Portfolio Optimization with Commodities
- Sub-Sector and Business Cycle Analysis

Kristina Filiptchuk
20678@student.hhs.se

Henrik Lindholm
20861@student.hhs.se

Abstract

Commodities have traditionally been viewed as good diversifiers in a portfolio of stocks and bonds. However, recent literature has challenged the alleged benefits of commodities and created a need for further research in this field. We update previous research on the role of commodities in a portfolio by studying the DJ-UBSCI and the GSCI during the period of 1991 to 2011, concluding that commodities still demonstrate equity-like returns. However, we find that commodity correlations with stocks and bonds have increased in recent years, indicating diminishing effects of diversification benefits. Additionally, we study the optimal portfolio allocation with commodities and suggest two different strategies to test strategic and tactical allocation. We reject the business cycle strategy and find that business cycle phases are a poor indicator for tactical allocation to commodities. However, we conclude that strategic allocation to commodities can be improved by using sub-sectors instead of a total commodity index. The optimal portfolio over the entire period using the sub-sector strategy consists of bonds, precious metals, stocks, industrial metals and energy in a descending order.

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1 INTRODUCTION

1.1 Purpose

Although investing in commodities has been around for hundreds of years, they have traditionally been seen as risky instruments for hedging or speculation rather than as an asset class for strategic allocation.[1] In recent years however, investors' interest in commodities has increased significantly. In fact, between 2003 and 2008, assets allocated to commodity indices have risen from $13 billion to $260 billion.[2] Some ascribe this extreme interest to the rise of emerging markets as a new source of demand, others claim that recent academic findings promoting strategic portfolio allocations to commodities have created a new trend among investors. Furthermore, investors have witnessed extreme price movements, especially in energy, precious and industrial metals, which have brought the spotlight to commodities. Overall, the view among investors on the role of commodities in a portfolio appears to have changed and this asset class has now become highly relevant. Therefore, it is necessary for an investor to know the benefits of commodities in a portfolio and how to manage such investments.

This thesis was inspired by an ongoing debate within previous research in the field. In 2006, Gorton and Rouwenhorst published a comprehensive study on commodity properties, showing promising investment characteristics of commodity futures. They found that between 1959 and 2004, commodities outperformed stocks both in terms of higher returns and lower volatility. Commodities were also shown to have negative correlation with stocks and bonds and positive correlation with inflation. The overall implication of these findings was that adding commodities to a traditional portfolio of stocks and bonds can greatly improve the risk return characteristics of that portfolio. Since then, the debate regarding properties of commodities has developed among researchers with some authors questioning the alleged benefits. This has inspired us to re-examine and update literature with more recent data and expand the research on commodity allocation with potential improvements in strategic and tactical allocation.

In this thesis we look at commodities from a portfolio optimization perspective. First, we evaluate a strategic allocation strategy to commodities based on dividing the total asset class into the following sub-sectors: energy, precious metals, industrial metals, agriculture, livestock and softs.[3] The reason for this strategy is that previous research has found individual commodities and commodity sub-sectors to be heterogeneous. Furthermore, commodity sub-sectors also tend to show low correlations among them. Given these properties we expect to find an improved optimal portfolio when applying a sub-sector strategy.

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[1] See Till, H. (2006)
[2] See Masters, M. W. (2008)
[3] See Appendix III for full composition of the sub-sectors

Second, we also examine a tactical allocation strategy to commodities based on business cycle phases: early/late expansion and early/late contraction. The reasoning behind is that tactical allocation benefits with commodities have been found in previous research using other macro factors, such as monetary policy. Moreover, commodities tend to perform differently over the business cycle phases which suggests that re-allocation in the beginning of each new business cycle phase can lead to an improved optimal portfolio.

Using portfolio optimization we wish to find the optimal portfolio weights for the two suggested strategies and evaluate their impact on portfolio performance.

1.2 Outline

We begin our thesis by discussing properties and benefits of investing in commodities, the portfolio optimization process and the potential outcomes of the two suggested commodity strategies in detail. In Section 3 we describe our method for portfolio optimization and performance evaluation along with choices of proxies. In Section 4, we analyze the underlying dataset in detail to update the alleged commodity benefits in previous research and to test the feasibility of the two suggested strategies, followed by a portfolio optimization analysis. In Section 5 and 6, we summarize our conclusions and contribution and make suggestions for further research.

2 RESEARCH DISCUSSION

2.1 Investing in Commodities

There are several methods for investing in commodities and the range of possibilities depends on the physical properties of the commodity itself as well as its supply and demand in the market. We discuss three main ways of gaining exposure to commodities: through direct investment in the physical commodity, investment in commodity related companies or investment in commodity derivatives and structured products.

2.1.1 Physical Commodities

It can be difficult for most investors to gain physical exposure to commodities. Demidova-Menzel and Heidorn (2007) explain that depending on the feasibility of commodity storing, physical investments are usually more applicable to metals and agricultural products, as opposed to for example coal and uranium, which cannot be easily stored. According to Pulvermacher (2005a), taking the physical delivery of a commodity is highly associated with greater transaction costs along with costs for insurance and storage, which makes such direct investment less efficient.

2.1.2 Commodity Related Companies

A common alternative to physical ownership is investing in stocks of commodity-related projects such as power plants, refineries or oil & gas exploration companies. According to Gorton and Rouwenhorst (2006), however, investments in companies that specialize in particular commodity sectors generally have only modest correlations with the actual commodity sector, which indicates that this method provides less than full exposure to commodity prices. Demidova-Menzel and Heidorn (2007) explain this low correlation by saying that the cash flows of commodity related companies are, on top of the commodity price risk itself, also sensitive to other types of risk, such as the overall state of the economy and managerial decisions. This argument is strongly supported by Kazemi et al (2009) who find higher correlation between commodity-related companies and equity markets than between commodity-related companies and commodity markets.

2.1.3 Commodity Futures

Commodity futures are the most common financial instruments in commodity markets. They are highly liquid exchange-traded standardized contracts that oblige the investor to buy or sell a set amount of a commodity at a predetermined price and date. The buyers commonly use these contracts to hedge against price fluctuations of a product or raw material, while sellers make sure to lock in prices for their products.

As in all financial markets, there is also a large market for speculators, who use these contracts to bet on price movements rather than taking physical delivery at the expiry date of the contract. [4]

Gorton and Rouwenhorst (2006) evaluate the performance of commodity futures and show that during the period of 1959 and 2004 an equally-weighted total return index of commodity futures has outperformed an equally-weighted portfolio of spot commodities - both adjusted for inflation - showing that commodity futures markets during that period were offering higher return than spot markets.

2.1.4 Commodity Indices

One convenient way of getting exposure to commodity futures is to invest in commodity indices, which are designed to track a basket of commodity futures contracts. According to Demidova-Menzel and Heidorn (2007) this investments strategy has two main advantages: first, the investor has the advantage of not taking the physical delivery as the indices are rolled on a regular basis, and second, by investing in an index the investor automatically gains the benefits of investing in a diversified basket of commodity futures.

Commodity indices are passive and long-only investments, which means that they are not actively managed and only track the long side of the market. [5] Standard & Poor's Goldman Sachs Commodity Index (GSCI), Dow Jones-UBS Commodity Index (DJ-UBS) and Thomson Reuters/Jefferies Commodity Research Bureau Index are the most commonly used commodity futures indices in the market. According to Erb and Harvey (2006) and Conover et al (2010), GSCI represented 86% of the combined total investment of these three indices in 2004 and was by large the dominant commodity index. It is therefore generally accepted by previous researchers as a benchmark to evaluate the investment benefits of commodity futures.

Each commodity index has its unique characteristics in terms of components, weightings, rolling methodology and rebalancing features. GSCI is a global production-weighted index and therefore dominated by energy products with over 66.5% of the index assigned to the energy sector as of December 2010.[6] DJ-USB, on the other hand, is designed to minimize concentration in one particular sector and can therefore be used as a complementary benchmark.[7]

2.2 Benefits of Investing in Commodities

Why should then an investor add commodities to a traditional portfolio of stocks and bonds? The first research that suggests portfolio allocation to commodities was published by Greer (1978) who showed

[4] See Hull, J. C. (2009)
[5] See Demidova-Menzel, N. and Heidorn T. (2007)
[6] See S&P GSCI Commodity Indices Factsheet, 2010
[7] See http://www.djindexes.com/commodity/

that between 1960 and 1974, a portfolio of equities with a moderate use of collateralized commodity futures could earn higher and less volatile returns than a portfolio consisting of only equities.[8] His paper has contributed to a growing interest in commodity futures by both researchers and market participants. Since then, many researchers have explored the main beneficial properties of commodities, such as equity-like performance, diversification benefits and inflation hedging, which make commodities valuable additions to a traditional portfolio of stocks and bonds.

2.2.1 Equity-like Performance

Several researchers have evaluated commodities as a standalone investment. Greer (2000) describes the return characteristics of commodity futures as similar to equities. Bodie and Rosansky (1980) and Gorton and Rouwenhorst (2006) also find commodity futures returns to be equity-like by constructing equally-weighted portfolios of futures for the periods of 1950 to 1976 and 1959 to 2004 respectively. Demidova-Menzel and Heidorn (2007) perform a similar study, but use sub-sample analysis to conclude that the equity-like returns are only evident in selected time periods. Erb and Harvey (2006) question the alleged performance of commodities and find that it is highly dependent on the composition of the commodity index analyzed.

2.2.2 Attractive Correlation with Stocks and Bonds

A common reason for adding commodities to a portfolio is due to the diversification benefits, which arise from their negative and low correlations with stocks and bonds. Several studies have found improved risk-adjusted return when adding commodities to an otherwise diversified portfolio, examples include Satyanarayan and Varangis (1994) between 1984 and 1992, Greer (1994) between 1970 and 1993, and Jensen et al (2000, 2002) for the period of 1973 to 1997 and 1970 to 1999 respectively. The longest spanning study is Gorton and Rouwenhorst (2006) which covers the years 1959 to 2004 and finds strong diversification benefits of commodity futures, especially when looking at long term correlations with equities and bonds, which are found to be negative. Recently, Conover et al (2010) found substantial benefits from adding commodity futures to several equity-only portfolio strategies.

Some researchers, however, challenge the diversification benefits of commodities. Garret and Taylor (2001), Demidova-Menzel and Heidorn (2007) and Cheung and Miu (2010) find that the optimal portfolio allocation to commodity futures strongly depends on the time period of the sample and that the alleged benefits mostly come from short and isolated periods of extraordinarily strong performance. Moreover, Daskalaki and Skiadopoulos (2011) find that the diversification benefits from previous research do not hold in an out-of-sample setting. To address these concerns, we will both look at correlations of

[8] A collateralized position in futures is a portfolio in which an investor takes a long position in futures for a given amount of underlying value and simultaneously invests the same amount in government securities, such as Treasury bills." - See Solnik, B. and McLeavey, D. (2009)

commodities with stocks and bonds over the entire studied time period as well as performing a sub-sample analysis to examine the consistency of the diversification benefits throughout the sample.

Furthermore, Cheung and Miu (2010) specifically refute that commodity correlation with stocks and bonds is negative during bear markets. Erb and Harvey (2006) point out that previous research in support of commodity diversification benefits is highly dependent on the composition of the analyzed commodity index. They also criticize the use of historical prices as a proxy for future returns, which they consider to be an especially far-reaching assumption in the case of commodities. To summarize, the opinion of previous research is mixed, which welcomes an additional study of commodity correlations with traditional asset classes over time.

