation increases during extreme conditions, defined as recession periods, extreme market return levels and extreme market volatility. The hypotheses can be rejected if the tests performed show correlation changes during extreme conditions. All results from the hypothesis tests are summarized in *Table 7.5.1*.

The tests indicate that correlations between the equity and commodity markets are neither constant over the time period studied (*Hypothesis 1*) nor during extreme conditions (*Hypotheses 2a, 2b* and *2c*), which is in line with our initial expectations of increased correlations. Although the β -values and significance levels differ slightly between different commodities and types of tests, all the regression results, as well as conditional correlations, imply increasing correlations during extreme conditions.

More commodity indices show significant results at a 5%-level for the recent financial crisis compared to recession periods in general. Further, the tests show that the correlation increases during recession periods driven by financial turmoil, while recessions driven by instable oil market tend to decrease the correlations.

The relationship between the correlations and the return levels of the S&P 500 is u-shaped, showing increased correlations at extreme return levels. The correlations are higher when the return levels are extremely negative compared to extreme positive returns, indicating that the problem of increased correlations is higher in bear markets than in bull markets.

Regressions and correlations conditional on the volatility level of the S&P 500 show that the correlations are higher when the volatility is extremely high. Overall, most tests support our initial belief of higher correlations during extreme conditions, as is shown in *Table 7.5.1*.

Table 7.5.1 Summary of all hypotheses and their results

Y=Can Reject N=Cannot Reject

(at 5%-level)

	Hypothesis 1	Hypothesis 2a				
	Simple yearly correlations (Table 11.2.1)	Regression on all recession periods, yearly data (Table 7.2.1)	Regression on the recent financial crisis, yearly data (Table 7.2.2)	Regression using three explanatory variables, daily data (Table 7.2.3)	Conditional correlations (Table 7.2.4) ³	
					Recession vs. expansion	Recent financial crisis vs. excl. recent financial crisis
GSCI	Y	N	Y	Y	Y	Y
Cru Oil	Y	N	Y	Y	Y	Y
BrCrOil	Y	Y	Y	Y ¹	Y	Y
Gas Oil	Y	N	N	Y ^{1,2}	Y	Y
Nat Gas	Y	N	Y	Y ¹	Y	Y
RBOB	Y	N	Y	Y ²	Y	Y
Heat Oil	Y	N	Y	Y ²	N	Y
Copper	Y	Y	N	Y	Y	Y
Corn	Y	Y	Y	Y	Y	Y
Wheat	Y	Y	Y	Y	Y	Y
Sugar	Y	Y	N	Y	Y	Y

1. Time period does not include oil recessions.

2. Dummy for other recessions not significant at a 5%-level, but significant for the other variables.

3. Correlation is higher and significant for recessions and the recent financial crisis vs. the rest of the sample.

	Hypothesis 2b			Hypothesis 2c		
	Regression with squared returns, daily data (Table 7.3.1)	Regression on extreme negative returns (Table 7.3.2)	Correlation conditional on percentiles of market returns ⁴ (Table 7.3.3)	Regression on volatility, yearly data (Table 7.4.1)	Regression on extreme high volatility (Table 7.4.2)	Correlation conditional on percentiles of market volatility ⁵ (Table 7.4.3)
GSCI	Y	Y	Y	N	Y	Y
Cru Oil	Y	Y	Y	N	Y	Y
BrCrOil	Y	Y	Y	N	Y	Y
Gas Oil	Y	Y	Y	N	Y	Y
Nat Gas	Y	Y	N	N	Y	Y
RBOB	Y	Y	Y	N	Y	Y
Heat Oil	Y	Y	Y	N	Y	Y
Copper	Y	Y	Y	Y	Y	Y
Corn	Y	N	Y	N	Y	Y
Wheat	Y	Y	Y	N	Y	Y
Sugar	Y	Y	N	Y	Y	Y

4. The hypothesis rejection decision is based on the results in the 5th percentile and below, representing extreme negative returns, which is of interest for the thesis.

5. The hypothesis rejection decision is based on the results in the 95th percentile and above, representing extreme high volatility, which is of interest for the thesis.

8. Analysis

In this section, the results presented in the previous section are discussed in more detail followed by a discussion of the implications of our findings for portfolio optimization and risk management. We will also conclude whether or not the gain of diversification has played out its role.

8.1 Result Analysis

All hypothesis tests more or less indicate that the correlations change during extreme conditions. The one-year moving correlation window analysis gives very similar graphical results as the one-year rolling correlation windows and shows that correlations are varying during the time period studied. Since the one-year moving window is moved forward one day at a time, the results should be auto-correlated and thereby give a smaller variation in the values. However, *Figures 7.1.1* and *7.1.2* show that both the rolling and moving one-year correlation window analysis follow the same pattern, and regardless of the analysis performed, the correlation seems to be far from constant. Although fluctuating, the correlation between the S&P GSCI and the S&P 500 has been historically low and is negative 16 out of the 40 years studied. These findings are similar to those of Coaker (2006) in which 17 out of 35 years studied showed negative correlations. However, strong increases have been seen in the recent years.

As reported in the article by Authers (2009) mentioned in the introduction, we show that the correlation between equities and commodities did indeed increase during the recent financial crisis, see *Tables 7.2.2* and *7.2.3*. Of the three explanatory variables, the recent financial crisis demonstrates the highest positive β -values while oil recessions generally tend to show negative β -values. Correlations measured over days of recession versus expansion, and on days during the recent financial crisis versus days excluding the financial crisis, as well as days excluding the oil recessions, clearly show higher correlations during periods of recession as seen in *Table 7.2.4*. Also, recessions driven by financial turmoil affects correlations positively while those driven by oil crisis drive down correlations. Oil related products show negative correlations over the time period studied when excluding the recent financial crisis, which could explain why they have often been used for diversification purposes. However, oil related commodities demonstrate some of the highest correlations and β -values during the recent financial crisis. Assuming that a financial crisis as severe as the recent one is unlikely to occur on a regular basis in the future, oil related products are still a

valuable diversification tool. Nevertheless, the global financial market is gradually becoming more intertwined and higher correlations could therefore be expected (Swedroe, 2009). However, there is no unanimous view on the matter of a general increases in correlations between different assets in the future.

Although this thesis deals with the correlation between equities and commodities, the findings are similar to Campbell, Koedijk and Kofman (2002), who find that the correlation between different international equity markets is greater for bear markets than for bull markets. Longin and Solnik (2001) also show that the correlation between different international equity markets is higher for negative return exceedances defined with lower thresholds. The results of the hypothesis tests suggest that the correlation conditional on market returns is higher and more significant when the returns are extremely negative, thus showing an asymmetric u-shaped relationship as illustrated in *Figure 7.3.2*. Unlike Büyüksahin, Haig, and Robe (2008), we find that there is indeed evidence of an increase in correlations during extreme events, see *Table 7.3.2*. The authors defined extreme events as returns greater or smaller than one or two standard deviations away from the mean return value. We define extreme market returns as the lower and upper five percent of the returns, which is a similar approach, but using percentiles rather than intervals from the cumulative distribution function (quantiles). Using quantiles instead of percentiles may have shown the u-shape in *Figure 7.3.2* more clearly, but the results from the regression (*Equation 7.3.3*) on extreme market returns would have been almost identical. The reasons for using percentiles are that there are not enough observations in some quantiles as we move towards the tails of the return distribution, the distribution also has slightly asymmetric tails, and the command is not supported by STATA. However, the percentiles serve as a good estimator of the true distribution and therefore the results and trends should be fairly the same regardless of the method used.

Chong and Miffre (2007 and 2008) found that the conditional correlation between commodity futures and equity returns fell in periods of above average market volatility. We find evidence of the opposite. *Table 7.4.3* shows the correlations conditional on different percentiles of the S&P 500 volatility distribution and they show an increase in the correlations as volatility increases. The difference in our findings and those of Chong and Miffre (2007 and 2008) is probably due to different types of datasets, time period and methods used.

The β -values of the regressions on correlation over extreme volatility of the S&P 500 are much higher than those of regressions on both recession periods and extreme market

returns. This could be interpreted as the correlation being more sensitive to changes in volatility than the other extreme conditions.

The three extreme conditions discussed above often coincide, making it difficult to detect which of them has the greatest influence on changes in the correlations. What is evident though, is that they all have significant impact on increased correlations. Out of the three extreme conditions; recession, extreme market returns and extreme market volatility, the estimated correlation conditional on extreme market volatility is the highest. The recent financial crisis has the greatest impact on correlation increase of the three recession categories; the recent financial crisis, oil recessions and other recessions. However, recessions driven by financial instability in general seem to increase correlation, while recessions driven by instable oil market seem to decrease correlations. Overall, we can see a larger increase in the correlations in bear markets compared to bull markets, and in particular during extreme negative market conditions, when the diversification is needed the most.

Studying the individual sub-indices, Brent Crude Oil has some of the highest β - and R-square values compared to the other indices for all regressions performed and the β -values are significant at a 5%-level. In short, Brent Crude Oil is the most sensitive index. On the other end, it is not as clear which index is the least sensitive to extreme conditions. Different indices show the lowest β - and R-square values, as well as correlations throughout the hypothesis tests, making it difficult to pinpoint just one or two indices more robust to changes in correlations. However, agriculture products such as Wheat and Sugar seem to be the least sensitive to extreme conditions. Copper has higher correlation to the equity market in general compared to the other sub-indices, and is therefore less valuable for diversification. The S&P GSCI, which is of our main interest, is neither one of the most sensitive nor robust indices. This is not surprising since the S&P GSCI is a composite of all the other ten commodity indices included in the hypothesis tests. It is, however, greatly influenced by commodities in the energy sector such as Crude Oil and Brent Crude Oil as these are assigned the largest component weights of the index.

The findings in this thesis both contradict and correspond to previous research, but generally show that the correlation increases during various forms of extreme conditions. The results also indicate that increasing correlations during extreme conditions is not a new phenomenon. However, the size of the correlation changes has increased with the recent financial crisis.

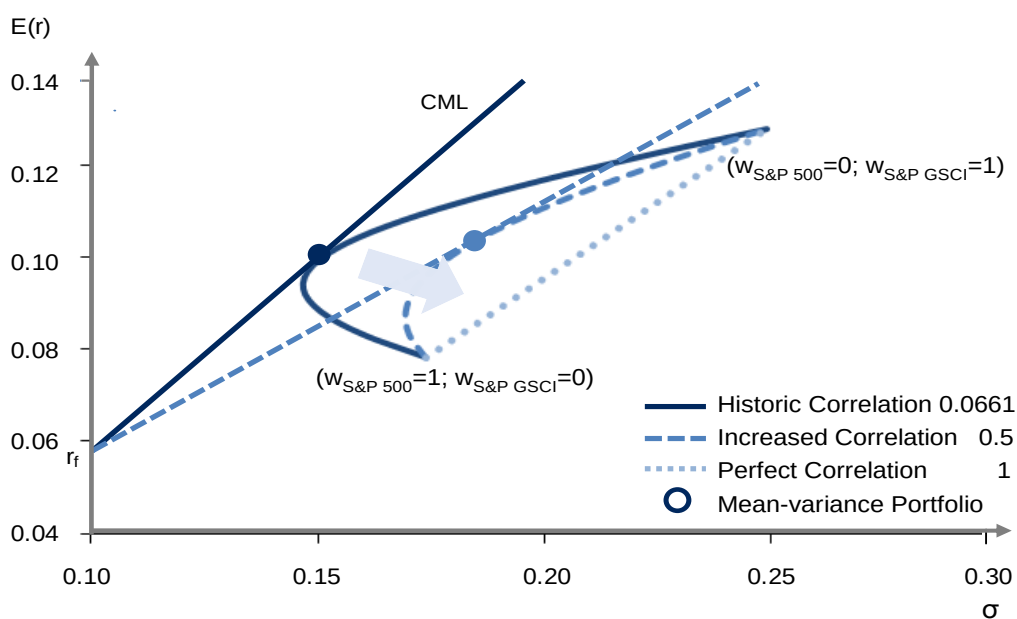
8.2 Implication for Investment Management

Section 8.1 concludes that the correlation between commodities and equities increase during extreme conditions. In this section, the implications of our findings for portfolio optimization and risk management are discussed further and the question on whether or not portfolio diversification has played out its role is answered.

