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Time-Varying Correlation and the Benefits of Cross-Asset Class Diversification

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Abstract

In this thesis, return data on the US stock and corporate bond markets together with gold and WTI-Crude Oil prices over the period 1987 – 2012 were used to examine the time-varying correlations and benefits from cross-asset class diversification. It concludes that correlations vary distinctly over time and an all-equity investor benefit from having positions in the bond market, as investment grade bonds have shown a generally low or negative correlation with the stock market during crises. For an investor, it could therefore be costly to ignore the benefits that the bond markets provide. Gold is shown to be a good source for diversification during severe financial crises, even if the volatility in returns are higher than for investment grade bonds.

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1. Introduction

The idea of diversification is an old one and the phrase "don't put all your eggs in one basket" existed long before modern finance theory. The principles of diversification in the financial markets was first published by Markowitz (1952) and earned him the Nobel Prize in Economics in 1990. According to *Modern Portfolio Theory* (MPT), an investor is only concerned about risk-return relationships, and that by diversifying into assets with a less than perfect correlation, the overall risk of the portfolio will be lower. However this theory rest on the assumption that correlation is in fact constant, leading to possible disasters from an investment management perspective if changes in correlation are not taken into consideration (Bodie et al 2008).

Several studies have been conducted to examine the changes in correlation between international stock markets over time and during extreme conditions, see Longin and Solnik (2001) and Campbell et al (2002). Coaker (2006) analyses how the return correlations between different asset classes varies over time, but little has been written about how the correlation varies during and between specific crises, in order to understand how the actual diversification benefits changes and what the underlying reasons behind these changes are.

This study takes the viewpoint of an equity investor and analyses the historical benefits of diversification by investigating how correlations have changed over times of crises, more specifically the Dotcom-crisis in the early 2000's, the Subprime-crisis in 2007-08 and the Sovereign debt crisis in 2011-12. The asset classes studied against the stock market are corporate bonds (both investment grade and high yield bonds) together with two of the most commonly traded commodities: WTI-Crude Oil and gold.

To reach the conclusions, a top-down approach will be taken by first confirming previous research that correlation is in fact time-varying, followed by an analysis on how the different assets' correlations with the stock market have changed before, during and after the specific crises. This will be followed by a case study that aims to quantify the benefits of diversification over the past 25 years, linking the correlation changes to investment management. As will be presented in Section 2, a rational investor is only concerned about returns in relation to its risk, and the risk of a portfolio is the sum of its covariances. This is in turn directly determined by the assets correlation: An increase in correlation implies an increased risk. To capture this, the case study compares the Sharpe ratio of a wide set of different portfolios over time, as it is a function of both the portfolio's risk and return, and thus provides an indication of the actual benefits of diversification for investors.

1.1 Objective

This thesis studies how the correlation in returns between the stock market and other asset classes varies over time in general and during crises in particular. It will discuss how diversification benefits from expanding the investment horizon into other asset classes changes with market trends.

The thesis objective is summarized as follows:

> *Study how return correlations between the stock market and other asset classes changes during crises, and what the implications of that are on the benefits of cross-asset class diversification.*

2. Theoretical framework

Bodie et al (2008) outlines the fundamental steps in a portfolio manager's investment process: (i) *Capital allocation* between a risky portfolio and a risk-free asset, (ii) *Asset allocation* between different asset classes and (iii) *Security selection* within each asset class. This process is derived from 'Modern Portfolio Theory' (MPT) that was developed in the 1950s originating with Markowitz (1952), giving rise for the "Markowitz Portfolio Selection Model" which will be presented in greater detail in this section, after the readers is provided with an intuitive understanding about the benefits of diversification. An important point is the fact that the MPT assumes constant correlation between different assets (Bodie et al, 2008).

2.1 Risk-return relationship

Depending on an investors risk aversion, he will allocate all of his funds between a risky portfolio, and a risk-free asset (generally expressed as T-bills) creating a complete, risky portfolio. All possible combinations between the risk-free asset and the risky portfolio are graphed below and called the investment opportunity set. This straight line is known as the capital allocation line (CAL) and equals the increase in expected return of the complete portfolio per unit of additional risk. The slope is the reward-to-variability ratio, also known as ***Sharpe ratio,*** **S**:

$$S = \frac{(E(r_p) - r_f)}{\sigma_p} \qquad \text{Eq. (2.1.1)}$$

Other things being equal, investors prefer as steep-sloping a CAL as possible, because this means higher expected returns for each level of risk. ***Thus the objective is to maximize S***.