2.2.3 Inflation Hedging Properties

Several papers document the inflation hedging properties of commodity futures, for example Bodie and Rosansky (1980), Becker and Finnerty (2000), Erb and Harvey (2006) and Kazemi et al. (2009). Furthermore, Greer (2005) and Gorton and Rouwenhorst (2006) find that commodities are an especially good hedge against unexpected inflation and changes in expected inflation. According to Demidova-Menzel and Heidorn (2007), the explanation for this is that commodities are real assets that rise in price parallel to inflation and therefore can act as an inflation hedge. This unique attribute of commodity returns plays a special role in a traditional portfolio, since stocks and bonds generally perform poorly in times of high inflation. Cheung and Miu (2010) even point out that the inflation hedging property is the most valuable characteristics of commodities in a portfolio.

2.3 Portfolio Optimization

Prior to Markowitz (1952), the common way of analyzing an investment was to focus on its expected return. Markowitz, however, provided a comprehensive theoretical framework for analysis of an investment portfolio that later gave rise to the modern portfolio theory.

One core concept of modern portfolio theory is to evaluate an investment alternative in a two-dimensional risk-reward space as opposed to only looking at the expected return. Usually, riskier assets offer higher return to compensate for the higher probability that the expected return may not be reached.

Another important concept of modern portfolio theory is to evaluate an investment alternative as a complement to other assets in the portfolio. As returns of various investments usually do not have perfect positive correlation, an investor can through diversification reduce the total risk of his portfolio by including an additional asset with dissimilar correlations. Previous research has demonstrated the correlations of commodities with stocks and bonds to be low or negative, which has motivated us to focus on portfolio optimization with commodities. In this thesis we therefore choose to add commodities to a traditional portfolio of stocks and bonds to evaluate their impact on the risk-adjusted performance of a portfolio.

By setting different weight on stocks, bonds and commodities, an investor can form an infinite number of different portfolios. However, only one unique set of weights gives a portfolio with the best risk-adjusted return. This specific combination of assets is called the optimal risky portfolio and has the highest Sharpe ratio.[9] In this thesis we will evaluate the possible benefits of the strategic and tactical commodity allocation strategies using portfolio optimization and establish the unique weights for each asset in the two optimal risky portfolios.[10]

2.4 Sub-Sectors

Overall, previous research seems to be positive to the inclusion of commodities in a traditional portfolio. Gorton and Rouwenhorst (2006) and Erb and Harvey (2006) make an interesting point by evaluating the properties of individual commodities as opposed to looking at the total asset class. This has inspired us to divide commodities into six sub-sectors and apply this approach on the portfolio optimization problem.

The sub-sectors are selected according to industry standards and are the following: energy, precious metals, industrial metals, agriculturals, livestock and softs. The economic intuition behind this type of analysis is the apparent differences between the sub-sectors. First of all, the physical characteristics of various commodities vary sharply. Metals, for example, can be stored conveniently, whereas livestock has a finite lifespan and cannot be stored in the same manner as metals. Furthermore, prices of agricultural commodities are sensitive to the pattern of harvests, while the demand for energy commodities is at its highest before the winter seasons. Overall, these fundamental differences among commodities suggest that there is much merit to a sub-sector strategy for an investor looking to find an optimal portfolio with commodities.

Sector variations have appeared in previous research and many researchers point towards commodity sub-sectors being heterogeneous within the total asset class. Erb and Harvey (2006) and Gorton and Rouwenhorst (2006) consider both individual commodities and commodity sub-sectors to be heterogeneous. Jensen et al (2002) conduct part of their study of commodity futures on a sub-sector basis and point out that there are significant differences and low correlations internally. Daskalaki and Skiadpoulus (2011) agree and find it hard to accept that a total commodity index can represent an "average" commodity. Vrugt (2004) also points out the drawbacks of analyzing commodities using

[9] Sharpe ratio is a common measure for performance evaluation and can be calculated as the expected excess return to the undertaken risk. – See Bodie, Z., Kane, A. and Marcus, A.J. (2009)
[10] See Appendix I and II for statistical basics and portfolio optimization problem

production-weighted indices that are heavily invested in energy and mentions the need for sub-sector analysis.

All this indicates a great potential for diversification benefits when using commodity sub-sectors in portfolio optimization instead of a total commodity index and supports our suggested strategic allocation strategy.

2.5 Business Cycles

Business cycles are a commonly accepted phenomenon that describes fluctuations in the economy where expansions denote periods of growth and contractions are characterized by declining economic activity. Previous research on commodities uses the business cycles defined by the National Bureau of Economic Research (NBER) to explore their impact on commodity returns.[11] Vrugt (2003, 2004) analyses several macro factors that influence commodity futures returns, such as monetary policy, inflation and business cycles. Gorton and Rouwenhorst (2006) find significant differences in commodity futures returns over the business cycle phases, suggesting potential benefits with tactical allocation to commodities. They also point out the need for further research in this area. In this thesis, we wish to extend previous research by examining a tactical allocation strategy based on the NBER business cycle phases, which are early/late expansion and early/late contraction.

The economic intuition behind tactical allocation to commodities based on business cycles phases lies in the cyclical variation of fundamentals that drive commodity supply and demand. For example, the notion of precious metals being defensive "safe-haven" investments during economic contractions drives the prices upwards due to increased demand in the market. When economic conditions improve, some investors are likely to decrease their exposure to precious metals affecting the demand negatively and thus lowering the prices. The same argument applied on industrial metals gives an opposite supply and demand pattern – increasing prices in expansions and decreasing in contractions. By dividing commodity returns into business cycle phases, we expect to observe considerable differences in optimal allocations in each phase and thus find an efficient tactical allocation strategy.

Traditionally, market timing and tactical allocation in general have been disputed academically and Vrugt (2004) explains that academic evidence of predictability in markets seldom appears in practice. Regarding commodities specifically, some researchers have studied timing using other macro factors than business cycles. Jensen et al (2000, 2002) show that in periods of restrictive and expansive monetary policy, investors should overweight and underweight their commodity futures holdings respectively. Conover et

[11] NBER specifies dates for economic peaks and troughs based on the fluctuations of the US economy. The period between a trough and a peak is an economic expansion, and the period between a peak and a trough is an economic contraction. We further divide the contractions and expansions in halves, to create early and late contractions and expansions respectively. See Appendix IV for NBER business cycle dates.

al (2010) also find tactical allocation benefits to commodities by adding commodity futures to a portfolio in periods of restrictive monetary policy.

A potential drawback of using the NBER business cycles could be the fact that they are based on the fluctuations of the US economy, which does not represent the global demand for commodities. Worth noting however, is that both Jensen et al (2000, 2002) and Conover et al (2010) base their tactical allocation strategies on US-only indicators (Fed monetary policy) and manage to find significant results. Finally, we also acknowledge that changing allocations over the business cycle phases naturally implies higher transaction costs than a buy-and-hold strategy. However, since business cycle phases change rather seldom with an average phase time of 28 months, we consider the implied transaction costs to be relatively small and negligible.

Overall, previous research seems to have demonstrated the benefits of tactical allocation to commodities based on macro factors and we wish to perform a similar analysis for business cycle phases.

2.6 Summary of Research Discussion

Based on previous research highlighting the benefits of commodities as an asset class, we choose to perform portfolio optimization with commodities. We use two different allocation strategies to add commodities to a traditional portfolio of stocks and bonds. First, we divide commodities in sub-sectors due to their fundamental differences, inspired by previous researchers who emphasize the diversification benefits of a sub-sector strategy. Second, we perform a portfolio optimization with commodities in different phases of a business cycle, as a result of previous research suggesting variation in commodity performance during a business cycle.

The research question of this thesis is threefold:

1. We update previous research by including more recent data, to test the persistency of the alleged commodity benefits in the literature.
2. We perform a detailed analysis of the data to ensure the validity of the results in both strategic and tactical allocation strategies.
3. We find the optimal risky portfolios in each strategy to establish the optimal weights in each asset class and measure the risk-adjusted performance of the portfolio using the Sharpe ratio.

3 METHOD AND DATA

3.1 Portfolio Optimization

We start by calculating the necessary statistical parameters of the studied portfolio assets. Based on discrete monthly returns, we find the expected returns, standard deviations, correlations and covariances between all individual assets and use these parameters to find the optimal risky portfolios. We include two conditions that limit the optimization problem: one that ensures that the weights of all assets in a portfolio sum up to one and another that only allows long positions in the assets. The optimizations are performed for the two suggested strategies. The first strategy divides commodities into sub-sectors expecting to find an improved strategic allocation to commodities. The second strategy examines commodity performance over the different phases of the business cycle, looking to find an optimal tactical allocation to commodities.

3.1.1 Sub-Sector Strategy

In the sub-sector optimization strategy we look at three different portfolios. We start with a traditional portfolio only consisting of stocks and bonds. By adding a total commodity index we test the benefits of commodities added as a group. Then, we replace the total commodity index with its underlying sub-sectors to test the benefits of a strategic investment in commodities according to the sub-sector strategy. These three portfolio scenarios are compared in two ways. First, we solve an optimization problem to find portfolios with the highest Sharpe ratio for each scenario. The compositions of these portfolios reveal historically optimal weights for each scenario and can serve as a guideline for long-term investments in commodities. Second, we evaluate the three scenarios by performing another optimization of the Sharpe ratio, while holding the amount of risk fixed. We choose to set the standard deviation of all three portfolios to that of the optimal stock and bond portfolio and compare the highest expected returns of the three portfolios achievable for a certain risk. This method allows for a more direct comparison of the three optimal portfolios and enables an evaluation of this commodity strategy.

3.1.2 Business Cycle Strategy

We use only three assets to test the business cycle strategy: stocks, bonds and a total commodity index. The reason for using a total commodity index is to isolate the results from the possible advantages of the sub-sector strategy described above. We divide the return data depending on business cycle phase and calculate the optimal portfolios for the specific phases. This way we find four optimal portfolios based on entirely separate sets of data. These portfolios provide unique sets of optimal weights for each specific phase of the business cycle, suggesting benefits from a re-allocation within the portfolio at the beginning of a new phase. To test the benefit of this tactical allocation strategy, we compare the performance of the four optimal portfolios with the performance of the optimal portfolio of the entire period.

3.2 Choice of Proxies

3.2.1 Commodity Benchmark

Previous research demonstrates a large spread in choices of commodity benchmarks. Originally Greer (1978) creates his own equally-weighted index, a method also used by Bodie and Rosansky (1980) and Gorton and Rouwenhorst (2006). Satyanarayan and Varangis (1994), Jensen et al (2000, 2002), Erb and Harvey (2006) and Conover et al (2010) use instead the GSCI and the DJ-UBS.

Both the GSCI and the DJ-UBS were launched in 1991 and 1998 respectively and are back-tested to 1970 and 1991 respectively. Demidova-Menzel and Heidorn (2007) point out the drawbacks of back-traced benchmarks by claiming that these indices may have been created to purposefully outperform their alternatives. Vrugt (2004) avoids this potential pitfall by refraining from using the back-tested values.

In this thesis we use the GSCI and the DJ-UBS as benchmarks for commodity markets for two reasons. First, these two indices are the most prominent proxies for commodities in previous research. Second, our own equally-weighted index would not be possible to invest in, making the thesis less applicable. We focus on the GSCI in our business cycle study since it has much longer historical data and on the DJ-UBS in the sub-sector analysis because of the advantage of its sub-sectors starting simultaneously. As proxies for each of the six sub-sectors: energy, precious, industrial, agriculture, livestock and softs, we use both the GSCI and the DJ-UBS subordinated sector indices.

3.2.2 Stock Benchmark

Many previous researchers have used local indices as stock benchmarks in portfolio optimization. Cheng and Miu (2010) find, however, that there exists a higher correlation between commodities and stocks in resource-based economies such as Canada, than between commodities and stocks in non-resource-based countries such as US and Japan. Choosing a local stock benchmark can thus distort the results of commodity performance in a portfolio depending on the local type of economy in a country. Although the S&P 500 is used by most other researchers as a benchmark for stocks in commodity studies, we believe that since commodities are global assets, the choice of a stock benchmark should also be as global as possible.