Figure 8.2.1 illustrates that correlation changes do matter when choosing the mean-variance portfolio and that the gain of diversification decreases as correlation increases.

The efficient frontier is created by portfolios consisting of different weights of the S&P GSCI and the S&P 500. The portfolio's expected return and standard deviation can be calculated using Equations 2.1.1 and 2.1.2. By increasing the correlation, it is possible to study how the efficient frontier and the mean-variance portfolio change. The solid line in Figure 8.2.1 illustrates the efficient frontier using the correlation for the whole sample, 0.0661. The dashed line shows that the efficient frontier moves as the correlation increases to 0.5, which was the approximate correlation during the recent crisis, resulting in an increased risk given any combination of the two indices. It is clearly shown that the slope of the CML, i.e. the Sharpe ratio (Equation 2.1.4), decreases as the correlation increases. Hence, the lower the correlation, the better is the risk-return profile. The dotted line illustrates a perfect correlation which shows that the benefit of diversification disappears completely and that the relationship between the asset weights and the standard deviation becomes linear.

Figure 8.2.1 The efficient frontier created by different portfolio weights and at different levels of correlation between the S&P GSCI and the S&P 500



When the correlation between the two asset classes increases, the original portfolio weights for the mean-variance portfolio are no longer optimal and investor needs to rebalance the portfolio to achieve the new mean-variance portfolio given the new correlation. If not, the investor may hold a portfolio with higher risk than anticipated, but not necessarily yielding higher expected return; i.e. not optimizing the portfolio given the investor's risk aversion.

If the correlation increases during extreme conditions, such as in times of recession, extreme negative returns, or extremely volatile markets, then the effect of diversification is reduced when needed the most. However, as long as the correlation remains fairly low, there are still benefits from diversifying the portfolio using commodities, although there is a need to understand that the risk exposure could turn out to be larger than expected.

There is also another gain from diversifying the portfolio using commodities, that is, inflation protection. The inflation is typically higher in time of financial distress and move in the opposite direction of the equity market, since commodities gain from high inflation as they are linked to rising prices. Hence, commodities could be used for hedging inflation (Barclays, 2010). This could also be seen as an explanation of the historically low correlation that we generally see between commodities and equities. Nevertheless, if this is now changing, with continuously higher correlations in the market in times of crisis, the inflation protection will not be very efficient.

When it come to risk management, the assumptions regarding the correlation are crucial. Using risk management models which disregard correlation as being dynamic can bring devastating consequences. Campbell, Koedijk, and Kofman (2000 and 2002) suggest a tail-adjusted mean-variance covariance matrix when calculating the VaR. They believe this could solve some of the problems with increased correlation in the tail of the distribution that is evident in international equity markets during bear markets. A similar approach is possible for commodities. However, estimating the correct correlation and changes in the correlation using historical data is not an easy task and this brings us to the question of whether it is possible to anticipate correlation changes or not.

There are models developed for anticipating correlation changes which could be of great interest for investment management. However, there is yet much to be done in this field of study. The current models are quite complex and difficult to use in practice. Engle (2009) addresses this topic in his book *Anticipating correlation – A new paradigm for risk management*. He describes the role of correlation in investment management, addresses the underpinnings and the theory of correlations, as well as introduces new powerful forecasting tools. Dynamic conditional correlation (DCC), which is an important new method for

correlation estimation for large systems of assets, is presented and compared to other correlation estimators; historic correlation, exponential smoothing and multivariate GARCH. Even though it would be possible to anticipate the correlation with high precision, this would mean rebalancing the portfolio as soon as the correlation changes. This strategy is both time consuming and costly given the present financial market and the trade-offs have to be evaluated.

The question of whether diversification has played out its role is complicated and does not have a straightforward answer. Correlations have been historically low between the equity and commodity markets, and therefore commodities have served as a good diversification tool. However, there is evidence of increased correlations when the equity market is in distress. This is a problem for investment management since the diversification is needed the most during such times. The risk-return profile of the portfolio can vastly change if the correlation increases from around 0.0 to 0.5, which has been shown in the study. The highest increase in correlation has been seen during the past three years, characterized by extreme market volatility, extreme market returns, and the most severe global financial crisis seen in modern times. The key concern is now whether this high correlation is a temporary phenomenon or if extreme conditions leading to higher correlations will recur on a regular basis. If investing with a long-term horizon, short term fluctuations in correlations such as in extreme conditions should not be of great concern. However, should the periods of increased correlation last longer, occur more frequently, or if the correlation in general should increase, the benefits from diversification would deteriorate. As long as the asset classes are not perfectly correlated, there are always possible gains of diversification, although there are great risks with underestimating the correlation during extreme conditions. For some risk management models such as VaR, also short-term fluctuations are of great concern. If the correlation is underestimated, the loss could be much higher than anticipated and this could potentially lead to an inadequate capital buffer that usually would serve as an insurance against losses on risky assets. If disregarded, increased correlation is a problem for investment management. New more dynamic models could reduce the possibility of holding a portfolio with a higher risk than wanted. However, anticipating correlations is a rather complex task and further research is necessary to make the models useful in practice.

9. Conclusion

Commodities are often used for diversification purposes to reduce portfolio risk without sacrificing the expected return. The gain from diversification depends on the correlation between the different asset classes and increases with lower correlation. The focus of this thesis has been to examine the correlation changes between commodities and equities during extreme conditions and to study the implications for investment management. Extreme conditions are defined as times of recession, extreme market returns and extreme market volatility. Different approaches; graphical illustrations and different types of regressions, as well as both conditional and unconditional estimated correlations, are used for the hypothesis tests.

Simple one-year rolling- and moving correlation windows show that the correlation between equities and commodities fluctuates from 1970 to 2009. The correlation distribution reminds of a normal distribution with the majority of its values clustered around a correlation of 0.0. The hypothesis of constant correlation can be rejected and correlation changes during extreme conditions are studied further.

Previous research suggests that the correlation between different international equity markets is greater during various types of extreme conditions, while the research on the commodity market correlations is not as extensive and gives ambiguous results. By using a broader dataset, both in terms of the time period and number of commodity indices, as well as different methodologies, it is shown that the commodity and equity markets yield higher correlations in times of extreme conditions.

The analysis show that correlations increase during recession periods driven by financial turmoil in general and during the recent financial crisis in particular, while recessions driven by instable oil market seem to decrease correlations. Correlations also increase when market returns and volatility are extreme, and are relatively higher in bear markets compared to bull markets. Regression results indicate that correlations are relatively more sensitive to extreme high market volatility, while the recent financial crisis has the highest explanatory power of correlation changes. Increased correlations can be seen in all three extreme conditions, which is not surprising since they usually coincide. It is therefore difficult to state which of the three extreme conditions has the greatest impact on changes in correlations.

Among the individual commodity indices, correlations of oil related commodities, such as Brent Crude Oil, increase more than others during extreme conditions, while

agricultural products are less sensitive. Copper has generally higher correlation with the equity market. The S&P GSCI is neither the most sensitive nor the most robust index. However, it is greatly influenced by the energy sector as large component weights are assigned to oil related products.

The question of whether diversification has played out its role is complicated and does not have a straightforward answer. Increased correlation does indeed give a new mean-variance portfolio with a higher risk profile. For an investor seeking to gain from diversification, this can bring negative consequences if the portfolio weights are not rebalanced given the new correlation. However, short-term fluctuations in correlations should not be of great concern for investors with a long-term horizon, while there are certain risk management models for which also short-term fluctuations are of importance. Should the periods of increased correlation last longer, occur more frequently, or if the correlation in general should increase, the benefits from diversification would deteriorate. On the other hand, there are always possible gains of diversification as long as the asset classes are not perfectly correlated. Nevertheless, there are great risks with underestimating the correlation during extreme conditions since the investor could end up with a higher risk profile than expected. New more dynamic models which can anticipate correlation changes could reduce the portfolio risk. To adjust to the new correlation, rebalancing of the portfolio may be needed. However, this is both time consuming and costly given the present financial market place. Current models anticipating correlations are still quite complicated and further research is necessary to make the models useful in practice.

9.1 Suggestions for Further Research

The focus of this thesis has been to examine if there are in fact changes in correlations during extreme conditions. We identify two main areas in the field of correlation changes in which further research would be interesting.

Firstly, the regressions and correlation estimates conducted in this thesis do not test for the underlying reasons of correlation changes between equities and commodities. Further research on the causes of shifting correlations would be of interest. Correlation estimated over periods without any crisis may underestimate the degree of correlation during extreme conditions, overestimating the gains of portfolio diversification. Behavioral finance could provide some explanation to correlation increases, especially in times of crisis. As the former

Federal Reserve Board Chairman Alan Greenspan (1999)⁶ expressed: “*Under these circumstances, fear and disengagement by investors often result in simultaneous declines in the values of private obligations, as investors no longer realistically differentiate among degrees of risk and liquidity, and increases in the values of riskless government securities.*”

This is connected to the question of whether increased correlation is a violation of the efficient market hypothesis, as discussed in the introduction. One of the main assumptions of the EMH is that the correlation between different assets is constant. As a result, many investment models may disregard the fact that historic correlations potentially underestimate the level of correlation during times of extreme conditions. However, the threat to the EMH may not be the increased correlations per se, but rather the tendency of investors not being rational in during extreme conditions. The assumption of rational investors is crucial for the validity of the EMH.

Secondly, as discussed in *Section 8.2*, anticipating correlation is a rather unexplored field of study. Developing more dynamic and simple models which take correlation changes into consideration would be of great benefit for investment and risk management. A great deal of work has been done by Engle (2009) in this area but there is still a gap between theory and the practical implications in the use of these models.

⁶ Cited from Kim and Finger (2000).