One generally accepted benchmark for global stock market is the Morgan Stanley Capital International World Index (MSCI World) which is a capitalization-weighted total return index that includes small-, medium- and large-capitalization companies in 24 developed countries.[12] A drawback of this index is, however, that it excludes the emerging markets. One way to include the emerging markets is to use the Morgan Stanley Capital International All Country World Index (MSCI ACWI), which as of March 2011

[12] See http://www.mscibarra.com/products/indices/

held stocks in 24 developed countries and 21 emerging markets.[13] The MSCI ACWI should therefore give a more accurate picture of the correlation between commodities and a global stock market. However, the data for MSCI ACWI only goes back to 1988 compared to MSCI World that starts in 1970. The MSCI World Index has been used in previous research by Satyanarayan and Varangis (1994), whereas the MSCI ACWI, as far as we know, has not yet been used as a global stock benchmark in commodity research.

In this thesis we use the MSCI ACWI in the sub-sector strategy due to the global composition of the index and the MSCI World in the business cycle strategy to take advantage of its longer historical data.

3.2.3 Bond Benchmark

In order to apply a global approach in the selection of bond benchmark, we use the JP Morgan Global Government Bond Index (JPM GGBI), which is a global market capitalization weighted total return bond index consisting of government investment-grade bonds from 13 leading developed markets.[14] The drawbacks of the JPM GGBI are however the relatively short historical data stretching back to 1986 and the fact that it excludes emerging markets. The latter is however understandable, considering that emerging markets are for the most part not considered to be investment-grade. The JPM GGBI is mentioned as a popular bond benchmark by Demidova-Menzel and Heidorn (2007).

Another widely used benchmark for bonds is the Barclays Capital US Government Bond Index (BarCap USGBI), which until 2008 was the Lehman Government Bond Index and is a market capitalization weighted total return index that represents US investment-grade bonds. Launched in 1986 and back-tested to 1973, it has since become a commonly used bond market benchmark both in academia among practitioners.[15] Demidova-Menzel and Heidorn (2007) use the BarCap USGBI in their study, while Erb and Harvey (2006) use the BarCap US Aggregate Bond Index (BarCap Agg), which is an equivalent bond index that in addition includes non-government bonds, but only stretches back to 1976.

For this thesis we therefore prefer the BarCap USGBI over the BarCap Agg for its longer data to test our business cycle strategy, but use the global JPM GGBI in the sub-sector strategy.

3.3 Data

All data used in this study is collected from Thomson Reuters Datastream. We use monthly prices of the total return indices suggested above to estimate the performance of stock, bond and commodity markets. Monthly prices are converted to discrete monthly returns and annualized to be used in portfolio optimization.

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[13] See http://www.mscibarra.com/products/indices/
[14] See http://www.jpmorgan.com/
[15] See http://ecommerce.barcap.com/indices/index.dxml

4 EMPIRICAL FINDINGS

This thesis aims at testing the benefits of adding commodities to a traditional portfolio of stocks and bonds. We propose two different strategies of using commodities in portfolio optimization. Previous research shows modest support for the business cycle approach, but is overall more positive to the sub-sector strategy. Prior to performing the portfolio optimization looking to find optimal allocation to individual assets in each strategy, we test the data to evaluate whether the suggested approaches are feasible.

In the following section we analyze our dataset and compare our findings to the literature. First, we update previous research by testing the persistency of the alleged commodity benefits. Second, we test whether the results from both strategic and tactical allocation strategies are valid and can be used for future application. Finally, we find the optimal weights in each asset class for the two suggested commodity allocation strategies.

4.1 Commodity Properties

First of all we look at the returns of commodities as a total asset class and compare them with stocks and bonds.

Figure 1: Indexed Historical Prices of Stocks, Bonds and Commodities (Jan 1991 - Apr 2011)

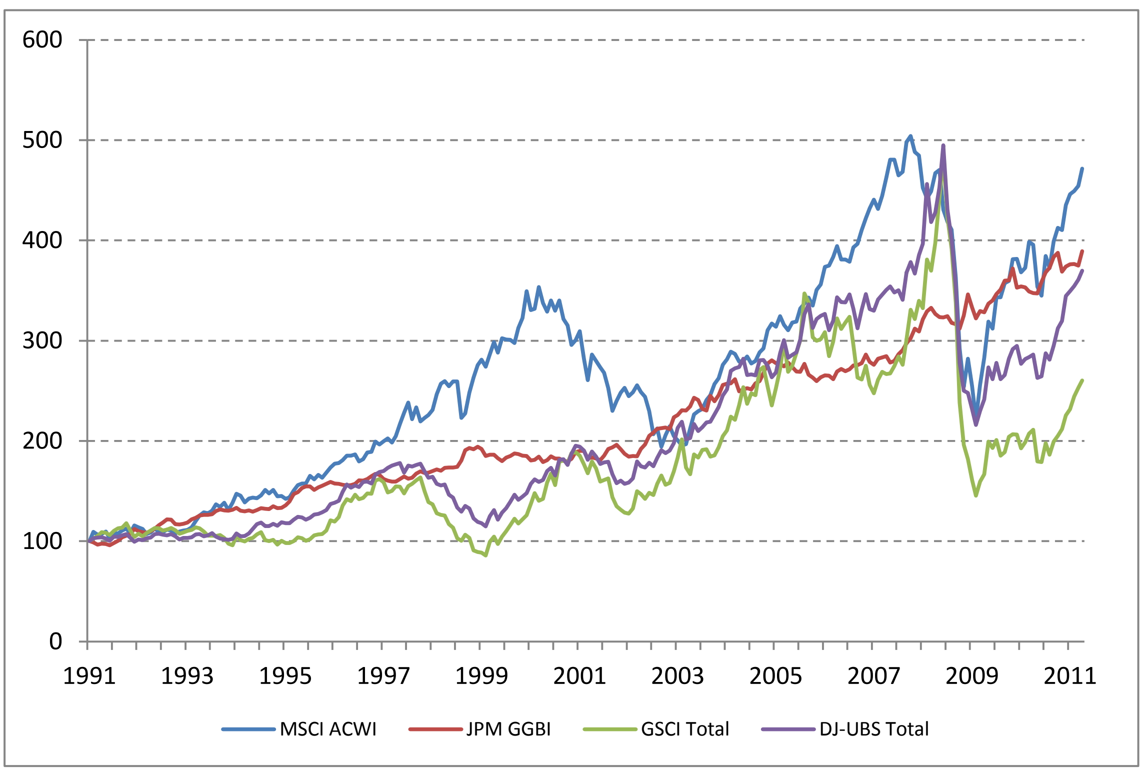


Figure 1 shows the difference in indexed prices between stocks, bonds and the two total commodity indices. The stock index has performed the best during the studied time period, however with high volatility. The bond index has a slightly lower overall return, but remains more stable over time. The two commodity indices have performed similarly for most of the time period, except for the last two years where the DJ-UBS has outperformed the GSCI. The deviation between the two indices can be explained by the different index compositions with the GSCI being much more heavily invested in the energy sector.

There is also evidence of low correlation between the three asset classes, albeit on and off over the time period. Throughout the entire time period, the price movements of stocks and commodities alternated between strong negative and positive correlation, compare, for example, the end of the 90's and the recent financial crisis. Bonds on the other hand, appear to have low correlation with both other assets throughout the entire period.

Table 1: Descriptive Statistics for Stocks, Bonds and Commodities (Jan 1991 - Apr 2011)

	MSCI ACWI	**JPM GGBI**	**GSCI Total**	**DJ-UBS Total**
Avg Ret	9.01%	6.96%	7.12%	7.65%
St Dev	16.18%	6.84%	21.63%	15.25%

Correlations	**MSCI ACWI**	**JPM GGBI**	**GSCI Total**	**DJ-UBS Total**
MSCI ACWI	1	0.18	0.36	0.41
JPM GGBI	0.18	1	0.13	0.16
GSCI Total	0.36	0.13	1	0.91
DJ-UBS Total	0.41	0.16	0.91	1

Comment: *Calculations are performed on annualized monthly returns*

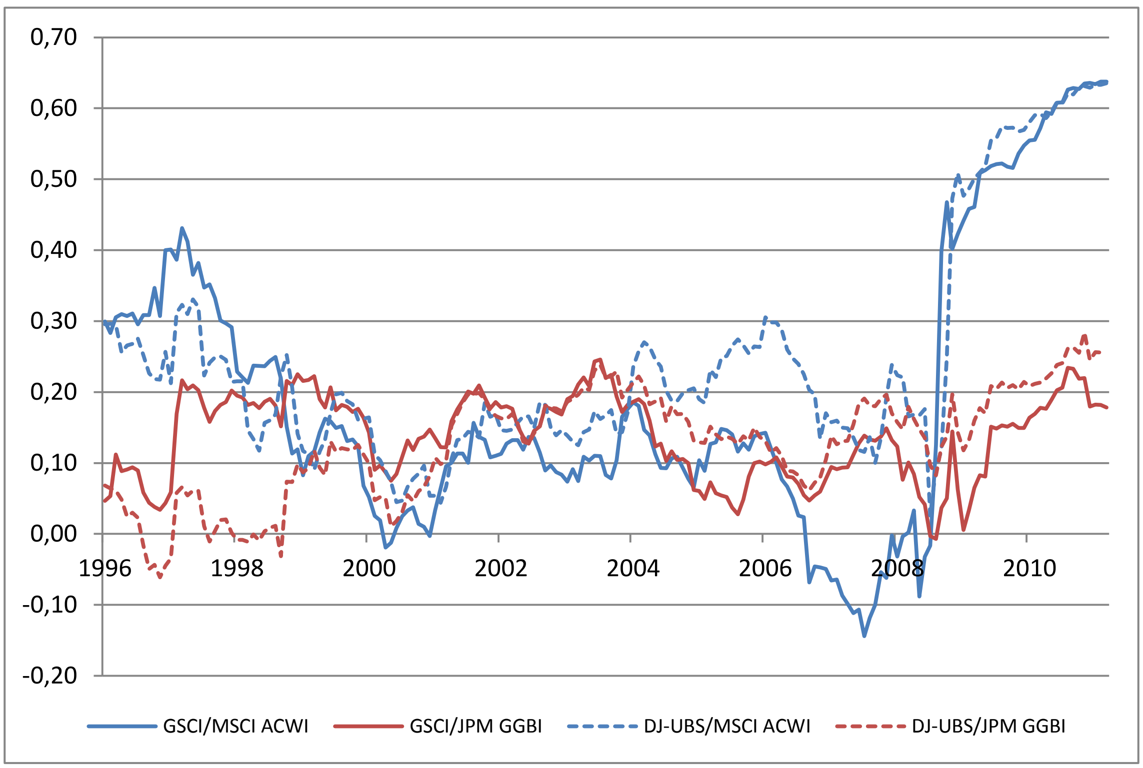
There is no previous research that uses the same stock and bond benchmarks over the same time period as our study, which makes a direct comparison of the results impossible. However, by comparing to equivalent proxies in previous research, we conclude that our expected returns and standard deviations for stocks are slightly worse than previously documented performance. Our bonds have instead demonstrated a better historical performance than similar benchmarks in previous research. Our commodity benchmarks appear frequently in previous research, however only Daskalaki and Skiadopoulos (2011) have studied the GSCI and the DJ-UBS over a comparable time period of 1991to 2009 and find similar statistics for both commodity indices.

The data in Table 1 reinforces the common view of commodities having equity-like returns, showing both high returns and standard deviations. This is in line with the findings of Gorton and Rouwenhorst (2006), Erb and Harvey (2006) and Cheung and Miu (2010). Internally between the two indices, we find that the

DJ-UBS outperforms the GSCI in the studied period, which has also been concluded by Erb and Harvey (2006) who explain the outperformance with differences in composition of the two indices.

During the studied period, both commodity indices have shown relatively low correlations with stocks and bonds, which indicates that commodities as an asset class is a good diversifier in a portfolio. However, compared to previous research our study shows higher correlations between stocks and commodities. The explanation for this difference could be derived from a surge in correlations during the past few years, pictured in Figure 2. From this we assume that the recent financial crisis has had a major impact on correlations between commodities and stocks, while keeping commodity correlations with bonds rather stable. Not enough time has passed to analyze the post-crisis effects, however investors should consider a potential regime-switch in correlation behavior, which could affect the long-term diversification benefits negatively and call into question the reliability of previous findings for future investment strategies.

Figure 2: Commodity Correlation with Stocks and Bonds over time (Jan 1996 - Apr 2011)

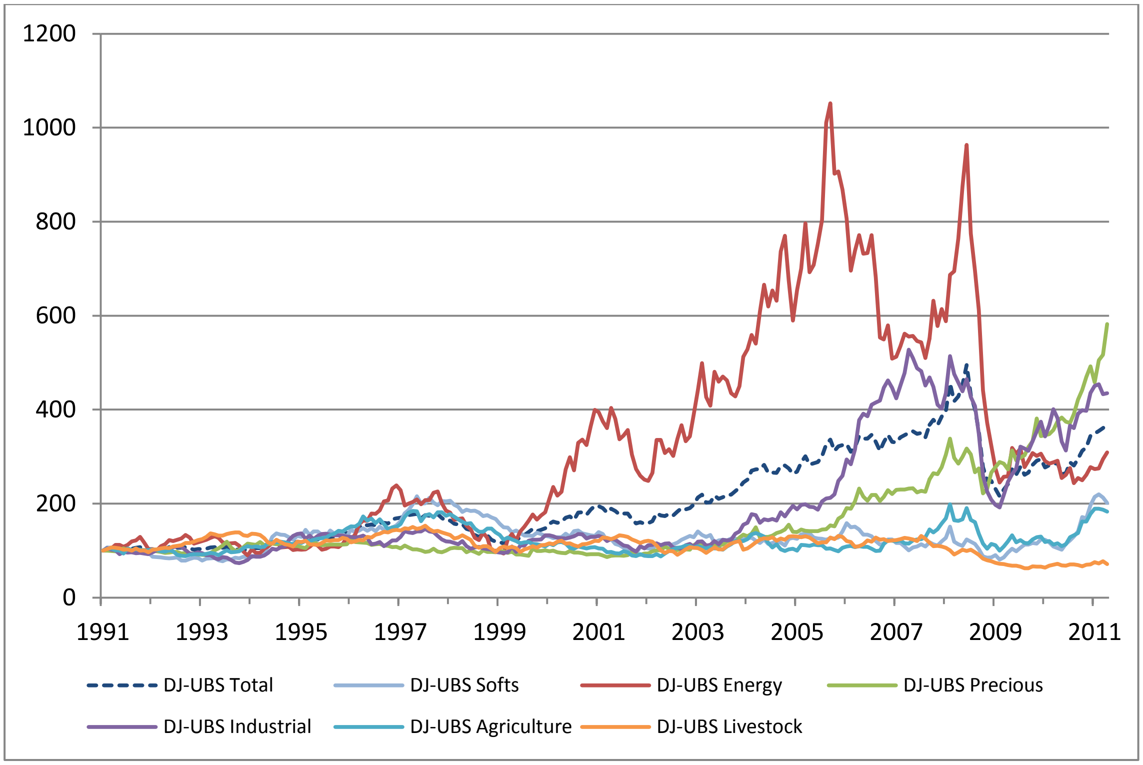


Comment: *Five years overlapping correlations*

4.2 Sub-Sector Strategy

We believe that there is much merit to dividing commodities into sub-sectors, which can also be seen in Figure 3 where we present the price development of DJ-UBS Total as well as its six sub-sectors.[16] The following study has been performed on both GSCI and DJ-UBS, including their sub-sector indices. The results were found to be similar and we therefore decide to only present the results of DJ-UBS, since its data for all sub-sectors is available from 1991, where GSCI sub-sectors start at different periods with the last sub-sector (Softs) being added in 1995.

Figure 3: Indexed Historical Prices of DJ-UBS and Sub-Sectors (Jan 1991 - Apr 2011)



Our initial intuition behind testing the sub-sector strategy is the fundamental differences between the six sub-sectors as mentioned in previous sections. Looking at the price development of the different sub-sectors, there are evidently large discrepancies in performance. Some sub-sectors stand out as very volatile, especially energy and industrials, whereas other sub-sectors, such as livestock, agriculture and softs, have much less varied price movements. Looking at the graph we find that the performance of the various sub-sectors is not necessarily captured by the total DJ-UBS index. This suggests considerable gains to a portfolio when allocation to commodities is based on the individual performance of each sub-sector, rather than on the pre-determined compositions of an already existing commodity index.

[16] See Appendix VII for indexed historical prices of GSCI and sub-sectors

Table 2: Descriptive Statistics for DJ-UBS Total and DJ-UBS Sub-Sectors (Jan 1991 - Apr 2011)

	DJ-UBS Total	Energy	Precious	Industrial	Agriculture	Livestock	Softs
Avg Ret	**7.65%**	10.33%	10.22%	9.51%	4.69%	-0.66%	5.52%
St Dev	**15.25%**	30.92%	17.34%	21.22%	18.49%	14.14%	20.52%

Comment: *Calculations are performed on annualized monthly returns*

The descriptive statistics further reinforce the substantial differences between the sub-sectors, with energy, precious and industrial metals outperforming agriculture, livestock and softs over the entire period. Also here, a direct comparison of our results to previous research is difficult, considering that our time period differs from other researchers and that some of the previous research is conducted on either individual commodities or differently constructed sub-sector. The only sub-sector study in literature that can be seen as comparable to ours in terms of time period is Erb and Harvey (2006), who analyze the same commodity sub-sectors during the period of 1982 to 2004. Our results are similar for energy and industrial metals, but substantially different for precious metals and agriculture, which suggests that the performance of the sub-sectors has varied throughout the years. Gorton and Rouwenhorst (2006) study commodities on a sub-sector basis, but use differently constructed sub-sectors over the time period of 1959 to 2004, which makes a comparison redundant.

Table 2 confirms also the perceived high volatility in Figure 3 in that all but one of the sub-sectors have higher standard deviations than our stock benchmark. The standard deviation for DJ-UBS Total is however rather low compared to the individual sub-sectors, which is most probably a sign of the internal diversification. Similar conclusions can be drawn for the results from GSCI Total and GSCI sub-sectors.[17]

Table 3: DJ-UBS Correlation with Stocks, Bonds and between Sub-Sectors (Jan 1991 - Apr 2011)

	MSCI ACWI	JPM GGBI	DJ-UBS Total	Energy	Precious	Industrial	Agriculture	Livestock	Softs
MSCI ACWI	1	0.18	0.41	0.24	0.18	0.44	0.32	0.09	0.18
JPM GGBI	0.18	1	0.16	0.12	0.26	0.07	0.10	-0.10	0.01
DJ-UBS Total	0.41	0.16	1	0.83	0.41	0.62	0.61	0.20	0.40
Energy	0.24	0.12	0.83	1	0.16	0.30	0.17	0.11	0.11
Precious	0.18	0.26	0.41	0.16	1	0.30	0.26	-0.03	0.21
Industrial	0.44	0.07	0.62	0.30	0.30	1	0.35	0.09	0.31
Agriculture	0.32	0.10	0.61	0.17	0.26	0.35	1	0.08	0.65
Livestock	0.09	-0.10	0.20	0.11	-0.03	0.09	0.08	1	-0.05
Softs	0.18	0.01	0.40	0.11	0.21	0.31	0.65	-0.05	1

Comment: *Correlations are calculated on monthly returns over the entire time period*

[17] See Appendix V for descriptive statistics for GSCI and sub-sectors

The correlations table shows the overall low correlations between individual sub-sectors, further justifying the sub-sector strategy.[18] However, compared to both Erb and Harvey (2006) who studied the period of 1982 to 2004 and Demidova-Menzel and Heidorn (2007) who studied the period of 2001 to 2006, our correlations are slightly higher in most cases.

In Figure 1 we showed the correlation over time for the two total commodity indices with stocks and bonds and found a significant increase for commodity correlations with stocks in recent years. This together with the discrepancy between our correlation results and previous research has inspired us to perform an additional study of correlation development over time for all six sub-sectors.

Table 4: DJ-UBS Correlation with Stocks and Bonds for 5-year Periods (Jan 1991 - Apr 2011)

Corr MSCI ACWI	**1991-1996**	**1996-2001**	**2001-2006**	**2006-2011**	**1991-2011**
DJ-UBS Total	0.29	0.07	0.29	0.64	**0.41**
Energy	0.22	0.02	0.09	0.52	**0.24**
Precious	-0.02	0.15	0.20	0.26	**0.18**
Industrial	-0.02	0.22	0.55	0.61	**0.44**
Agriculture	0.21	0.01	0.23	0.50	**0.32**
Livestock	0.10	-0.10	0.07	0.21	**0.09**
Softs	-0.02	-0.02	0.24	0.31	**0.18**

Corr JPM GGBI	**1991-1996**	**1996-2001**	**2001-2006**	**2006-2011**	**1991-2011**
DJ-UBS Total	0.06	0.10	0.12	0.25	**0.16**
Energy	0.18	0.19	0.09	0.12	**0.12**
Precious	-0.14	0.25	0.28	0.42	**0.26**
Industrial	0.00	-0.06	0.01	0.18	**0.07**
Agriculture	-0.16	-0.18	0.11	0.28	**0.10**
Livestock	0.02	0.00	-0.20	-0.11	**-0.10**
Softs	-0.18	-0.21	0.02	0.18	**0.01**

Comment: *Correlations are calculated on monthly returns*

In Table 4 we present our commodity sub-sector correlation with stocks and bonds over the four separate five-year periods in the entire sample. From 2001 and onwards there has been a noticeable increase in correlations with stocks for all sub-sectors, with the last period of 2006 to 2011 showing substantially higher correlations than in previous periods. Sub-sector correlations with bonds have also increased in the last period, although not as remarkably.

Tang and Xiong (2010) explain this development with the concept of financialization. They claim that ever since the alleged benefits of commodities to a diversified portfolio were widely recognized, large flows of strategic allocations to commodity futures have taken place almost exclusively in the two most popular commodity indexes, GSCI and DJ-UBS. These investments have to a large extent been placed in total commodity indices, meaning a simultaneous allocation to and out of the sub-sectors, which according to the authors has contributed to the increased internal correlations between the sub-sectors.

[18] See Appendix VI for GSCI and sub-sector correlations

This can be compared to a similar situation in equity markets where Barberis et al. (2005) have shown that a stocks correlation with the S&P 500 increases after its inclusion in this index. Krugman (2008) argues instead that the rise in correlations occurs due to a universal increased demand for all commodities from emerging markets rather than financialization.

The increase in correlation itself and the implied lower potential benefits from diversification are however not disputed in the literature. Still, this does not necessarily indicate a permanent regime-switch in correlation behavior. Buyuksahin et al (2009) and Silvennoinen and Thorp (2010) for example attribute the current increase in correlations to the recent financial crisis and claim that it could be temporary. Regardless, correlations over the entire period are rather low, meaning that commodities are still a valuable contribution to a portfolio.