10. List of References

- Authers, J. September 28th 2009, "Wanted: New Model for Markets", *The Financial Times*, The Financial Times Limited 2010. Retrieved December 2009. Available at www.ft.com
- Barclays. 2010, "Using Commodities to Diversify Your Portfolio", *Barclays Bank PLC*. Retrieved June 11th 2010. Available at www.ipathetn.com
- BBC. May 29th 2008, "Opec: The oil cartel in profile", *BBC*. Retrieved July 13th 2010. Available at www.bbc.co.uk/news
- Benninga, S. and Wiener, Z. 1998, "Value-at-Risk (VaR) ", *Mathematica in Education and Research*, vol. 7, no. 4, pp. 1-7
- Bodie, Z., Kane, A. and Marcus, A. J. 2008, "Investments", 7th Edition, International Edition, New York, N.Y.: McGraw-Hill.
- Büyüksahin, B., Haigh, M.S. and Robe, M.A. 2008, "Commodities and Equities: 'A Market of One'?", *SSRN Working Paper Series*.
- Campbell, R.A.J., Koedijk, K.C.G. and Kofman, P. 2000, "Covariance and Correlation in International Equity Returns: A Value-at-Risk Approach", *Erasmus University Rotterdam Working Paper No. 004*.
- Campbell, R.A.J., Koedijk, K.C.G. and Kofman, P. 2002, "Increased Correlation in Bear Markets", *Financial Analysts Journal*, vol. 58, no.1, pp.87-94.
- Chong, J. and Miffre, J. 2007, "Conditional Risk Premia and Correlations in Commodity Futures Markets", Working paper, EDHEC.
- Chong, J. and Miffre, J. 2008, "Conditional Return Correlations between Commodity Futures and Traditional Assets", Working paper, EDHEC, April.
- CME. 2010, "CMEG Exchange Volume Report - Monthly", *CME Group Inc*. Retrieved June 11th 2010. Available at www.cmegroup.com
- Coaker II, W.J. 2006, "The Volatility of Correlation", *Journal of Financial Planning*, vol. 19, no. 2, pp. 58-69.
- Dow Jones & Company Inc., 2009a. April 20th 2009, "Dow Jones-UBS Commodity Index Methodology", *Dow Jones & Company Inc*. Retrieved March 19th 2010. Available at www.djindexes.com
- Dow Jones & Company Inc., 2009b. July 2009, "Dow Jones-UBS Commodity Indexes", *Dow Jones & Company Inc*. Retrieved March 20th 2010. Available at www.djindexes.com
- Engle, R. 2009, "Anticipating Correlations: A New Paradigm for Risk Management", Princeton, N.J.: Princeton University Press
- Greenspan, A. October 14th 1999, Measuring Financial Risk in the Twenty-first Century. Conference sponsored by the Office of the Comptroller of the Currency, Washington, D.C. Retrieved August 11th, 2010. Available at www.federalreserve.gov
- Haugen, R.A. 1999, "The New Finance: The Case against Efficient Markets", 2nd Edition, Upper Saddle River, N.J.: Prentice Hall.

- Jia, J.H. and Adland, R. 2002, "An Empirical Analysis of the Time-varying Correlation of Returns in International Shipping", Presented at the IAME Panama 2002 Conference. Retrieved March 10th 2010. Available at <http://www.eclac.cl/>
- Kim, J. and Finger, C.C. 2000, "A Stress Test to Incorporate Correlation Breakdown", *Journal of Risk*, vol. 2, no. 3.
- Longin, F. and Solnik, B. 2001, "Extreme Correlation of International Equity Markets", *Journal of Finance*, vol. 56, no. 2, pp. 649-676.
- NBER. 2010, "US Business Cycle Expansions and Contractions", *The National Bureau of Economic Research*. Retrieved April 2nd, 2010. Available at www.nber.org
- Siegel, J.J. 2008, "Stocks for the Long Run", 4th Edition, New York, N.Y.: McGraw-Hill
- Standard & Poor's. May 2007, "S&P GSCI, S&P Risk Control Indices – Frequently Asked Questions", *Standard & Poor's*, McGraw-Hill. Retrieved March 17th 2010. Available at http://www2.standardandpoors.com/spf/pdf/index/SP_GSCI_FAQ_Web.pdf
- Standard & Poor's. December 31st 2009, "S&P 500 Equity Indices", *Standard & Poor's*, McGraw-Hill. Retrieved March 20th 2010. Available at www.standardandpoors.com
- Standard & Poor's. January 2010. "S&P GSCI Index Methodology", *Standard & Poor's*, McGraw-Hill. Retrieved March 17th 2010. Available at www.standardandpoors.com
- Swedroe, L. July 13th 2009, "International Diversification: Rising Correlations", CBS Business Network. Retrieved August 11th 2010. Available at www.moneywatch.bnet.com
- The Economist. July 16th 2009, "Efficiency and Beyond", *The Economist*, New York. Retrieved January 2010. Available at www.economist.com
- Thomson Reuters DataStream
- Thomson Reuters/Jefferies, 2010a. February 2010, "The Thomson Reuters/Jefferies CRB Index", *Thomson Reuters/Jefferies*. Retrieved March 17th 2010. Available at www.jefferies.com
- Thomson Reuters/Jefferies, 2010b. 2010, "CRB, Index Materials", *Thomson Reuters Jefferies*. Retrieved March 17th 2010. Available at www.jefferies.com
- WFE, 2010, "Derivative Markets, Commodity Futures", *World Federation of Exchanges*. Retrieved June 11th 2010. Available at www.world-exchanges.org
- Wharton Research Data Services
- Zeevi, A. and Mashal, R. 2002, "Beyond Correlation: Extreme Co-movements Between financial Assets", *SSRN Working Paper Series*.
- Zivot, E. and Wang, J. 2003, "Modeling financial time series with S-Plus", Heidelberg and New York, N.Y.: Springer.

11. Appendix

11.1 Data

Table 11.1.1 Summary statistics for all indices

Variable	Obs.	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
S&P	10096	0.000431	0.010738	-0.194583	0.115127	0	0
GSCI	10096	0.000449	0.011867	-0.168326	0.078962	0	0
Cru Oil	5797	0.000715	0.022240	-0.318750	0.146058	0	0
BrCrOil	2762	0.001010	0.022231	-0.129641	0.137476	0.004	0
Gas Oil	2762	0.000942	0.021423	-0.134311	0.113291	0.304	0
Nat Gas	4025	-0.000393	0.032829	-0.153413	0.206541	0	0
RBOB	5544	0.000844	0.022218	-0.257584	0.138509	0	0
Heat Oil	6807	0.000587	0.021189	-0.295812	0.137194	0	0
Copper	8323	0.000596	0.016613	-0.117528	0.126414	0.074	0
Corn	10096	0.000117	0.014152	-0.078067	0.090572	0	0
Wheat	10096	0.000210	0.015963	-0.094914	0.091959	0	0
Sugar	9335	0.000386	0.024168	-0.166325	0.152739	0.048	0

Table 11.1.2 CRB index components and dollar weights as of 2005 after the latest revision

Group I	33%	Group II	42%	Group III	20%	Group IV	5%
WTI Crude Oil	23	Natural Gas	6	Sugar	5	Nickel	1
Heating Oil	5	Corn	6	Cotton	5	Wheat	1
RBOB Gasoline	5	Soybeans	6	Coffee	5	Lean Hogs	1
		Live Cattle	6	Cocoa	5	Orange Juice	1
		Gold	6			Silver	1
		Aluminum	6				
		Copper	6				

Table 11.1.3 DJ-USBCI components and the dollar weights as of January 2009

Energy	33%	Industrial Metals	20.3%	Precious Metals	10.8%	Agriculture	29.3%	Livestock	6.7%
Crude Oil		Aluminum		Gold		Coffee		Lean Hogs	
Heating Oil		Copper		Silver		Corn		Live Cattle	
Natural Gas		Nickel				Cotton			
Unleaded Gasoline		Zinc				Soybeans			
						Soybean Oil			
						Sugar			
						Wheat			

11.2 Results

Table 11.2.1 Correlation between the commodity indices and the S&P 500, one-year rolling window

Year	GSCI	Cru Oil	BrCrOil	Gas Oil	Nat Gas	RBOB	Heat Oil	Copper	Corn	Wheat	Sugar
1970	0.1150								0.0236	0.0458	
1971	0.0449								-0.0658	0.0478	
1972	0.0245								0.0734	0.0912	
1973	0.0572								-0.0073	0.0090	0.1335*
1974	-0.0974								-0.0258	-0.0427	-0.0356
1975	-0.0561								-0.0471	-0.0923	0.0270
1976	0.0225								0.0300	0.0512	0.0485
1977	0.0535							0.0190	-0.0177	0.0712	0.0921
1978	-0.0694							-0.0949	-0.0379	-0.0144	-0.0370
1979	-0.0581							-0.0139	-0.0015	-0.0192	-0.0261
1980	0.2986*							0.2365*	0.2263*	0.2204*	0.2219*
1981	0.1699*							0.1991*	0.0989	0.1068	0.1476*
1982	0.2593*							0.4518*	0.2943*	0.1740*	0.1391*
1983	0.2562*						0.1329*	0.3338*	0.2024*	0.2649*	-0.0039
1984	0.1432*						0.0633	0.1615*	0.0485	0.0154	0.0358
1985	0.1435*						0.0614	0.1393*	0.0665	-0.0054	0.1301*
1986	-0.0638						-0.0990	-0.0113	-0.0427	-0.0985	0.1325*
1987	0.0967	0.0102					0.0256	0.1064	0.0873	0.1648*	-0.0692
1988	-0.0223	-0.0143				-0.0490	-0.0070	0.0100	0.0528	0.0183	0.0159
1989	0.0181	-0.0144				0.0291	0.0394	0.0623	0.0525	0.0481	-0.0085
1990	-0.4120*	-0.3961*				-0.3505*	-0.3693*	0.1419*	-0.1183	0.0285	-0.0247
1991	-0.2327*	-0.2446*				-0.2042*	-0.2735*	0.1736*	0.1247*	0.0719	0.1016
1992	0.0253	0.0417				0.0399	-0.0075	0.1340*	-0.0169	0.0359	-0.1729*
1993	0.0211	0.0120				0.0544	0.0267	0.0199	-0.1095	-0.1061	-0.1886*
1994	-0.1505*	-0.1655*			-0.0462	-0.1255*	-0.1462*	0.0432	0.0051	-0.0592	-0.1726*
1995	0.0024	-0.0014			0.0037	0.0253	0.0498	-0.0460	0.1069	-0.0517	-0.0629
1996	0.0111	-0.0076			0.0684	-0.0427	0.0062	-0.0299	-0.0409	0.0026	-0.0052
1997	-0.1630*	-0.0945			-0.1565*	-0.0364	-0.0645	0.0271	0.0288	0.0232	-0.0171
1998	0.0821	0.0394			0.0457	0.0355	0.0331	0.1322*	0.1122	0.0682	0.0122
1999	-0.0469	-0.0187	-0.0314	-0.0786	-0.1016	-0.0191	-0.0232	-0.0202	-0.0465	0.0655	-0.0340
2000	-0.0820	-0.0561	-0.0368	-0.0903	-0.0717	-0.0295	-0.0324	0.2036*	-0.0572	-0.1337*	0.0912
2001	-0.0312	-0.0428	-0.0209	-0.0367	-0.0483	-0.0076	-0.0246	0.1732*	0.0792	0.0749	0.0930
2002	0.1929*	0.1722*	0.1248*	0.0749	0.1209	0.1599*	0.1525*	0.2503*	0.0246	0.0874	-0.0516
2003	-0.2393*	-0.2784*	-0.2698*	-0.2249*	-0.0796	-0.2435*	-0.2576*	0.1548*	0.0309	0.0149	-0.0320
2004	-0.0772	-0.1029	-0.1212	-0.1324*	0.0242	-0.1104	-0.0645	0.1603*	0.0745	0.0088	-0.1171
2005	-0.0472	-0.0549	-0.0674	-0.0386	0.0046	-0.0338	-0.0713	-0.0163	0.0681	-0.0125	0.0270
2006	0.0328	-0.0006	0.0064	-0.0539	0.0677	0.0274	-0.0003	0.1501*	0.0264	-0.0107	0.0102
2007	0.0712	0.0384	0.0169	-0.0874	0.0049	-0.0130	-0.0352	0.2583*	0.1248*	0.0590	-0.0494
2008	0.2947*	0.3032*	0.3067*	0.1049	0.0767	0.3460*	0.2836*	0.2649*	0.1512*	0.1527*	0.1634*
2009	0.5582*	0.5228*	0.5479*	0.3588*	0.2306*	0.4060*	0.5246*	0.4333*	0.3310*	0.3626*	0.2679*