Overall, we find that in accordance to the economic intuition the sub-sectors show properties that suggest significant diversification benefits when using the sub-sector strategy in portfolio optimization instead of a total commodity index. This confirms the findings of Jensen et al (2002), Erb and Harvey (2006) and Gorton and Rouwenhorst (2006) even after including the most recent data.

4.3 Business Cycle Strategy

The economic intuition behind the business cycle strategy is to exploit the differences in performance of commodities over the different phases of a business cycle. We believe that by studying returns in the business cycle phases separately and establishing the optimal allocations for each business cycle phase, we can find a tactical allocation that can outperform a conventional buy and hold strategy.

We choose to perform the business cycle study on GSCI Total because of its long historical data that stretches back to 1970. This allows for the examination of six business cycles as opposed to only three when using DJ-UBS Total that only goes back to 1991. Table 5 shows the average returns and standard deviations in each of the four business cycle phases.

Table 5: Descriptive Statistics for Commodities, Stocks and Bonds for each Business Cycle Phase (Jan 1973 - Apr 2011)

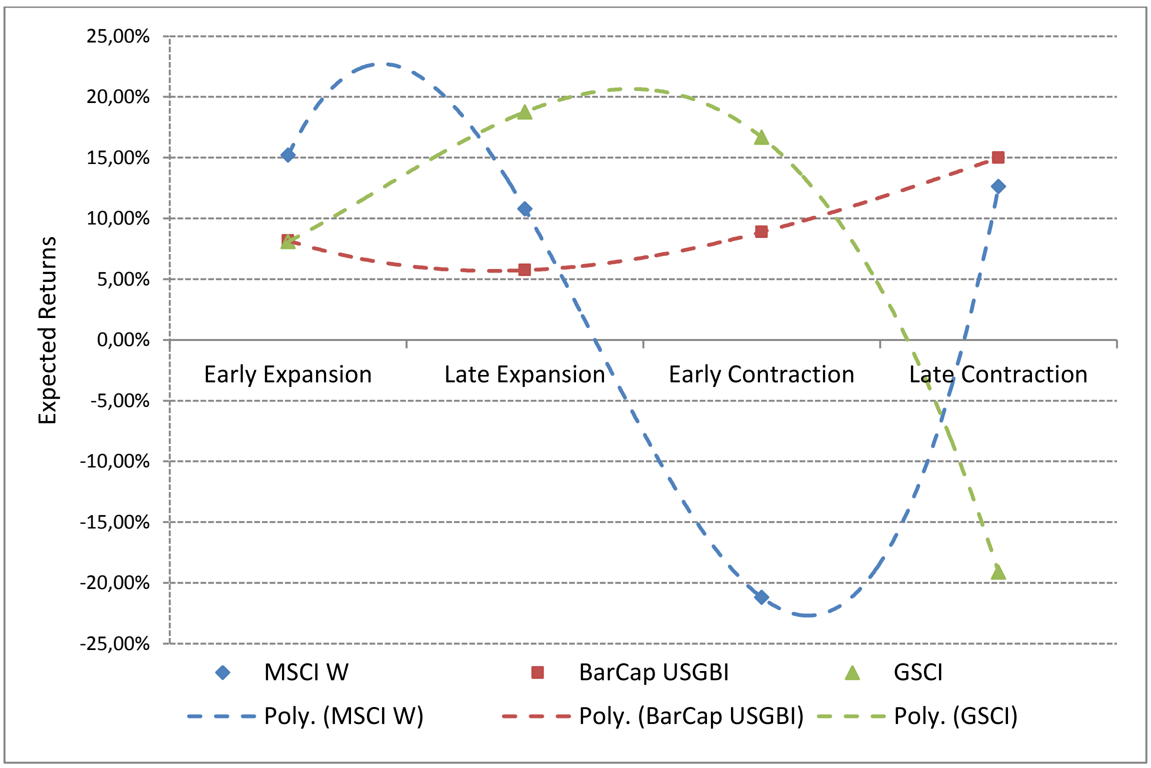
	MSCI World		**BarCap USGBI**		**GSCI**	
	Avg Ret	**St Dev**	**Avg Ret**	**St Dev**	**Avg Ret**	**St Dev**
Early Expansion	15.22%	12.60%	8.18%	4.99%	8.09%	16.24%
Late Expansion	10.77%	13.96%	5.74%	4.35%	18.77%	19.35%
Early Contraction	-21.20%	18.08%	8.88%	8.64%	16.67%	32.75%
Late Contraction	12.62%	28.77%	14.99%	6.70%	-19.11%	32.27%
Total	**9.01%**	**16.18%**	**6.96%**	**6.84%**	**7.12%**	**21.63%**

Comment: *Data includes six business cycles and calculations are performed on annualized monthly returns*

Dividing a business cycle into four phases appears reasonable, as the performance in each of the four phases differ substantially across all three analyzed asset classes. Our results can partly be compared to Gorton and Rouwenhorst (2006) who only look at average returns for the same business cycle phases during the period of 1959 to 2004. Using S&P 500, Ibbotson corporate bond index and their own equally-weighted commodity index, the authors find similar phase variations despite the different time period. The variation between the phases indicates that asset class performance changes over the business cycle and that a tactical allocation strategy could be beneficial compared to maintaining the same portfolio weights at all times.

In Figure 5 we use the calculated average returns from Table 5 to create a polynomial trend line over the four phases which illustrates performance of stocks, bonds and commodities over the business cycle.

Figure 4: Illustration of Business Cycle Performance of Commodities, Stocks and Bonds

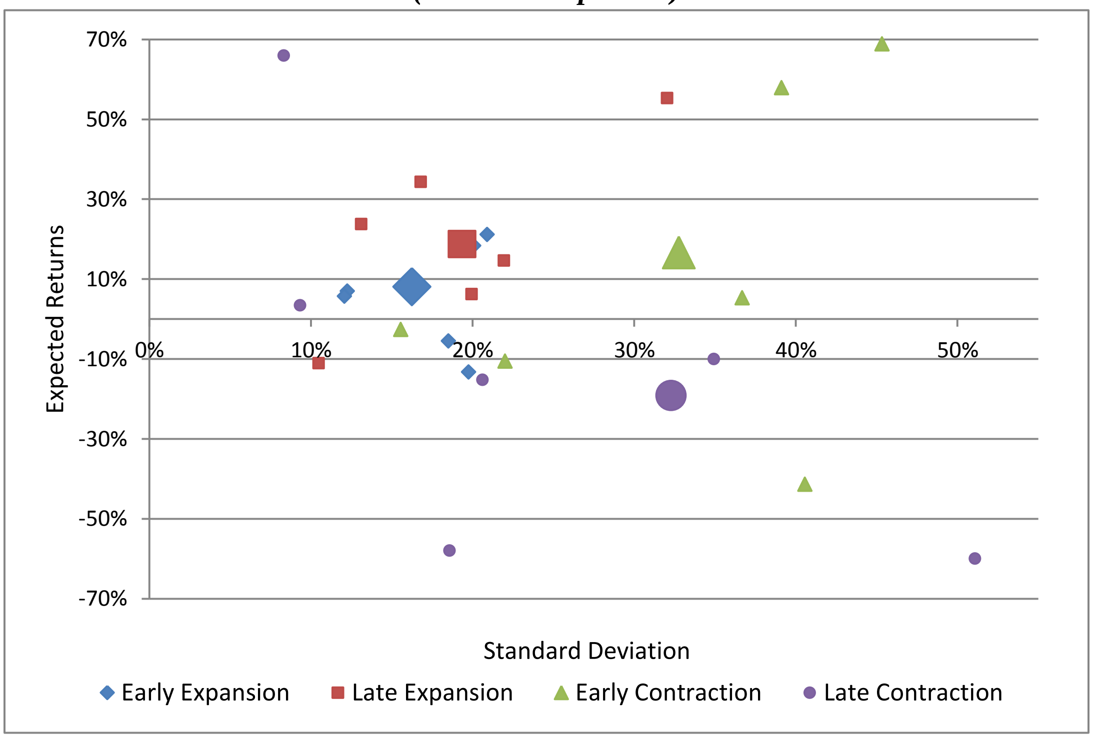


Comment: *Polynomial trend lines shows movements throughout the business cycle. Data points are average expected returns for each business cycle phase.*

Figure 4 shows that stock and commodity prices move cyclically, although commodities seem to be lagging one period behind. Bonds, however, show contra-cyclical tendencies as expected. These movements indicate that the optimal portfolio weights are different between the four business cycle phases and suggest potential benefits of a tactical allocation strategy.

Using the performance parameters from Table 5, the optimal allocations in each business cycle phase can be found by solving a portfolio optimization problem. To ensure that the optimal weights calculated for each phase are sustainable over time, we perform a more detailed study for each of the four business cycle phases. Our study period stretches back to 1973 and includes a total of six business cycles, that each can be divided in four different phases: early/late expansion and early/late contraction. Each business cycle phase thus gets six separate samples, where average returns and standard deviations are calculated on monthly annualized returns. The average returns and standard deviations for each of the 24 samples are plotted in Figure 5. The small data points in the figure show the performance of each sample, whereas the large data points are the combined averages for the four phases respectively.

Figure 5: Expected Returns and Standard Deviations for GSCI Total in each Business Cycle Phase (Jan 1973 - Apr 2011)



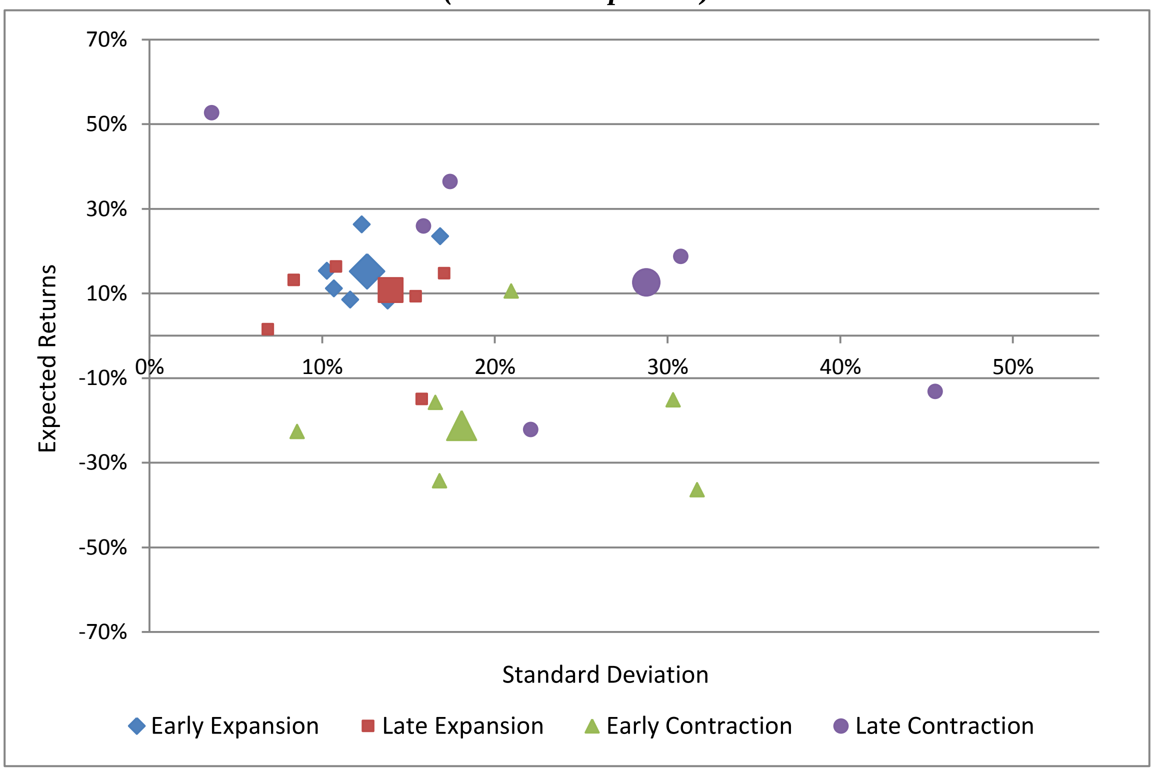
Comment: *Early Expansion, Late Expansion, Early Contraction and Late Contraction are the four business cycle phases. The small points are the expected returns and standard deviations for all six samples in a specific business cycle phase. The large points represent the average across the six underlying phase samples.*

Figure 5 reveals a weakness in the business cycle strategy. The wide spread of the results in the figure indicate that equivalent phases across different business cycles do not necessarily perform similarly. This means that the average over the total phase period, which would be used to optimize the portfolio in the business cycle strategy, is a poor estimate for individual phase samples. Ideally, the plots in the figure should be clustered around each respective phase average, which would indicate sustainable results across all samples.