* Significant at a 5%-level

11.3 Regression Results

Table 11.3.1 Results from the regression on recession periods for all commodity indices, yearly data

GSCI	Source	SS	df	MS	Number of obs = 40		
	Model	0.0267	1	0.0267	F(1, 38)	0.93	
	Residual	1.0882	38	0.0286	Prob > F	0.3400	
	Total	1.1149	39	0.0286	R-squared	0.0240	
					Adj R-squared	-0.0017	
					Root MSE	0.1692	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recession	0.0597	0.0618	0.97	0.3400	-0.0654	0.1848
	Constant	0.0137	0.0309	0.44	0.6600	-0.0488	0.0763
Cru Oil	Source	SS	df	MS	Number of obs = 23		
	Model	0.0168	1	0.0168	F(1, 38)	0.48	
	Residual	0.7277	21	0.0347	Prob > F	0.4939	
	Total	0.7445	22	0.0338	R-squared	0.0226	
					Adj R-squared	-0.0240	
					Root MSE	0.1862	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recession	0.0616	0.0884	0.7	0.4940	-0.1223	0.2454
	Constant	-0.0314	0.0451	-0.7	0.4940	-0.1253	0.0625
BrCrOil	Source	SS	df	MS	Number of obs = 11		
	Model	0.1844	1	0.1844	F(1, 38)	5.50	
	Residual	0.3017	9	0.0335	Prob > F	0.0437	
	Total	0.4861	10	0.0486	R-squared	0.3793	
					Adj R-squared	0.3103	
					Root MSE	0.1831	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recession	0.2691	0.1148	2.35	0.0440	0.0095	0.5288
	Constant	-0.0565	0.0692	-0.82	0.4350	-0.2130	0.1001
Gas Oil	Source	SS	df	MS	Number of obs = 11		
	Model	0.0673	1	0.0673	F(1, 38)	3.56	
	Residual	0.1701	9	0.0189	Prob > F	0.0918	
	Total	0.2374	10	0.0237	R-squared	0.2835	
					Adj R-squared	0.2038	
					Root MSE	0.1375	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recession	0.1626	0.0862	1.89	0.0920	-0.0323	0.3575
	Constant	-0.0777	0.0520	-1.5	0.1690	-0.1952	0.0399
Nat Gas	Source	SS	df	MS	Number of obs = 16		
	Model	0.0173	1	0.0173	F(1, 38)	2.06	
	Residual	0.1178	14	0.0084	Prob > F	0.1732	
	Total	0.1351	15	0.0090	R-squared	0.1282	
					Adj R-squared	0.0660	
					Root MSE	0.0917	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recession	0.0760	0.0530	1.44	0.1730	-0.0376	0.1896
	Constant	-0.0100	0.0265	-0.38	0.7100	-0.0668	0.0468
RBOB	Source	SS	df	MS	Number of obs = 22		
	Model	0.0106	1	0.0106	F(1, 38)	0.38	
	Residual	0.5666	20	0.0283	Prob > F	0.5471	
	Total	0.5772	21	0.0275	R-squared	0.0184	
					Adj R-squared	-0.0307	
					Root MSE	0.1683	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recession	0.0494	0.0806	0.61	0.5470	-0.1187	0.2174
	Constant	-0.0199	0.0421	-0.47	0.6410	-0.1077	0.0679

Heat Oil	Source	SS	df	MS	Number of obs =	27
	Model	0.0032	1	0.0032	F(1, 38)	0.11
	Residual	0.7331	25	0.0293	Prob > F	0.7429
	Total	0.7363	26	0.0283	R-squared	0.0044
					Adj R-squared	-0.0354
					Root MSE	0.1712
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Recession	0.0263	0.0793	0.33	0.7430	-0.1370 0.1896
	Constant	-0.0087	0.0374	-0.23	0.8180	-0.0857 0.0683
Copper	Source	SS	df	MS	Number of obs =	33
	Model	0.1222	1	0.1222	F(1, 38)	8.49
	Residual	0.4461	31	0.0144	Prob > F	0.0066
	Total	0.5684	32	0.0178	R-squared	0.2151
					Adj R-squared	0.1897
					Root MSE	0.1200
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Recession	0.1420	0.0487	2.91	0.0070	0.0426 0.2414
	Constant	0.0931	0.0240	3.88	0.0010	0.0442 0.1420
Corn	Source	SS	df	MS	Number of obs =	40
	Model	0.0386	1	0.0386	F(1, 38)	4.36
	Residual	0.3369	38	0.0089	Prob > F	0.0437
	Total	0.3755	39	0.0096	R-squared	0.1028
					Adj R-squared	0.0792
					Root MSE	0.0942
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Recession	0.0718	0.0344	2.09	0.0440	0.0021 0.1414
	Constant	0.0298	0.0172	1.73	0.0910	-0.0050 0.0646
Wheat	Source	SS	df	MS	Number of obs =	40
	Model	0.0555	1	0.0555	F(1, 38)	6.50
	Residual	0.3247	38	0.0085	Prob > F	0.0150
	Total	0.3802	39	0.0097	R-squared	0.1460
					Adj R-squared	0.1235
					Root MSE	0.0924
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Recession	0.0860	0.0338	2.55	0.0150	0.0177 0.1544
	Constant	0.0220	0.0169	1.3	0.2010	-0.0122 0.0561
Sugar	Source	SS	df	MS	Number of obs =	40
	Model	0.0710	1	0.0710	F(1, 38)	7.66
	Residual	0.3243	35	0.0093	Prob > F	0.0089
	Total	0.3953	36	0.0110	R-squared	0.1796
					Adj R-squared	0.1562
					Root MSE	0.0963
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Recession	0.1021	0.0369	2.77	0.0090	0.0272 0.1770
	Constant	-0.0037	0.0182	-0.2	0.8400	-0.0406 0.0332

Table 11.3.2 Results from the regression on recent financial crisis for all commodity indices, yearly data

GSCI	Source	SS	df	MS	Number of obs =	40
	Model	0.2532	1	0.2532	F(1, 38)	11.16
	Residual	0.8618	38	0.0227	Prob > F	0.0019
	Total	1.1149	39	0.0286	R-squared	0.2271
					Adj R-squared	0.2067
					Root MSE	0.1506
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Recent recession	0.3020	0.0904	3.34	0.0020	0.1190 0.4850
	Constant	0.0060	0.0248	0.24	0.8100	-0.0441 0.0561

Cru Oil	Source	SS	df	MS	Number of obs = 23		
	Model	0.3177	1	0.3177	F(1, 38) 15.64		
	Residual	0.4267	21	0.0203	Prob > F 0.0007		
	Total	0.7445	22	0.0338	R-squared 0.4268		
					Adj R-squared 0.3995		
					Root MSE 0.1426		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.3490	0.0883	3.95	0.0010	0.1655	0.5325
	Constant	-0.0609	0.0319	-1.91	0.0700	-0.1272	0.0054
BrCrOil	Source	SS	df	MS	Number of obs = 11		
	Model	0.2560	1	0.2560	F(1, 38) 10.01		
	Residual	0.2301	9	0.0256	Prob > F 0.0115		
	Total	0.4861	10	0.0486	R-squared 0.5266		
					Adj R-squared 0.4740		
					Root MSE 0.1599		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.3425	0.1083	3.16	0.0110	0.0976	0.5874
	Constant	-0.0520	0.0565	-0.92	0.3810	-0.1799	0.0759
Gas Oil	Source	SS	df	MS	Number of obs = 11		
	Model	0.0855	1	0.0855	F(1, 38) 5.07		
	Residual	0.1519	9	0.0169	Prob > F 0.0509		
	Total	0.2374	10	0.0237	R-squared 0.3603		
					Adj R-squared 0.2892		
					Root MSE 0.1299		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.1980	0.0879	2.25	0.0510	-0.0009	0.3969
	Constant	-0.0726	0.0459	-1.58	0.1490	-0.1765	0.0313
Nat Gas	Source	SS	df	MS	Number of obs = 16		
	Model	0.0334	1	0.0334	F(1, 38) 4.59		
	Residual	0.1018	14	0.0073	Prob > F 0.0501		
	Total	0.1351	15	0.0090	R-squared 0.2471		
					Adj R-squared 0.1933		
					Root MSE 0.0853		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.1170	0.0546	2.14	0.0500	-0.0001	0.2342
	Constant	-0.0130	0.0236	-0.55	0.5920	-0.0637	0.0377
RBOB	Source	SS	df	MS	Number of obs = 22		
	Model	0.2220	1	0.2220	F(1, 38) 12.50		
	Residual	0.3552	20	0.0178	Prob > F 0.0021		
	Total	0.5772	21	0.0275	R-squared 0.3845		
					Adj R-squared 0.3538		
					Root MSE 0.1333		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.2927	0.0828	3.53	0.0020	0.1200	0.4654
	Constant	-0.0464	0.0306	-1.52	0.1450	-0.1101	0.0174
Heat Oil	Source	SS	df	MS	Number of obs = 27		
	Model	0.2291	1	0.2291	F(1, 38) 11.29		
	Residual	0.5072	25	0.0203	Prob > F 0.0025		
	Total	0.7363	26	0.0283	R-squared 0.3111		
					Adj R-squared 0.2835		
					Root MSE 0.1424		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.2931	0.0872	3.36	0.0030	0.1134	0.4727
	Constant	-0.0354	0.0291	-1.22	0.2350	-0.0953	0.0245

Copper	Source	SS	df	MS	Number of obs = 33		
	Model	0.1208	1	0.1208	F(1, 38) 8.37		
	Residual	0.4476	31	0.0144	Prob > F 0.0069		
	Total	0.5684	32	0.0178	R-squared 0.2125		
					Adj R-squared 0.1871		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.2105	0.0728	2.89	0.0070	0.0621	0.3588
	Constant	0.1084	0.0219	4.94	0.0000	0.0636	0.1531
Corn	Source	SS	df	MS	Number of obs = 40		
	Model	0.0775	1	0.0775	F(1, 38) 9.88		
	Residual	0.2980	38	0.0078	Prob > F 0.0032		
	Total	0.3755	39	0.0096	R-squared 0.2064		
					Adj R-squared 0.1855		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.1671	0.0532	3.14	0.0030	0.0595	0.2747
	Constant	0.0352	0.0146	2.42	0.0200	0.0057	0.0647
Wheat	Source	SS	df	MS	Number of obs = 40		
	Model	0.0710	1	0.0710	F(1, 38) 8.73		
	Residual	0.3092	38	0.0081	Prob > F 0.0054		
	Total	0.3802	39	0.0097	R-squared 0.1868		
					Adj R-squared 0.1654		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.1600	0.0541	2.95	0.0050	0.0503	0.2696
	Constant	0.0315	0.0148	2.12	0.0400	0.0014	0.0615
Sugar	Source	SS	df	MS	Number of obs = 37		
	Model	0.0368	1	0.0368	F(1, 38) 3.59		
	Residual	0.3585	35	0.0102	Prob > F 0.0663		
	Total	0.3953	36	0.0110	R-squared 0.0931		
					Adj R-squared 0.0672		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.1155	0.0610	1.9	0.0660	-0.0082	0.2393
	Constant	0.0118	0.0174	0.68	0.5020	-0.0235	0.0470

Table 11.3.3 Results from the regression using three explanatory variables for all commodity indices and one-year moving correlation windows, daily data

GSCI	Source	SS	df	MS	Number of obs = 9845		
	Model	41.0322	3	13.6774	F(1, 38) 728.68		
	Residual	184.7176	9841	0.0188	Prob > F 0.0000		
	Total	225.7498	9844	0.0229	R-squared 0.1818		
					Adj R-squared 0.1815		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	0.0962	0.0057	16.74	0.0000	0.0850	0.1075
	Oil recessions	-0.1210	0.0063	-19.23	0.0000	-0.1333	-0.1087
	Recent fin. crisis	0.2372	0.0062	38.46	0.0000	0.2251	0.2493
	Constant	0.0066	0.0015	4.38	0.0000	0.0037	0.0096
Cru Oil	Source	SS	df	MS	Number of obs = 5546		
	Model	51.2254	3	17.0751	F(1, 38) 1151.64		
	Residual	82.1699	5542	0.0148	Prob > F 0.0000		
	Total	133.3953	5545	0.0241	R-squared 0.3840		
					Adj R-squared 0.3837		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Recent recession	0.1155	0.0610	1.9	0.0660	-0.0082	0.2393
	Constant	0.0118	0.0174	0.68	0.5020	-0.0235	0.0470

	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	0.0204	0.0096	2.13	0.0330	0.0016	0.0392
	Oil recessions	-0.2677	0.0096	-28	0.0000	-0.2864	-0.2490
	Recent fin. crisis	0.2799	0.0056	49.94	0.0000	0.2689	0.2908
	Constant	-0.0493	0.0018	-27.71	0.0000	-0.0528	-0.0458
BrCrOil	Source	SS	df	MS	Number of obs = 2511		
	Model	33.1217	2	16.5608	F(1, 38) 1054.96		
	Residual	39.3708	2508	0.0157	Prob > F 0.0000		
	Total	72.4925	2510	0.0289	R-squared 0.4569		
					Adj R-squared 0.4565		
					Root MSE 0.1253		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	0.0538	0.0101	5.31	0.0000	0.0340	0.0737
	Oil recessions (dropped)						
	Recent fin. crisis	0.2851	0.0062	45.92	0.0000	0.2729	0.2972
	Constant	-0.0540	0.0029	-18.39	0.0000	-0.0598	-0.0483
Gas Oil	Source	SS	df	MS	Number of obs = 2511		
	Model	10.8757	2	5.4379	F(1, 38) 582.18		
	Residual	23.4261	2508	0.0093	Prob > F 0.0000		
	Total	34.3019	2510	0.0137	R-squared 0.3171		
					Adj R-squared 0.3165		
					Root MSE 0.0967		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	0.0069	0.0078	0.89	0.3740	-0.0084	0.0223
	Oil recessions (dropped)						
	Recent fin. crisis	0.1624	0.0048	33.91	0.0000	0.1530	0.1718
	Constant	-0.0795	0.0023	-35.1	0.0000	-0.0840	-0.0751
Nat Gas	Source	SS	df	MS	Number of obs = 3774		
	Model	4.6467	2	2.3233	F(1, 38) 456.04		
	Residual	19.2116	3771	0.0051	Prob > F 0.0000		
	Total	23.8583	3773	0.0063	R-squared 0.1948		
					Adj R-squared 0.1943		
					Root MSE 0.0714		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	-0.0973	0.0057	-17.15	0.0000	-0.1084	-0.0862
	Oil recessions (dropped)						
	Recent fin. crisis	0.0785	0.0034	23.28	0.0000	0.0718	0.0851
	Constant	-0.0027	0.0013	-2.09	0.0360	-0.0052	-0.0002
RBOB	Source	SS	df	MS	Number of obs = 5293		
	Model	44.4417	3	14.8139	F(1, 38) 1091.76		
	Residual	71.7652	5289	0.0136	Prob > F 0.0000		
	Total	116.2070	5292	0.0220	R-squared 0.3824		
					Adj R-squared 0.3821		
					Root MSE 0.1165		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	-0.0073	0.0092	-0.8	0.4240	-0.0253	0.0107
	Oil recessions	-0.2538	0.0092	-27.72	0.0000	-0.2718	-0.2359
	Recent fin. crisis	0.2590	0.0054	48.17	0.0000	0.2484	0.2695
	Constant	-0.0339	0.0017	-19.36	0.0000	-0.0373	-0.0304
Heat Oil	Source	SS	df	MS	Number of obs = 6556		
	Model	37.4128	3	12.4709	F(1, 38) 828.11		
	Residual	98.6699	6552	0.0151	Prob > F 0.0000		
	Total	136.0827	6555	0.0208	R-squared 0.2749		
					Adj R-squared 0.2746		
					Root MSE 0.1227		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	0.0167	0.0096	1.73	0.0830	-0.0022	0.0356
	Oil recessions	-0.2259	0.0096	-23.51	0.0000	-0.2447	-0.2070
	Recent fin. crisis	0.2392	0.0056	42.74	0.0000	0.2282	0.2502
	Constant	-0.0350	0.0016	-21.52	0.0000	-0.0382	-0.0318

Copper	Source	SS	df	MS	Number of obs = 8072		
	Model	24.1498	3	8.0499	F(1, 38)	653.97	
	Residual	99.3114	8068	0.0123	Prob > F	0.0000	
	Total	123.4612	8071	0.0153	R-squared	0.1956	
					Adj R-squared	0.1953	
					Root MSE	0.1110	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	0.1387	0.0047	29.58	0.0000	0.1295	0.1479
	Oil recessions	0.0381	0.0087	4.39	0.0000	0.0211	0.0550
	Recent fin. crisis	0.1765	0.0050	35.11	0.0000	0.1666	0.1863
	Constant	0.1005	0.0013	74.49	0.0000	0.0978	0.1031
Corn	Source	SS	df	MS	Number of obs = 9845		
	Model	13.2303	3	4.4101	F(1, 38)	575.94	
	Residual	75.3545	9841	0.0077	Prob > F	0.0000	
	Total	88.5847	9844	0.0090	R-squared	0.1494	
					Adj R-squared	0.1491	
					Root MSE	0.0875	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	0.0561	0.0037	15.28	0.0000	0.0489	0.0633
	Oil recessions	-0.0874	0.0040	-21.75	0.0000	-0.0953	-0.0796
	Recent fin. crisis	0.1216	0.0039	30.87	0.0000	0.1139	0.1293
	Constant	0.0365	0.0010	37.81	0.0000	0.0346	0.0384
Wheat	Source	SS	df	MS	Number of obs = 9845		
	Model	10.4839	3	3.4946	F(1, 38)	423.09	
	Residual	81.2842	9841	0.0083	Prob > F	0.0000	
	Total	91.7681	9844	0.0093	R-squared	0.1142	
					Adj R-squared	0.1140	
					Root MSE	0.0909	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	0.0472	0.0038	12.37	0.0000	0.0397	0.0547
	Oil recessions	-0.0409	0.0042	-9.79	0.0000	-0.0491	-0.0327
	Recent fin. crisis	0.1300	0.0041	31.79	0.0000	0.1220	0.1381
	Constant	0.0316	0.0010	31.54	0.0000	0.0297	0.0336
Sugar	Source	SS	df	MS	Number of obs = 9084		
	Model	13.9600	3	4.6533	F(1, 38)	551.11	
	Residual	76.6668	9080	0.0084	Prob > F	0.0000	
	Total	90.6267	9083	0.0100	R-squared	0.1540	
					Adj R-squared	0.1538	
					Root MSE	0.0919	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Other recessions	0.1032	0.0039	26.68	0.0000	0.0956	0.1108
	Oil recessions	0.0251	0.0044	5.67	0.0000	0.0164	0.0337
	Recent fin. crisis	0.1344	0.0041	32.41	0.0000	0.1263	0.1426
	Constant	0.0024	0.0011	2.26	0.0240	0.0003	0.0045

Table 11.3.4 Results from the regression on the return level of the S&P 500 for all commodity indices, yearly data

GSCI	Source	SS	df	MS	Number of obs = 40		
	Model	0.0024	1	0.0024	F(1, 38)	0.080	
	Residual	1.1126	38	0.0293	Prob > F	0.7774	
	Total	1.1149	39	0.0286	R-squared	0.0021	
					Adj R-squared	-0.0241	
					Root MSE	0.1711	
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Return	-0.0449	0.1576	-0.28	0.7770	-0.3640	0.2742
	Constant	0.0322	0.0297	1.08	0.2860	-0.0280	0.0924
Cru Oil	Source	SS	df	MS	Number of obs = 23		
	Model	0.0302	1	0.0302	F(1, 38)	0.890	
	Residual	0.7143	21	0.0340	Prob > F	0.3568	
	Total	0.7445	22	0.0338	R-squared	0.0406	
					Adj R-squared	-0.0051	
					Root MSE	0.1844	

Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return	-0.2050	0.2175	-0.94	0.3570	-0.6574	0.2474
Constant	0.0013	0.0423	0.03	0.9750	-0.0867	0.0894
BrCrOil	Source	SS	df	MS	Number of obs = 11	
	Model	0.0353	1	0.0353	F(1, 38)	0.710
	Residual	0.4508	9	0.0501	Prob > F	0.4227
	Total	0.4861	10	0.0486	R-squared	0.0727
					Adj R-squared	-0.0303
					Root MSE	0.2238
Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return	-0.3093	0.3683	-0.84	0.4230	-1.1425	0.5238
Constant	0.0439	0.0675	0.65	0.5320	-0.1089	0.1967
Gas Oil	Source	SS	df	MS	Number of obs = 11	
	Model	0.0103	1	0.0103	F(1, 38)	0.410
	Residual	0.2271	9	0.0252	Prob > F	0.5382
	Total	0.2374	10	0.0237	R-squared	0.0435
					Adj R-squared	-0.0628
					Root MSE	0.1588
Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return	-0.1673	0.2614	-0.64	0.5380	-0.7585	0.4240
Constant	-0.0172	0.0479	-0.36	0.7280	-0.1256	0.0913
Nat Gas	Source	SS	df	MS	Number of obs = 16	
	Model	0.0061	1	0.0061	F(1, 38)	0.670
	Residual	0.1290	14	0.0092	Prob > F	0.4284
	Total	0.1351	15	0.0090	R-squared	0.0454
					Adj R-squared	-0.0228
					Root MSE	0.0960
Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return	-0.1007	0.1235	-0.82	0.4280	-0.3656	0.1642
Constant	0.0165	0.0257	0.64	0.5320	-0.0387	0.0716
RBOB	Source	SS	df	MS	Number of obs = 22	
	Model	0.0351	1	0.0351	F(1, 38)	1.290
	Residual	0.5421	20	0.0271	Prob > F	0.2687
	Total	0.5772	21	0.0275	R-squared	0.0608
					Adj R-squared	0.0138
					Root MSE	0.1646
Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return	-0.2220	0.1951	-1.14	0.2690	-0.6289	0.1850
Constant	0.0124	0.0388	0.32	0.7520	-0.0686	0.0934
Heat Oil	Source	SS	df	MS	Number of obs = 27	
	Model	0.0118	1	0.0118	F(1, 38)	0.410
	Residual	0.7245	25	0.0290	Prob > F	0.5288
	Total	0.7363	26	0.0283	R-squared	0.0161
					Adj R-squared	-0.0233
					Root MSE	0.1702
Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return	-0.1235	0.1934	-0.64	0.5290	-0.5218	0.2747
Constant	0.0087	0.0374	0.23	0.8190	-0.0683	0.0857
Copper	Source	SS	df	MS	Number of obs = 33	
	Model	0.0137	1	0.0137	F(1, 38)	0.760
	Residual	0.5547	31	0.0179	Prob > F	0.3888
	Total	0.5684	32	0.0178	R-squared	0.0241
					Adj R-squared	-0.0074
					Root MSE	0.1338
Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return	-0.1234	0.1412	-0.87	0.3890	-0.4114	0.1645
Constant	0.1383	0.0263	5.25	0.0000	0.0846	0.1920