When comparing the phases, we can see that early expansion has the least spread of the results, while both early and late contractions are very scattered. One reason for the large spread in contraction samples is the often increased volatility during market downturns. This can also be seen in Table 5 as a significant increase in standard deviations for all asset classes in the two contraction phases as compared to the expansions. Another explanation for the large spread in contractions is their short duration, which on average is six months long as opposed to 30 months for expansions.

Additionally, we examine the individual business cycle phases for stocks and bonds to see if a similar spread in samples exists for these two asset classes. The results are presented in Figures 6 and 7.

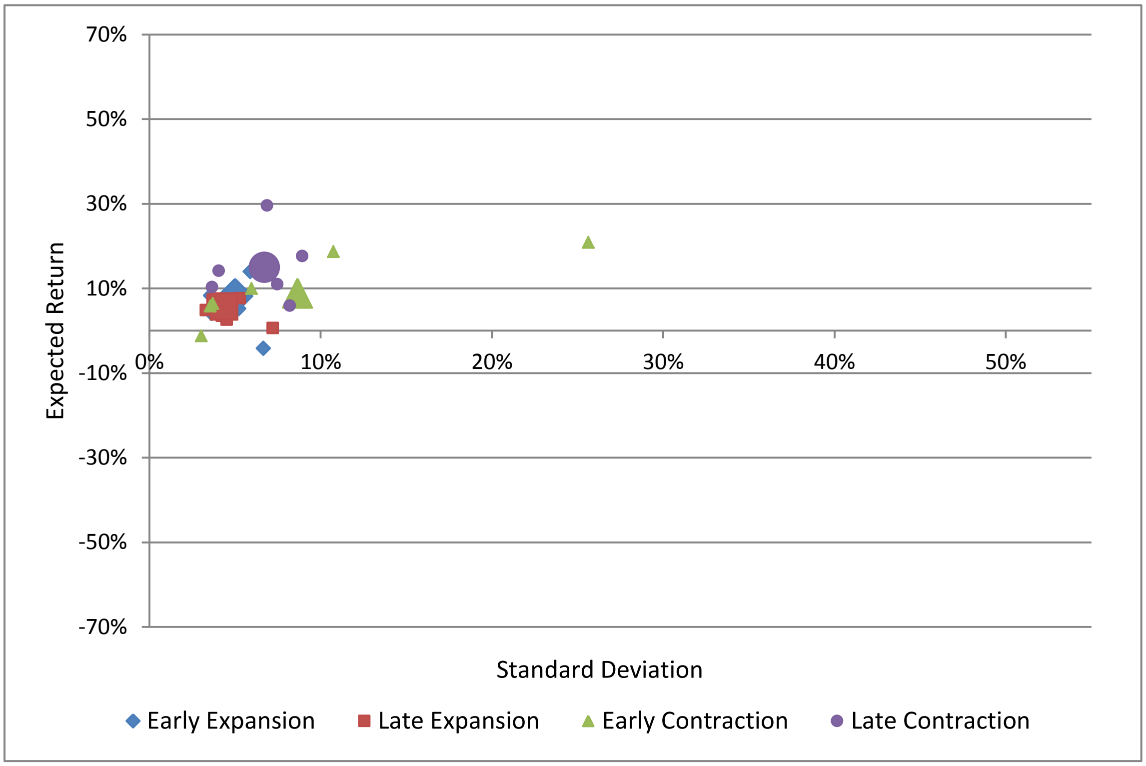
Figure 6: Expected Returns and Standard Deviations for MSCI World in each Business Cycle Phase (Jan 1973 - Apr 2011)



Comment: *Early Expansion, Late Expansion, Early Contraction and Late Contraction are the four business cycle phases. The small points are the expected returns and standard deviations for all six samples in a specific business cycle phase. The large points represent the average across the six underlying phase samples.*

Stocks show the same weakness as commodities in that the average of each business cycle phase is a poor representation of the individual phase samples. Another similarity is that the expansion phase samples are much more clustered than the contraction phase samples. Overall, the spread of the samples is too wide for the average to have any predictive power for future phases.

Figure 7: Expected Returns and Standard Deviations for BarCap USGBI in each Business Cycle Phase (Jan 1973 - Apr 2011)



Comment: *Early Expansion, Late Expansion, Early Contraction and Late Contraction are the four business cycle phases. The small points are the expected returns and standard deviations for all six samples in a specific business cycle phase. The large points represent the average across the six underlying phase samples.*

Although the bonds are more clustered around the sample average, they still show high spreads relative to their returns. Furthermore, the same pattern of expansions being more clustered than contractions also appears in this asset class.

Overall, our closer study of phase samples reveals that any portfolio optimization based on the average historical performance of the underlying phase samples, would give misleading weights for future application. If the samples from each business cycle phase would be more similar, an average of the samples could be more reliable for predicting optimal weights of stocks, bonds and commodities in tactical allocation. As this is not the case, we decide not to perform portfolio optimization with the suggested business cycle strategy. However, we still agree with Gorton and Rouwenhorst (2006) that an investor should be aware of the considerable cyclicality in commodity performance, which unfortunately cannot be generalized for each business cycle phase. Unlike previous research where Jensen et al (2000, 2002) and Conover et al (2010) have successfully tested timing strategies based on monetary policy, we find that tactical allocation to commodities should not be based on business cycle phases.

4.4 Portfolio Optimization

Above, we conclude that sub-sectors show properties that suggest significant diversification benefits when dividing the total commodity index into sub-sectors. This means that by finding an optimal risky portfolio for the sub-sector strategy, we can establish historically optimal weights in each commodity sub-sector, which can serve as a guideline for enhanced strategic allocation to commodity investments.

For the business cycle strategy, we conclude that an attempt to find optimal weights for each specific business cycle phase, based on the average historical performance of the phase samples, would most likely generate misleading results for future application. An investor would therefore not be able to rely on the results of this strategy, which makes us refute the benefits with tactical allocation to commodities based on business cycle phases. Therefore, we choose only to present the results for the sub-sector strategy.

4.4.1 Sub-Sector Strategy - Entire Time Period

Table 6 contains the results from the portfolio optimizations in the period of 1991 to 2011 when adding commodities or commodity sub-sectors to the traditional portfolio of stocks and bonds. We choose to perform the sub-sector strategy on DJ-UBS for the reasons outlined above.

Each row in Table 6 corresponds to a unique portfolio scenario. The first rows of each panel show the traditional portfolios consisting of stocks and bonds, the second rows show the addition of a total commodity index and the third rows show the addition of commodity sub-sectors.

The evaluations of the three scenarios in the sub-sector strategy are performed in two ways. Panel A shows the composition of optimal risky portfolios for each suggested scenario. This demonstrates how the Sharpe ratios evolve when adding a total commodity index or commodity sub-sectors to a traditional portfolio.

Panel B demonstrates instead the improvement of expected returns when adding commodities to a portfolio of stocks and bonds. To determine the direct impact on the expected return of a portfolio, we hold the risk level constant and maximize the expected returns for each of the three scenarios. The fixed risk level is equal to the standard deviation of an optimal stocks and bonds portfolio. This allows for a direct comparison of the increase in expected return when adding a total commodity index or commodity sub-sectors. Due to the fixed risk level, each scenario in Panel B demonstrates lower Sharpe ratios and expected returns than in Panel A.

Table 6: Descriptive Statistics and Asset Weights for Commodities, Stocks and Bonds for the Sub-Sector test, the entire period (Jan 1991 - Apr 2011)

Panel A: Optimal Portfolios

Descriptive Statistics			**Portfolio Weights**									
Avg Ret	**St Dev**	**SR**	**MSCI ACWI**	**JPM USGBI**	**DJ-UBS Total**	**Ener.**	**Prec.**	**Indu.**	**Agric.**	**Lives.**	**Softs**
7.34%	6.80%	**0.59**	18.69%	81.31%	.	.	.	.	.	.	.
7.29%	6.60%	**0.60**	13.07%	78.07%	8.85%	.	.	.	.	.	.
7.84%	6.97%	**0.65**	11.42%	67.69%	.	2.33%	13.27%	5.29%	0.00%	0.00%	0.00%

Panel B: Risk-Adjusted Returns

Descriptive Statistics			**Portfolio Weights**									
Avg Ret	**St Dev**	**SR**	**MSCI ACWI**	**JPM USGBI**	**DJ-UBS Total**	**Ener.**	**Prec.**	**Indu.**	**Agric.**	**Lives.**	**Softs**
7.34%	6.80%	0.59	18.69%	81.31%	.	.	.	.	.	.	.
7.40%	6.80%	0.60	18.45%	73.26%	8.29%	.	.	.	.	.	.
7.72%	6.80%	0.64	10.37%	70.79%	.	1.90%	11.12%	5.00%	0.00%	0.00%	0.82%

Comment: *Each row in a panel shows three different scenarios: 1) stocks and bonds, 2) stocks, bonds and the total commodity index and 3) stocks, bonds and the commodity sub-sector indices. Panel A demonstrates portfolios with highest Sharpe ratio for each scenario. Panel B demonstrates highest expected return given a fixed level of standard deviation, which we set equal to the risk of the optimal portfolio without commodities.*

Our results in Table 6 show very slight improvements in risk-adjusted returns when adding a total commodity index to a stocks and bonds portfolio. The benefits nevertheless exist, as we see an increase in Sharpe ratios and risk-adjusted expected returns in both panels. The objective of our analysis is however to evaluate the improvement of splitting the total commodity index into sub-sectors. Table 6 shows that both the Sharpe ratio and the risk-adjusted return increase when we replace the total commodity index with the underlying sub-sectors.

The weights presented in the table show the composition of optimal portfolios and we see that the total weight in commodities increase when we apply the sub-sector approach. Total allocation to commodities changes from 8-9% in a total commodity index to about 20% in the different sub-sectors, while we see a reduction in allocation to both stocks and bonds. In the optimal portfolio for this period, only energy, precious and industrial metals receive an allocation, with precious metals being the prominent sector. This change in optimal weights generates a higher risk-adjusted portfolio performance, which confirms our assumption that a sub-sector strategy should be more efficient than adding a total commodity index.

The benefits of the sub-sector strategy are however smaller than we expected. Based on the overall positive view on commodities in previous research in addition to the equity-like returns and relatively low correlations with other asset classes, we expected to see a more significant improvement of the overall portfolio performance. One explanation to this could be the variation in commodity performance over time as suggested by Demidova-Menzel and Heidorn (2007) and Cheung and Miu (2010). The authors claim that the alleged benefits of commodities mostly come from short and isolated periods of extraordinarily strong commodity performance. Therefore, we decide to divide our time period into four five-year time periods and perform portfolio optimization in each of the four periods. This sub-sample analysis is similar to the one performed in the correlation study above.