Corn	Source	SS	df	MS	Number of obs = 40		
	Model	0.0170	1	0.0170	F(1, 38) 1.800		
	Residual	0.3585	38	0.0094	Prob > F 0.1876		
	Total	0.3755	39	0.0096	R-squared 0.0452		
					Adj R-squared 0.0201		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Return	0.1201	0.0895	1.34	0.1880	-0.0611	0.3012
	Constant	0.0383	0.0169	2.27	0.0290	0.0042	0.0725
Wheat	Source	SS	df	MS	Number of obs = 40		
	Model	0.0008	1	0.0008	F(1, 38) 0.080		
	Residual	0.3794	38	0.0100	Prob > F 0.7829		
	Total	0.3802	39	0.0097	R-squared 0.0020		
					Adj R-squared -0.0242		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Return	0.0255	0.0920	0.28	0.7830	-0.1608	0.2119
	Constant	0.0415	0.0174	2.39	0.0220	0.0063	0.0766
Sugar	Source	SS	df	MS	Number of obs = 37		
	Model	0.0000	1	0.0000	F(1, 38) 0.000		
	Residual	0.3953	35	0.0113	Prob > F 0.9983		
	Total	0.3953	36	0.0110	R-squared 0.0000		
					Adj R-squared -0.0286		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Return	-0.0002	0.0986	0	0.9980	-0.2003	0.1999
	Constant	0.0212	0.0191	1.11	0.2750	-0.0175	0.0599

Table 11.3.5 Results from the regression on the return level of the S&P 500 for all commodity indices, daily data

GSCI	Source	SS	df	MS	Number of obs = 9845		
	Model	0.0010	1	0.0010	F(1, 38) 0.040		
	Residual	225.7489	9843	0.0229	Prob > F 0.8380		
	Total	225.7498	9844	0.0229	R-squared 0.0000		
					Adj R-squared -0.0001		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Return	-0.0290	0.1418	-0.2	0.8380	-0.3069	0.2489
	Constant	0.0191	0.0015	12.48	0.0000	0.0161	0.0221
Cru Oil	Source	SS	df	MS	Number of obs = 5546		
	Model	0.0022	1	0.0022	F(1, 38) 0.090		
	Residual	133.3931	5544	0.0241	Prob > F 0.7617		
	Total	133.3953	5545	0.0241	R-squared 0.0000		
					Adj R-squared -0.0002		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Return	-0.0550	0.1813	-0.3	0.7620	-0.4103	0.3004
	Constant	-0.0303	0.0021	-14.52	0.0000	-0.0344	-0.0262
BrCrOil	Source	SS	df	MS	Number of obs = 2511		
	Model	0.0130	1	0.0130	F(1, 38) 0.450		
	Residual	72.4795	2509	0.0289	Prob > F 0.5031		
	Total	72.4925	2510	0.0289	R-squared 0.0002		
					Adj R-squared -0.0002		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Return	0.1629	0.2432	0.67	0.5030	-0.3140	0.6397
	Constant	0.0091	0.0034	2.7	0.0070	0.0025	0.0158

Gas Oil	Source	SS	df	MS	Number of obs = 2511		
	Model	0.0055	1	0.0055	F(1, 38) 0.400		
	Residual	34.2964	2509	0.0137	Prob > F 0.5262		
	Total	34.3019	2510	0.0137	R-squared 0.0002		
					Adj R-squared -0.0002		
					Root MSE 0.1169		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return		0.1060	0.1673	0.63	0.5260	-0.2220	0.4341
Constant		-0.0451	0.0023	-19.35	0.0000	-0.0497	-0.0406
Nat Gas	Source	SS	df	MS	Number of obs = 3774		
	Model	0.0128	1	0.0128	F(1, 38) 2.020		
	Residual	23.8455	3772	0.0063	Prob > F 0.1549		
	Total	23.8583	3773	0.0063	R-squared 0.0005		
					Adj R-squared 0.0003		
					Root MSE 0.0795		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return		0.1441	0.1013	1.42	0.1550	-0.0545	0.3427
Constant		0.0039	0.0013	2.98	0.0030	0.0013	0.0064
RBOB	Source	SS	df	MS	Number of obs = 5293		
	Model	0.0044	1	0.0044	F(1, 38) 0.200		
	Residual	116.2025	5291	0.0220	Prob > F 0.6528		
	Total	116.2070	5292	0.0220	R-squared 0.0000		
					Adj R-squared -0.0002		
					Root MSE 0.1482		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return		-0.0794	0.1765	-0.45	0.6530	-0.4255	0.2667
Constant		-0.0164	0.0020	-8.07	0.0000	-0.0204	-0.0124
Heat Oil	Source	SS	df	MS	Number of obs = 6556		
	Model	0.0000	1	0.0000	F(1, 38) 0.000		
	Residual	136.0826	6554	0.0208	Prob > F 0.9615		
	Total	136.0827	6555	0.0208	R-squared 0.0000		
					Adj R-squared -0.0002		
					Root MSE 0.1441		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return		-0.0074	0.1537	-0.05	0.9620	-0.3088	0.2939
Constant		-0.0212	0.0018	-11.9	0.0000	-0.0247	-0.0177
Copper	Source	SS	df	MS	Number of obs = 8072		
	Model	0.0052	1	0.0052	F(1, 38) 0.340		
	Residual	123.4561	8070	0.0153	Prob > F 0.5616		
	Total	123.4612	8071	0.0153	R-squared 0.0000		
					Adj R-squared -0.0001		
					Root MSE 0.1237		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return		-0.0716	0.1234	-0.58	0.5620	-0.3136	0.1703
Constant		0.1232	0.0014	89.44	0.0000	0.1205	0.1259
Corn	Source	SS	df	MS	Number of obs = 9845		
	Model	0.0022	1	0.0022	F(1, 38) 0.240		
	Residual	88.5826	9843	0.0090	Prob > F 0.6214		
	Total	88.5847	9844	0.0090	R-squared 0.0000		
					Adj R-squared -0.0001		
					Root MSE 0.0949		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Return		0.0439	0.0888	0.49	0.6210	-0.1302	0.2180
Constant		0.0420	0.0010	43.89	0.0000	0.0401	0.0439
Wheat	Source	SS	df	MS	Number of obs = 9845		
	Model	0.0002	1	0.0002	F(1, 38) 0.020		
	Residual	91.7679	9843	0.0093	Prob > F 0.8791		
	Total	91.7681	9844	0.0093	R-squared 0.0000		
					Adj R-squared -0.0001		
					Root MSE 0.0966		

	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Return	-0.0138	0.0904	-0.15	0.8790	-0.1909	0.1634
	Constant	0.0394	0.0010	40.48	0.0000	0.0375	0.0413
Sugar	Source	SS	df	MS			
	Model	0.0002	1	0.0002	Number of obs = 9084		
	Residual	90.6265	9082	0.0100	F(1, 38) 0.020		
	Total	90.6267	9083	0.0100	Prob > F 0.8785		
					R-squared 0.0000		
					Adj R-squared -0.0001		
					Root MSE 0.0999		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Return	-0.0146	0.0953	-0.15	0.8780	-0.2014	0.1723
	Constant	0.0184	0.0010	17.51	0.0000	0.0163	0.0204

Table 11.3.6 Results from the regression on correlation between the commodity indices and the S&P 500 over the squared S&P 500 returns and S&P 500 returns using one-year moving correlation windows, daily data

GSCI	Source	SS	df	MS			
	Model	0.6989	2	0.3494	Number of obs = 9845		
	Residual	225.0510	9842	0.0229	F(1, 38) 15.28		
	Total	225.7498	9844	0.0229	Prob > F 0.0000		
					R-squared 0.0031		
					Adj R-squared 0.0029		
					Root MSE 0.1512		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Squared return	16.0072	2.8974	5.52	0.0000	10.3276	21.6868
	Return	0.0607	0.1425	0.43	0.6700	-0.2186	0.3400
	Constant	0.0172	0.0016	10.98	0.0000	0.0141	0.0202
Cru Oil	Source	SS	df	MS			
	Model	2.7172	2	1.3586	Number of obs = 5546		
	Residual	130.6781	5543	0.0236	F(1, 38) 57.63		
	Total	133.3953	5545	0.0241	Prob > F 0.0000		
					R-squared 0.0204		
					Adj R-squared 0.0200		
					Root MSE 0.1535		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Squared return	49.7924	4.6399	10.73	0.0000	40.6965	58.8884
	Return	-0.0567	0.1794	-0.32	0.7520	-0.4084	0.2951
	Constant	-0.0369	0.0022	-17.12	0.0000	-0.0411	-0.0326
BrCrOil	Source	SS	df	MS			
	Model	1.8589	2	0.9294	Number of obs = 2511		
	Residual	70.6336	2508	0.0282	F(1, 38) 33.00		
	Total	72.4925	2510	0.0289	Prob > F 0.0000		
					R-squared 0.0256		
					Adj R-squared 0.0249		
					Root MSE 0.1678		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Squared return	44.6615	5.5165	8.1	0.0000	33.8441	55.4789
	Return	0.0857	0.2403	0.36	0.7210	-0.3855	0.5569
	Constant	0.0005	0.0035	0.13	0.8960	-0.0064	0.0074
Gas Oil	Source	SS	df	MS			
	Model	0.7710	2	0.3855	Number of obs = 2511		
	Residual	33.5309	2508	0.0134	F(1, 38) 28.83		
	Total	34.3019	2510	0.0137	Prob > F 0.0000		
					R-squared 0.0225		
					Adj R-squared 0.0217		
					Root MSE 0.1156		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Squared return	28.7610	3.8009	7.57	0.0000	21.3079	36.2142
	Return	0.0564	0.1656	0.34	0.7340	-0.2683	0.3810
	Constant	-0.0507	0.0024	-20.94	0.0000	-0.0555	-0.0460

Nat Gas	Source	SS	df	MS	Number of obs = 3774		
	Model	0.0469	2	0.0235	F(1, 38) 3.72		
	Residual	23.8114	3771	0.0063	Prob > F 0.0244		
	Total	23.8583	3773	0.0063	R-squared 0.0020		
					Adj R-squared 0.0014		
					Root MSE 0.0795		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Squared return	5.7800	2.4857	2.33	0.0200	0.9065	10.6534
	Return	0.1396	0.1012	1.38	0.1680	-0.0589	0.3381
	Constant	0.0029	0.0014	2.15	0.0310	0.0003	0.0056
RBOB	Source	SS	df	MS	Number of obs = 5293		
	Model	3.0072	2	1.5036	F(1, 38) 70.27		
	Residual	113.1998	5290	0.0214	Prob > F 0.0000		
	Total	116.2070	5292	0.0220	R-squared 0.0259		
					Adj R-squared 0.0255		
					Root MSE 0.1463		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Squared return	53.0505	4.4784	11.85	0.0000	44.2709	61.8300
	Return	-0.1021	0.1743	-0.59	0.5580	-0.4438	0.2395
	Constant	-0.0235	0.0021	-11.2	0.0000	-0.0276	-0.0194
Heat Oil	Source	SS	df	MS	Number of obs = 6556		
	Model	0.9703	2	0.4851	F(1, 38) 23.53		
	Residual	135.1124	6553	0.0206	Prob > F 0.0000		
	Total	136.0827	6555	0.0208	R-squared 0.0071		
					Adj R-squared 0.0068		
					Root MSE 0.1436		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Squared return	19.2739	2.8097	6.86	0.0000	13.7660	24.7817
	Return	0.1514	0.1549	0.98	0.3280	-0.1523	0.4551
	Constant	-0.0238	0.0018	-13.13	0.0000	-0.0274	-0.0203
Copper	Source	SS	df	MS	Number of obs = 8072		
	Model	0.5486	2	0.2743	F(1, 38) 18.01		
	Residual	122.9126	8069	0.0152	Prob > F 0.0000		
	Total	123.4612	8071	0.0153	R-squared 0.0044		
					Adj R-squared 0.0042		
					Root MSE 0.1234		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Squared return	14.2756	2.3901	5.97	0.0000	9.5904	18.9607
	Return	0.0253	0.1242	0.2	0.8390	-0.2182	0.2688
	Constant	0.1214	0.0014	86.19	0.0000	0.1187	0.1242
Corn	Source	SS	df	MS	Number of obs = 9845		
	Model	0.0855	2	0.0427	F(1, 38) 4.75		
	Residual	88.4993	9842	0.0090	Prob > F 0.0086		
	Total	88.5847	9844	0.0090	R-squared 0.0010		
					Adj R-squared 0.0008		
					Root MSE 0.0948		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Squared return	5.5300	1.8170	3.04	0.0020	1.9684	9.0916
	Return	0.0749	0.0894	0.84	0.4020	-0.1003	0.2500
	Constant	0.0413	0.0010	42.17	0.0000	0.0394	0.0433
Wheat	Source	SS	df	MS	Number of obs = 9845		
	Model	0.2468	2	0.1234	F(1, 38) 13.27		
	Residual	91.5213	9842	0.0093	Prob > F 0.0000		
	Total	91.7681	9844	0.0093	R-squared 0.0027		
					Adj R-squared 0.0025		
					Root MSE 0.0964		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Squared return	9.5151	1.8477	5.15	0.0000	5.8932	13.1370
	Return	0.0396	0.0909	0.44	0.6630	-0.1386	0.2177
	Constant	0.0383	0.0010	38.41	0.0000	0.0363	0.0402

Sugar	Source	SS	df	MS	Number of obs = 9084	
	Model	0.2250	2	0.1125	F(1, 38)	11.30
	Residual	90.4018	9081	0.0100	Prob > F	0.0000
	Total	90.6267	9083	0.0100	R-squared	0.0025
					Adj R-squared	0.0023
					Root MSE	0.0998
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Squared return	9.1078	1.9170	4.75	0.0000	5.3501 12.8654
	Return	0.0391	0.0959	0.41	0.6830	-0.1488 0.2271
	Constant	0.0172	0.0011	16.05	0.0000	0.0151 0.0193

Table 11.3.7 Results from regression on correlation between the commodity indices and the S&P 500 over the S&P 500 returns using dummies for extreme positive and negative market returns, daily data

GSCI	Source	SS	df	MS	Number of obs = 9845	
	Model	1.0839	2	0.5419	F(1, 38)	23.74
	Residual	224.6660	9842	0.0228	Prob > F	0.0000
	Total	225.7498	9844	0.0229	R-squared	0.0048
					Adj R-squared	0.0046
					Root MSE	0.1511
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Extr. positive returns	0.0385	0.0070	5.5	0.0000	0.0248 0.0522
	Extr. negative returns	0.0310	0.0070	4.43	0.0000	0.0173 0.0447
	Constant	0.0156	0.0016	9.7	0.0000	0.0124 0.0187
Cru Oil	Source	SS	df	MS	Number of obs = 5546	
	Model	3.3184	2	1.6592	F(1, 38)	70.70
	Residual	130.0769	5543	0.0235	Prob > F	0.0000
	Total	133.3953	5545	0.0241	R-squared	0.0249
					Adj R-squared	0.0245
					Root MSE	0.1532
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Extr. positive returns	0.0761	0.0095	8.05	0.0000	0.0576 0.0946
	Extr. negative returns	0.0867	0.0095	9.17	0.0000	0.0681 0.1052
	Constant	-0.0384	0.0022	-17.72	0.0000	-0.0427 -0.0342
BrCrOil	Source	SS	df	MS	Number of obs = 2511	
	Model	2.8409	2	1.4204	F(1, 38)	51.15
	Residual	69.6516	2508	0.0278	Prob > F	0.0000
	Total	72.4925	2510	0.0289	R-squared	0.0392
					Adj R-squared	0.0384
					Root MSE	0.1667
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Extr. positive returns	0.1146	0.0153	7.48	0.0000	0.0846 0.1446
	Extr. negative returns	0.1100	0.0153	7.19	0.0000	0.0800 0.1401
	Constant	-0.0020	0.0035	-0.58	0.5630	-0.0089 0.0048
Gas Oil	Source	SS	df	MS	Number of obs = 2511	
	Model	1.1638	2	0.5819	F(1, 38)	44.04
	Residual	33.1380	2508	0.0132	Prob > F	0.0000
	Total	34.3019	2510	0.0137	R-squared	0.0339
					Adj R-squared	0.0332
					Root MSE	0.1150
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Extr. positive returns	0.0742	0.0106	7.03	0.0000	0.0535 0.0949
	Extr. negative returns	0.0695	0.0106	6.58	0.0000	0.0488 0.0902
	Constant	-0.0523	0.0024	-21.63	0.0000	-0.0570 -0.0475
Nat Gas	Source	SS	df	MS	Number of obs = 3774	
	Model	0.0724	2	0.0362	F(1, 38)	5.74
	Residual	23.7859	3771	0.0063	Prob > F	0.0032
	Total	23.8583	3773	0.0063	R-squared	0.0030
					Adj R-squared	0.0025
					Root MSE	0.0794

Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Extr. positive returns		0.0157	0.0060	2.65	0.0080	0.0041	0.0274
Extr. negative returns		0.0134	0.0060	2.25	0.0240	0.0017	0.0251
Constant		0.0025	0.0014	1.81	0.0700	-0.0002	0.0051
RBOB	Source	SS	df	MS			
	Model	3.3694	2	1.6847	Number of obs = 5293		
	Residual	112.8375	5290	0.0213	F(1, 38) 78.98		
	Total	116.2070	5292	0.0220	Prob > F 0.0000		
					R-squared 0.0290		
					Adj R-squared 0.0286		
					Root MSE 0.1461		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Extr. positive returns		0.0788	0.0092	8.54	0.0000	0.0607	0.0969
Extr. negative returns		0.0892	0.0092	9.66	0.0000	0.0711	0.1073
Constant		-0.0249	0.0021	-11.75	0.0000	-0.0290	-0.0207
Heat Oil	Source	SS	df	MS			
	Model	2.2261	2	1.1130	Number of obs = 6556		
	Residual	133.8566	6553	0.0204	F(1, 38) 54.49		
	Total	136.0827	6555	0.0208	Prob > F 0.0000		
					R-squared 0.0164		
					Adj R-squared 0.0161		
					Root MSE 0.1429		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Extr. positive returns		0.0601	0.0081	7.4	0.0000	0.0442	0.0760
Extr. negative returns		0.0628	0.0081	7.74	0.0000	0.0469	0.0788
Constant		-0.0273	0.0019	-14.69	0.0000	-0.0310	-0.0237
Copper	Source	SS	df	MS			
	Model	1.5594	2	0.7797	Number of obs = 8072		
	Residual	121.9018	8069	0.0151	F(1, 38) 51.61		
	Total	123.4612	8071	0.0153	Prob > F 0.0000		
					R-squared 0.0126		
					Adj R-squared 0.0124		
					Root MSE 0.1229		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Extr. positive returns		0.0537	0.0063	8.54	0.0000	0.0414	0.0660
Extr. negative returns		0.0374	0.0063	5.94	0.0000	0.0251	0.0497
Constant		0.1187	0.0014	82.29	0.0000	0.1158	0.1215
Corn	Source	SS	df	MS			
	Model	0.0848	2	0.0424	Number of obs = 9845		
	Residual	88.4999	9842	0.0090	F(1, 38) 4.72		
	Total	88.5847	9844	0.0090	Prob > F 0.0000		
					R-squared 0.0010		
					Adj R-squared 0.0008		
					Root MSE 0.0948		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Extr. positive returns		0.0125	0.0044	2.85	0.0040	0.0039	0.0211
Extr. negative returns		0.0057	0.0044	1.3	0.1950	-0.0029	0.0143
Constant		0.0411	0.0010	40.81	0.0000	0.0391	0.0431
Wheat	Source	SS	df	MS			
	Model	0.2551	2	0.1275	Number of obs = 9845		
	Residual	91.5130	9842	0.0093	F(1, 38) 13.72		
	Total	91.7681	9844	0.0093	Prob > F 0.0000		
					R-squared 0.0028		
					Adj R-squared 0.0026		
					Root MSE 0.0964		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Extr. positive returns		0.0205	0.0045	4.6	0.0000	0.0118	0.0293
Extr. negative returns		0.0123	0.0045	2.75	0.0060	0.0035	0.0210
Constant		0.0378	0.0010	36.88	0.0000	0.0358	0.0398
Sugar	Source	SS	df	MS			
	Model	0.8674	2	0.4337	Number of obs = 9084		
	Residual	89.7593	9081	0.0099	F(1, 38) 43.88		
	Total	90.6267	9083	0.0100	Prob > F 0.0000		
					R-squared 0.0096		
					Adj R-squared 0.0094		
					Root MSE 0.0994		

Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Extr. positive returns	0.0310	0.0048	6.48	0.0000	0.0216	0.0404
Extr. negative returns	0.0340	0.0048	7.1	0.0000	0.0246	0.0434
Constant	0.0151	0.0011	13.74	0.0000	0.0130	0.0173

Table 11.3.8 Results from the regression on the volatility level of the S&P 500 for all commodity indices, yearly data