4.4.2 Sub-Sector Strategy – Sub-Sample Analysis

The results for all portfolio optimizations in each time period are presented in Table 7.

Table 7: Descriptive Statistics and Asset Weights for Commodities, Stocks and Bonds for the Sub-Sector test, Time Period 1 (Jan 1991 - Dec 1995)

Panel 1.A: Optimal Portfolios (1991-1995)

Descriptive Statistics			Portfolio Weights								
Avg Ret	St Dev	SR	MSCI ACWI	JPM USGBI	DJ-UBS Total	Ener.	Prec.	Indu.	Agric.	Lives.	Softs
9.99%	6.20%	**0.92**	24.67%	75.33%	.	.	.	.	.	.	.
9.44%	5.50%	**0.94**	18.33%	66.82%	14.85%	.	.	.	.	.	.
9.31%	4.70%	**1.07**	10.89%	62.16%	.	0.00%	2.59%	4.20%	13.68%	0.00%	6.48%

Panel 1.B: Risk-Adjusted Performance (1991-1995)

Descriptive Statistics			Portfolio Weights								
Avg Ret	St Dev	SR	MSCI ACWI	JPM USGBI	DJ-UBS Total	Ener.	Prec.	Indu.	Agric.	Lives.	Softs
9.99%	6.20%	0.92	24.67%	75.33%	.	.	.	.	.	.	.
10.01%	6.20%	0.92	28.41%	68.06%	3.52%	.	.	.	.	.	.
10.31%	6.20%	0.97	36.91%	48.11%	.	0.00%	0.00%	0.00%	6.96%	0.00%	8.01%

Panel 2.A: Optimal Portfolios (1996-2000)

Descriptive Statistics			Portfolio Weights								
Avg Ret	St Dev	SR	MSCI ACWI	JPM USGBI	DJ-UBS Total	Ener.	Prec.	Indu.	Agric.	Lives.	Softs
12.25%	14.61%	**0.49**	100.00%	0.00%	.	.	.	.	.	.	.
11.02%	11.44%	**0.52**	72.82%	0.00%	27.18%	.	.	.	.	.	.
18.56%	15.63%	**0.86**	61.75%	0.00%	.	38.25%	0.00%	0.00%	0.00%	0.00%	0.00%

Panel 2.B: Risk-Adjusted Performance (1996-2000)

Descriptive Statistics			Portfolio Weights								
Avg Ret	St Dev	SR	MSCI ACWI	JPM USGBI	DJ-UBS Total	Ener.	Prec.	Indu.	Agric.	Lives.	Softs
12.25%	14.61%	0.49	100.00%	0.00%	.	.	.	.	.	.	.
12.25%	14.61%	0.49	100.00%	0.00%	0.00%	.	.	.	.	.	.
17.59%	14.61%	0.86	64.41%	2.14%	.	33.45%	0.00%	0.00%	0.00%	0.00%	0.00%

Panel 3.A: Optimal Portfolios (2001-2005)

Descriptive Statistics			Portfolio Weights								
Avg Ret	St Dev	SR	MSCI ACWI	JPM USGBI	DJ-UBS Total	Ener.	Prec.	Indu.	Agric.	Lives.	Softs
6.71%	7.20%	**0.64**	13.44%	86.56%	.	.	.	.	.	.	.
8.69%	7.69%	**0.86**	0.00%	61.68%	38.32%	.	.	.	.	.	.
12.73%	9.22%	**1.15**	0.00%	44.36%	.	8.45%	24.99%	21.97%	0.00%	0.23%	0.00%

Panel 3.B: Risk-Adjusted Performance (2001-2005)

Descriptive Statistics			Portfolio Weights								
Avg Ret	St Dev	SR	MSCI ACWI	JPM USGBI	DJ-UBS Total	Ener.	Prec.	Indu.	Agric.	Lives.	Softs
6.71%	7.20%	0.64	13.44%	86.56%	.	.	.	.	.	.	.
8.19%	7.20%	0.85	5.63%	64.54%	29.84%	.	.	.	.	.	.
10.02%	7.20%	1.10	0.00%	55.69%	.	5.34%	14.06%	14.94%	0.00%	9.98%	0.00%

Panel 4.A: Optimal Portfolios (2006-2011)

Descriptive Statistics			Portfolio Weights								
Avg Ret	**St Dev**	**SR**	**MSCI ACWI**	**JPM USGBI**	**DJ-UBS Total**	**Ener.**	**Prec.**	**Indu.**	**Agric.**	**Lives.**	**Softs**
7.58%	7.54%	**0.75**	0.69%	99.31%	.	.	.	.	.	.	.
7.58%	7.54%	**0.75**	0.69%	99.31%	0.00%	.	.	.	.	.	.
13.65%	11.50%	**1.02**	0.00%	63.39%	.	0.00%	36.48%	0.13%	0.00%	0.00%	0.00%

Panel 4.B: Risk-Adjusted Performance (2006-2011)

Descriptive Statistics			Portfolio Weights								
Avg Ret	**St Dev**	**SR**	**MSCI ACWI**	**JPM USGBI**	**DJ-UBS Total**	**Ener.**	**Prec.**	**Indu.**	**Agric.**	**Lives.**	**Softs**
7.58%	7.54%	0.75	0.69%	99.31%	.	.	.	.	.	.	.
7.58%	7.54%	0.75	0.68%	99.32%	0.00%	.	.	.	.	.	.
8.19%	7.54%	0.83	0.00%	85.62%	.	0.00%	8.05%	1.27%	0.00%	4.84%	0.22%

Comment: *Each row in a panel shows three different scenarios: 1) stocks and bonds, 2) stocks, bonds and the total commodity index and 3) stocks, bonds and the commodity sub-sector indices. Panel A demonstrates portfolios with highest Sharpe ratio for each scenario. Panel B demonstrates highest expected return given a fixed level of standard deviation, which we set equal to the risk of the optimal portfolio without commodities.*

By comparing Table 7 to Table 6 we conclude that the impact of the sub-sector strategy on portfolio performance is more prominent when we divide the total time period into the sub-samples. Once again we observe the benefits of the sub-sector strategy as we see the increase of both Sharpe ratios and risk-adjusted returns when replacing a total commodity index with its sub-sectors. For the period of 2006 to 2011, we even see that the optimal weight in commodities when adding a total commodity index is set to zero, while splitting commodities into sub-sectors increases the optimal allocation to commodities to 36.61%. The composition of optimal portfolios in the remaining three periods also suggests significantly higher optimal allocation to commodities when applying the sub-sector approach, although showing a less dramatic increase in commodity allocation.

Throughout the four time periods, three sub-sectors receive the highest optimal weights: energy, precious and industrial metals. Agriculture and livestock receive considerably smaller weights and the allocation to softs is almost negligible. Precious metals is the only sector that receives an allocation in the optimal portfolio during three out of four time periods, which indicates its important role in portfolio composition. This is also in line with the optimal weights in Table 6, where precious metals is the most prominent sector. Finally,

5 CONCLUSION

Over the last decade the allocations to commodity instruments has increased dramatically. The view on commodities in literature has traditionally been positive and previous researchers have suggested significant diversification benefits by adding commodities to a portfolio. However, in recent years, research has been contradictory as the alleged benefits seem to appear and vanish over time depending on commodity index composition and the time period studied. In this thesis, we update previous research on commodities with recent data and test two commodity allocation strategies. The first strategy divides a total commodity index into sub-sectors to evaluate a strategic commodity allocation. The second strategy suggests tactical allocation to commodities based on business cycle phases.

We study commodity performance over the period of 1991 to 2011 to update the current view on commodities in previous research. Despite the fact that commodities as an asset class still demonstrate equity-like performance, commodity correlations with stocks and bonds have increased in the past few years. This development is detrimental to diversification benefits, but can be attributed to the recent financial crisis and thus does not necessarily indicate a regime-switch in correlations.

We also analyze commodities on a sector basis and find that the performance of commodity sub-sectors has varied throughout the years. Moreover, we find an increase in correlations of commodity sub-sectors with stocks and bonds, challenging commodities reputation as a good diversifier in a portfolio. The recent increase in correlations can be explained with financialization, increased demand for commodities from emerging markets and the effects of the recent financial crisis.

Prior to the business cycle strategy, we examine commodity performance in different phases of a business cycle and find variations that indicate benefits with a tactical allocation strategy. A sub-sample analysis reveals however that a portfolio optimization based on business cycle phases would give misleading results for future application and we decide not to perform portfolio optimization with the business cycle strategy.

We conclude that the sub-sector strategy in portfolio optimization is more efficient than adding a total commodity index, which also leads to an increased optimal allocation to commodities. By performing a portfolio optimization in the period of 1991 and 2011 using the sub-sector strategy, we find that an optimal portfolio should consists of bonds, precious metals, stocks, industrial metals and energy in a descending order. The effect of the sub-sector strategy is smaller than expected over the entire time period of 1991 to 2011, but more prominent during three out of four sub-sample periods.

The contribution of this thesis, as we see it, is threefold. First, we update conventional research on commodity benefits in a portfolio. Second, we test two commodity allocation strategies to reject business cycle phases as a tactical allocation indicator for commodities. However, we find that strategic allocation to commodities in a traditional portfolio of stocks and bonds can be improved by using sub-sectors instead of a total commodity index. Third, we find the optimal portfolio weights of the sub-sector strategy that give an improved risk-adjusted performance.

6 SUGGESTIONS FOR FURTHER RESEARCH

Based on the experience from the thesis, we would like to suggest a few interesting topics for further research.

In recent years we have witnessed a rise in correlations of commodities with stocks and bonds. This diminishes the diversification benefits of commodities and puts into question their role as a good diversifier in a portfolio. This increase may be attributed to the financial crisis and thus could only be temporary. However, we cannot rule out a possibility of a regime-switch. A post-crisis analysis of commodity correlations would be important to detect potential permanent effects.

We have also found that business cycles are a poor indicator for tactical allocation in commodities. However, it would be interesting to apply the sub-sector approach on the already established tactical allocation strategies, such as monetary policy.

7 REFERENCE LIST

Academic

Barberis, N., A. Shleifer and J. Wurgler (2005), ”Comovement”, *Journal of Financial Economics* 75, 283-317

Becker, K. and J. Finnerty (2000), **“**Indexed Commodity Futures and the Risk and Return of Institutional Portfolios”, Office of Futures and Options Research, Working Paper, 2000

Bodie, Z., A. Kane and A.J. Marcus (2009), “Investments”, Eights edition, McGraw-Hill, New York

Bodie, Z. and V. Rosansky (1980), “Risk and return in commodity futures”, *Financial Analysts Journal* 36, 27–39

Buyuksahin, B., M. Haigh, and M. Robe (2010), “Commodities and equities: Ever a “market of one”?”, *Journal of Alternative Investments* 12, 76-95.