GSCI	Source	SS	df	MS	Number of obs =		40
	Model	0.0134	1	0.0134	F(1, 38)		0.46
	Residual	1.1015	38	0.0290	Prob > F		0.5006
	Total	1.1149	39	0.0286	R-squared		0.0120
					Adj R-squared		-0.0140
					Root MSE		0.1703
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.1769	0.2602	0.68	0.5010	-0.3498	0.7037
Constant		0.0042	0.0449	0.09	0.9260	-0.0867	0.0951
Cru Oil	Source	SS	df	MS	Number of obs =		23
	Model	0.0209	1	0.0209	F(1, 38)		0.61
	Residual	0.7236	21	0.0345	Prob > F		0.4451
	Total	0.7445	22	0.0338	R-squared		0.0280
					Adj R-squared		-0.0182
					Root MSE		0.1856
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.2784	0.3577	0.78	0.4450	-0.4655	1.0223
Constant		-0.0537	0.0626	-0.86	0.4010	-0.1839	0.0766
BrCrOil	Source	SS	df	MS	Number of obs =		11
	Model	0.1153	1	0.1153	F(1, 38)		2.80
	Residual	0.3708	9	0.0412	Prob > F		0.1287
	Total	0.4861	10	0.0486	R-squared		0.2371
					Adj R-squared		0.1524
					Root MSE		0.2030
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.7872	0.4706	1.67	0.1290	-0.2774	1.8519
Constant		-0.0745	0.0924	-0.81	0.4410	-0.2836	0.1346
Gas Oil	Source	SS	df	MS	Number of obs =		11
	Model	0.0491	1	0.0491	F(1, 38)		2.35
	Residual	0.1883	9	0.0209	Prob > F		0.1600
	Total	0.2374	10	0.0237	R-squared		0.2068
					Adj R-squared		0.1186
					Root MSE		0.1447
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.5137	0.3354	1.53	0.1600	-0.2450	1.2723
Constant		-0.0942	0.0659	-1.43	0.1870	-0.2432	0.0548
Nat Gas	Source	SS	df	MS	Number of obs =		16
	Model	0.0175	1	0.0175	F(1, 38)		2.09
	Residual	0.1176	14	0.0084	Prob > F		0.1704
	Total	0.1351	15	0.0090	R-squared		0.1298
					Adj R-squared		0.0677
					Root MSE		0.0917
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.2830	0.1958	1.45	0.1700	-0.1370	0.7030
Constant		-0.0293	0.0350	-0.84	0.4170	-0.1043	0.0458
RBOB	Source	SS	df	MS	Number of obs =		22
	Model	0.0143	1	0.0143	F(1, 38)		0.51
	Residual	0.5629	20	0.0281	Prob > F		0.4848
	Total	0.5772	21	0.0275	R-squared		0.0247
					Adj R-squared		-0.0241
					Root MSE		0.1678

Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.2305	0.3238	0.71	0.4850	-0.4450	0.9060
Constant		-0.0385	0.0575	-0.67	0.5110	-0.1584	0.0814
Heat Oil	Source	SS	df	MS	Number of obs =		
	Model	0.0192	1	0.0192	F(1, 38)		
	Residual	0.7171	25	0.0287	Prob > F		
	Total	0.7363	26	0.0283	R-squared		
					Adj R-squared		
					Root MSE		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.2600	0.3175	0.82	0.4210	-0.3938	0.9139
Constant		-0.0374	0.0533	-0.7	0.4890	-0.1472	0.0724
Copper	Source	SS	df	MS	Number of obs =		
	Model	0.0801	1	0.0801	F(1, 38)		
	Residual	0.4882	31	0.0157	Prob > F		
	Total	0.5684	32	0.0178	R-squared		
					Adj R-squared		
					Root MSE		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.5028	0.2229	2.26	0.0310	0.0482	0.9575
Constant		0.0586	0.0376	1.56	0.1290	-0.0180	0.1352
Corn	Source	SS	df	MS	Number of obs =		
	Model	0.0125	1	0.0125	F(1, 38)		
	Residual	0.3631	38	0.0096	Prob > F		
	Total	0.3755	39	0.0096	R-squared		
					Adj R-squared		
					Root MSE		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.1707	0.1494	1.14	0.2600	-0.1317	0.4731
Constant		0.0242	0.0258	0.94	0.3550	-0.0280	0.0764
Wheat	Source	SS	df	MS	Number of obs =		
	Model	0.0086	1	0.0086	F(1, 38)		
	Residual	0.3715	38	0.0098	Prob > F		
	Total	0.3802	39	0.0097	R-squared		
					Adj R-squared		
					Root MSE		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.1421	0.1511	0.94	0.3530	-0.1638	0.4480
Constant		0.0238	0.0261	0.91	0.3670	-0.0290	0.0766
Sugar	Source	SS	df	MS	Number of obs =		
	Model	0.0741	1	0.0741	F(1, 38)		
	Residual	0.3212	35	0.0092	Prob > F		
	Total	0.3953	36	0.0110	R-squared		
					Adj R-squared		
					Root MSE		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Volatility		0.4258	0.1499	2.84	0.0070	0.1215	0.7300
Constant		-0.0402	0.0267	-1.5	0.1410	-0.0945	0.0140

Table 11.3.9 Results from the regression on correlation between the commodity indices and the S&P 500 using dummies for extreme high and low S&P 500 volatility, daily data

GSCI	Source	SS	df	MS	Number of obs =		
	Model	32.1636	2	16.0818	F(1, 38)		
	Residual	193.5862	9842	0.0197	Prob > F		
	Total	225.7498	9844	0.0229	R-squared		
					Adj R-squared		
					Root MSE		
Correlation		Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Extr. high volatility		0.2535	0.0065	39.03	0.0000	0.2408	0.2663
Extr. low volatility		-0.0553	0.0065	-8.52	0.0000	-0.0681	-0.0426
Constant		0.0091	0.0015	6.14	0.0000	0.0062	0.0121

Cru Oil	Source	SS	df	MS	Number of obs =	5546
	Model	1.7090	2	0.8545	F(1, 38)	35.97
	Residual	131.6864	5543	0.0238	Prob > F	0.0000
	Total	133.3953	5545	0.0241	R-squared	0.0128
					Adj R-squared	0.0125
					Root MSE	0.1541
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Extr. high volatility	0.0206	0.0095	2.17	0.0300	0.0020 0.0393
	Extr. low volatility	0.0790	0.0095	8.3	0.0000	0.0603 0.0976
	Constant	-0.0353	0.0022	-16.17	0.0000	-0.0395 -0.0310
BrCrOil	Source	SS	df	MS	Number of obs =	2511
	Model	24.1479	2	12.0739	F(1, 38)	626.37
	Residual	48.3446	2508	0.0193	Prob > F	0.0000
	Total	72.4925	2510	0.0289	R-squared	0.3331
					Adj R-squared	0.3326
					Root MSE	0.1388
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Extr. high volatility	0.4515	0.0128	35.39	0.0000	0.4265 0.4765
	Extr. low volatility	0.0245	0.0128	1.92	0.0550	-0.0005 0.0495
	Constant	-0.0145	0.0029	-4.98	0.0000	-0.0203 -0.0088
Gas Oil	Source	SS	df	MS	Number of obs =	2511
	Model	11.0044	2	5.5022	F(1, 38)	592.32
	Residual	23.2975	2508	0.0093	Prob > F	0.0000
	Total	34.3019	2510	0.0137	R-squared	0.3208
					Adj R-squared	0.3203
					Root MSE	0.0964
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Extr. high volatility	0.3026	0.0089	34.17	0.0000	0.2852 0.3200
	Extr. low volatility	-0.0205	0.0089	-2.32	0.0200	-0.0379 -0.0032
	Constant	-0.0592	0.0020	-29.19	0.0000	-0.0631 -0.0552
Nat Gas	Source	SS	df	MS	Number of obs =	3774
	Model	1.7946	2	0.8973	F(1, 38)	153.36
	Residual	22.0637	3771	0.0059	Prob > F	0.0000
	Total	23.8583	3773	0.0063	R-squared	0.0752
					Adj R-squared	0.0747
					Root MSE	0.0765
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Extr. high volatility	-0.0993	0.0057	-17.32	0.0000	-0.1105 -0.0880
	Extr. low volatility	-0.0199	0.0057	-3.47	0.0010	-0.0311 -0.0087
	Constant	0.0099	0.0013	7.51	0.0000	0.0073 0.0124
RBOB	Source	SS	df	MS	Number of obs =	5293
	Model	24.3506	2	12.1753	F(1, 38)	701.18
	Residual	91.8563	5290	0.0174	Prob > F	0.0000
	Total	116.2070	5292	0.0220	R-squared	0.2095
					Adj R-squared	0.2092
					Root MSE	0.1318
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Extr. high volatility	0.2918	0.0083	35.03	0.0000	0.2755 0.3082
	Extr. low volatility	0.1253	0.0083	15.07	0.0000	0.1090 0.1416
	Constant	-0.0373	0.0019	-19.54	0.0000	-0.0411 -0.0336
Heat Oil	Source	SS	df	MS	Number of obs =	6556
	Model	11.6893	2	5.8446	F(1, 38)	307.89
	Residual	124.3934	6553	0.0190	Prob > F	0.0000
	Total	136.0827	6555	0.0208	R-squared	0.0859
					Adj R-squared	0.0856
					Root MSE	0.1378
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]
	Extr. high volatility	-0.1597	0.0078	-20.4	0.0000	-0.1750 -0.1443
	Extr. low volatility	0.1021	0.0078	13.04	0.0000	0.0867 0.1174
	Constant	-0.0183	0.0018	-10.21	0.0000	-0.0218 -0.0148

Copper	Source	SS	df	MS	Number of obs = 8072		
	Model	7.8621	2	3.9311	F(1, 38) 274.39		
	Residual	115.5991	8069	0.0143	Prob > F 0.0000		
	Total	123.4612	8071	0.0153	R-squared 0.0637		
					Adj R-squared 0.0634		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Extr. high volatility	0.1260	0.0061	20.57	0.0000	0.1140	0.1380
	Extr. low volatility	-0.0619	0.0061	-10.1	0.0000	-0.0739	-0.0499
	Constant	0.1200	0.0014	85.46	0.0000	0.1173	0.1228
Corn	Source	SS	df	MS	Number of obs = 9845		
	Model	3.4500	2	1.7250	F(1, 38) 199.42		
	Residual	85.1347	9842	0.0087	Prob > F 0.0000		
	Total	88.5847	9844	0.0090	R-squared 0.0389		
					Adj R-squared 0.0388		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Extr. high volatility	0.0848	0.0043	19.69	0.0000	0.0764	0.0933
	Extr. low volatility	0.0187	0.0043	4.34	0.0000	0.0103	0.0272
	Constant	0.0368	0.0010	37.29	0.0000	0.0349	0.0388
Wheat	Source	SS	df	MS	Number of obs = 9845		
	Model	1.6374	2	0.8187	F(1, 38) 89.40		
	Residual	90.1307	9842	0.0092	Prob > F 0.0000		
	Total	91.7681	9844	0.0093	R-squared 0.0178		
					Adj R-squared 0.0176		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Extr. high volatility	0.0583	0.0044	13.16	0.0000	0.0496	0.0670
	Extr. low volatility	0.0136	0.0044	3.06	0.0020	0.0049	0.0222
	Constant	0.0358	0.0010	35.24	0.0000	0.0338	0.0378
Sugar	Source	SS	df	MS	Number of obs = 9084		
	Model	4.3388	2	2.1694	F(1, 38) 228.31		
	Residual	86.2879	9081	0.0095	Prob > F 0.0000		
	Total	90.6267	9083	0.0100	R-squared 0.0479		
					Adj R-squared 0.0477		
	Correlation	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
	Extr. high volatility	0.0994	0.0047	21.16	0.0000	0.0902	0.1087
	Extr. low volatility	-0.0088	0.0047	-1.87	0.0610	-0.0180	0.0004
	Constant	0.0138	0.0011	12.83	0.0000	0.0117	0.0159