Cheung, S. C. and P. Miu (2010), “Diversification benefits of commodity futures”, *Journal of International Financial Markets, Institutions & Money* 20, 451-474

Conover, C.M., G.R. Jensen, R.R. Johnson, and J.M. Mercer (2010), “Is now the time to add commodities to your portfolio?”, *Journal of Investing* 19, 10–19

Daskalaki, C. and G. Skiadopoulos (2011), “Should investors include commodities in their portfolios after all? New evidence”, *J. Bank Finance* (2011), doi:10.1016/j.jbankfin.2011.02.022

Demidova-Menzel, N. and T. Heidorn (2007), “Commodities in Asset Management”, Frankfurt School - Working Paper Series 81, Frankfurt School of Finance and Management

Erb, C. B. and C. R. Harvey (2006), “The Strategic and Tactical Value of Commodity Futures”, *Financial Analysts Journal* 62, 69-97

Garrett, I. and N. Taylor (2001), “Portfolio diversification and excess comovement in commodity prices”, The Manchester School, 69: 351–368. doi: 10.1111/1467-9957.00252

Gorton, G. and G. Rouwenhorst (2006), “Facts and Fantasies about Commodity Futures”, *Financial Analysts Journal* 62, 47-68

Greer, R. J. (1978), “Conservative Commodities: A Key Inflation Hedge”, *Journal of Portfolio Management* 4, 26-29

Greer, R. J. (1994), “Methods for Institutional Investment in Commodity Futures”, *The Journal of Derivatives* Winter 1994, Vol. 2, No. 2: pp. 28-36

Greer, R. J. (2000), “The nature of commodity index returns”, *Journal of Alternative Investments*, 45-53

Greer, R. J. (2005), “Commodity Indexes for Real Return & Efficient Diversification”; In: An Investor Guide to Commodities, Deutsche Bank, April 2005, pp.24-34

Hull, J.C. (2009), ”Options, Futures and other Derivatives”, Seventh edition, Pearson Prentice Hall, Upper Saddle River, New Jersey

Jensen, G. R., R. R. Johnson and J. M. Mercer (2000), "Efficient Use of Commodity Futures in Diversified Portfolios", *The Journal of Futures Markets* 20, 489-506

Jensen, G. R., R. R. Johnson and J. M. Mercer (2002), "Tactical Asset Allocation and Commodity Futures" *The Journal of Portfolio Management* 28, 100-111

Kazemi, H., T. Schneeweis and R. Spurgin (2009), "The Benefits of Commodity Investment", *AIA Research Report.* Avaliable online: http://www.alternativeanalytics.com/pdfs/BenefitsofCommodityInvestment200908update.pdf

Markowitz, H.M. (1952), "Portfolio Selection", *Journal of Finance,* 7.Vol., No. 1, March 1952, pp.77-91

Satyanarayan, S. and P. Varangis (1994), "An Efficient Frontier for International Portfolios with Commodity Assets", Policy Research Working Paper 1266, The World Bank, March 1994

Silvennoinen, A. and S. Thorp (2010), "Financialization, crisis and commodity correlation Dynamics", Working paper, Queensland University of Technology.

Solnik B. and D. McLeavey (2009), "Global Investments", Sixth edition, Pearson Prentice Hall, Upper Saddle River, New Jersey

Tang, K. and W. Xiong (2010), "Index Investing and the Financialization of Commodities. NBER Working Paper No. 16325, September 2010

Till, H. (2006), "A Long-Term Perspective on Commodity Futures Returns". EDHEC Risk and Asset Management Research Centre. October 2006. Available online: http://www.premiacap.com/publications/EDHEC_Till_Working_Paper_A_Long_Term_Perspective_Oct_2006.pdf

Pulvermacher, K. (2005a), "What are Commodities?", March 2005; World Gold Council. Available online: http://www.gold.org/value/stats/research/index.html

Vrugt, E. B. (2003), "Tactical Commodity Strategies in Reality: An Economic Theory Approach," ABP Working Paper.

Vrugt, E. B., R. Bauer, R. Molenaar and T. Steenkamp (2004), "Dynamic Commodity Timing Strategies", Avaliable online: Available at SSRN: http://ssrn.com/abstract=581423

Non-Academic

Krugman, Paul (2008), "Fuels on the hill", *The New York Times*, June 27

Masters, M. W. (2008), "Are Index Investors Driving Up Commodity Prices", *Journal of Indexes* vol. 11 no. 6, 14-19

Electronic

S&P GSCI Commodity Indices Factsheet, (2010), Standard & Poors, http://www.standardandpoors.com

8 APPENDIX

8.1 Appendix I – Statistical Basics in Portfolio Theory

Discrete returns for each asset are calculated using monthly historical prices:

$$r_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$$

$r_{i,t}$ is continuous return of asset *i* in period *t-1* till *t*

$P_{i,t}$ is price of asset *i* in period *t*

$P_{i,t-1}$ is price of asset *i* in period *t-1*

Expected return of a single asset is computed using discrete returns:

$$E(r_i) = \bar{r_i} = \frac{1}{T}\sum_{t=1}^{T} r_{i,t}$$

$E(r_i)$ = expected return of asset *i*

$\bar{r_i}$ = average return (mean) of the asset *i*

n = number of observations in the sample

Standard deviation of a single asset:

$$\sigma(r_i) = \sqrt{Var(r_i)} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_{i,t} - \bar{r_i})^2}$$

$\sigma(r_i)$ = standard deviation of asset *i*

$Var(r_i)$ = variance of asset *i*

To annualize the calculated parameters we multiply monthly expected returns by 12 and monthly standard deviations by $\sqrt{12}$.

Correlation between two assets:

$$\rho(r_i, r_j) = \frac{\sum_{t=1}^{n}(r_{i,t} - \bar{r_i})(r_{j,t} - \bar{r_j})}{(n-1)\sigma(r_i)\sigma(r_j)}$$

$\rho(r_i, r_j)$ = correlation between asset *i* and asset *j*

$\sigma(r_j)$ is = standard deviation of the asset *j*

$r_{j,t}$ = continuous return of asset *j* in period *t-1* till *t*

$\overline{r_j}$ = average return (mean) of asset *j*

Covariance between two assets:

$$Cov(r_i, r_j) = \sigma(r_i)\sigma(r_j)\rho(r_i, r_j)$$

where $Cov(r_i, r_j)$ = covariance between asset *i* and asset *j*

Expected return of a portfolio:

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

$E(r_p)$ = expected return of a portfolio

w_i= weight in asset *i*

Standard deviation of a portfolio:

$$\sigma(r_p) = \sqrt{\sum_{i=1}^{n} w_i^2 Var(r_i) + 2 * \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} w_i w_j Cov(r_i, r_j)}$$

where $\sigma(r_p)$ = standard deviation of a portfolio

8.2 Appendix II – Portfolio Optimization Problem

In order to identify the efficient frontier, an investor needs to start by finding the ***minimum variance frontier***, which can be done by solving an optimization problem where we minimize the variance of a portfolio given each stated level of expected portfolio return. It is also crucial to take into account two important conditions that limit the optimization problem: one that makes sure the weights of all assets in a portfolio sum up to one and another that only allows long positions in the assets, in accordance with the assumptions above. This results in the following optimization problem:

$$Minimize\ \sigma(r_p) = \sqrt{\sum_{i=1}^{n} w_i^2 Var(r_i) + \sum_{i=1}^{n}\sum_{\substack{j=1 \\ j\neq i}}^{n} w_i w_j Cov(r_i, r_j)}$$

$$s.t \quad E(r_p) = \sum_{i=1}^{n} w_i\, E(r_i) = k$$

$$\sum_{i=1}^{n} w_i = 1 \quad , \quad w_i \geq 0$$

Solving the problem above for different values of *k* and connecting the results gives the minimum variance frontier. If the condition of the required return is removed and the problem that only minimizes the total variance of the portfolio is solved, the investor will get the ***minimum variance portfolio***, which will have variance smaller than that of each individual asset in the portfolio. Every portfolio choice that lies on the minimum variance frontier above the minimum variance portfolio will be the ***efficient frontier*** and will give a graph of all efficient combinations of individual assets that either maximize the return given a certain risk level or minimize the risk given a certain level of return.

To find the ***optimal risky portfolio*** we add a risk free asset to the analysis and draw a so called ***capital allocation line*** from the risk free rate to the efficient frontier. The optimal risky portfolio will be the tangency point of the highest capital allocation line to the efficient frontier and can be solved with an optimization problem that maximizes the slope of the capital allocation line. The slope is measured with the reward-to-variability ratio (also called ***Sharpe ratio***) because the return increases continuously with the increase of the risk in a trading strategy as measured by the standard deviation and can be calculated as the amount of excess return to the undertaken risk:

$$Sharpe\ Ratio = \frac{E(r_p) - r_f}{\sigma(r_p)}$$

8.3 Appendix III – Composition of Commodity Sub-Sectors

Table A1: Underlying commodities in GSCI as of December 2010

Energy	Precious Metals	Industrial Metals	Agricultures	Livestock	Softs
Crude Oil	Gold	Aluminium	Wheat	Live Cattle	Cotton
Brent Crude	Silver	Copper	Kansas Wheat	Feeder Cattle	Sugar
Unleaded Gasoline		Lead	Corn	Lean Hogs	Coffee
Heating Oil		Nickel	Soybeans		Cocoa
Gas Oil		Zink			
Natural Gas					

Table A2: Underlying Commodities in DJ-UBS as if April 2011

Energy	Precious Metals	Industrial Metals	Agricultures	Livestock	Softs
Crude Oil	Gold	Aluminium	Wheat	Live Cattle	Cotton
Unleaded Gasoline	Silver	Copper	Corn	Lean Hogs	Sugar
Heating Oil		Nickel	Soybeans		Coffee
Natural Gas		Zink	Soybean Oil		

8.4 Appendix IV – Business cycle dates

Table A3: Peak and Trough Dates and Durations of the NBER Business Cycle Phases

Dates		Months per phase			
		Contraction		Expansion	
Peak	**Trough**	**Early**	**Late**	**Early**	**Late**
December 1969(IV)	November 1970 (IV)	5	6	18	18
November 1973(IV)	March 1975 (I)	8	8	29	29
January 1980(I)	July 1980 (III)	3	3	6	6
July 1981(III)	November 1982 (IV)	8	8	46	46
July 1990(III)	March 1991(I)	4	4	60	60
March 2001(I)	November 2001 (IV)	4	4	36.5	36.5
December 2007 (IV)	June 2009 (II)	9	9	11	11

8.5 Appendix V – Descriptive Statistics for GSCI and Sub-Sectors

Table A4: Descriptive Statistics for GSCI Total and Sub-Sectors using Monthly Annualized Returns (Jan 1991 - Apr 2011)

	GSCI Total	Energy	Precious	Industrial	Agriculture	Livestock	Softs
Avg Ret	**7.12%**	10.42%	9.53%	8.63%	2.49%	-0.31%	3.89%
St Dev	**21.63%**	31.09%	15.71%	20.68%	19.10%	13.70%	22.03%

8.6 Appendix VI – Correlation Matrix for GSCI and Sub-Sectors

Table A5: Correlation for GSCI and Sub-Sectors with Stocks and Bonds (Jan 1996 - Apr 2011)

	MSCI ACWI	JPM GGBI	GSCI Total	Energy	Precious	Industrial	Agriculture	Livestock	Softs
MSCI ACWI	1	0.18	0.36	0.29	0.16	0.44	0.32	0.10	0.22
JPM GGBI	0.18	1	0.13	0.13	0.29	0.07	0.11	-0.12	0.04
GSCI Total	0.36	0.13	1	0.97	0.25	0.46	0.38	0.18	0.26
Energy	0.29	0.13	0.97	1	0.17	0.34	0.20	0.11	0.15
Precious	0.16	0.29	0.25	0.17	1	0.28	0.22	-0.03	0.19
Industrial	0.44	0.07	0.46	0.34	0.28	1	0.31	0.09	0.33
Agriculture	0.32	0.11	0.38	0.20	0.22	0.31	1	0.08	0.64
Livestock	0.10	-0.12	0.18	0.11	-0.03	0.09	0.08	1	-0.06
Softs	0.22	0.04	0.26	0.15	0.19	0.33	0.64	-0.06	1

8.7 Appendix VII – Historical Price Movement of GSCI and Sub-Sectors

Figure A1: Indexed Historical Prices of GSCI and Sub-Sectors (Jan 1991 - Apr 2011)