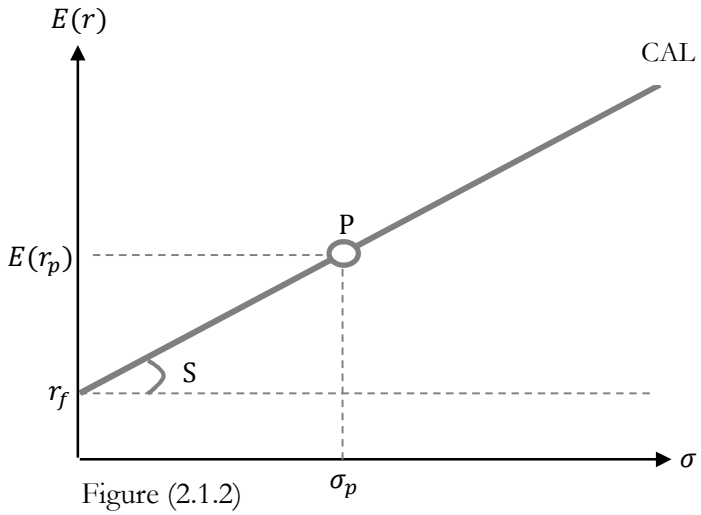


Figure (2.1.2)

As investors care about returns in relation to risk, the risk-return combinations from the set of assets should be identified. The expected return of a portfolio equals the weighted average of the expected return of the individual assets in the risky portfolio:

$$E(r_p) = \sum_{i=1}^{n} w_i E(r_i) \qquad \text{Eq. (2.2.1)}$$

The risk of the portfolio however is mainly determined by how the assets' returns move relative to each other. Thus, the portfolio variance is not the weighted average of the volatility on the individual assets, rather it is the weighted sum of covariances, and each weight is the product of the portfolio proportions of the pair of assets in the covariance term:

$$\sigma_p = \sqrt{\sum_{j=1}^{n} \sum_{i=1}^{n} w_j w_i Cov(r_j r_i)} \qquad \text{Eq. (2.2.2)}$$

As shown in the formula below, the covariance is computed through the correlation coefficient (ρ), and the standard deviations (i.e. volatilities) for each pair of assets. This yields an expression for portfolio variance depending on correlation, and the volatility of the assets.

$$Cov(r_j r_i) = \rho_{j,i} \sigma_j \sigma_i \quad \xrightarrow{yields} \quad \sigma_p = \sqrt{\sum_{j=1}^{n} \sum_{i=1}^{n} w_j w_i \rho_{j,i} \sigma_j \sigma_i} \qquad \text{Eq. (2.2.3)}$$

The correlation coefficient can take continuous values between -1 and +1. If the correlation is +1, the correlation is said to perfectly positive, and the returns from the assets will exactly follow each other. The opposite is true when the correlation is -1, and a correlation of zero indicates that the asset movements are completely random in relation to each other. ***The equations above reveals that the lower the correlation, the lower the portfolio variance, and the possibility of a higher Sharpe ratio.*** It further reveals that the standard deviation of the portfolio will always be less than the weighted average of the asset volatilities, unless the assets are perfectly positively correlated. This implies that the lower the correlation between assets, the greater is the diversification benefits (Siegel, 2008).

2.2 The Markowitz Portfolio Selection Model

After identifying the risk-return opportunities for the set of assets, these can be summarized by the *minimum-variance frontier,* illustrated below in Figure 2.3.1. The *minimum-variance frontier* shows the lowest attainable variance, given an expected portfolio return. All the portfolios that lie on the minimum-variance frontier, above the *global minimum-variance portfolio,* provide the best risk-return opportunities and are said to lie on *the efficient frontier.*

The second part of the selection process involves the risk-free asset, and as above it is desired to find the CAL with the highest Sharpe ratio (i.e. steepest slope). The steepest possible CAL supported by the set of assets is tangent to the efficient frontier, and is known as *the capital market line* (CML). This tangency point is the best combination of risky assets, and known as *the optimal risky portfolio*.

The final step is to allocate the funds between the risk-free asset and the optimal risky portfolio, depending on the investor's *indifference curve*, which is given by his risk aversion. Hence, the optimal allocation is given by *the optimal complete portfolio* on the CML.

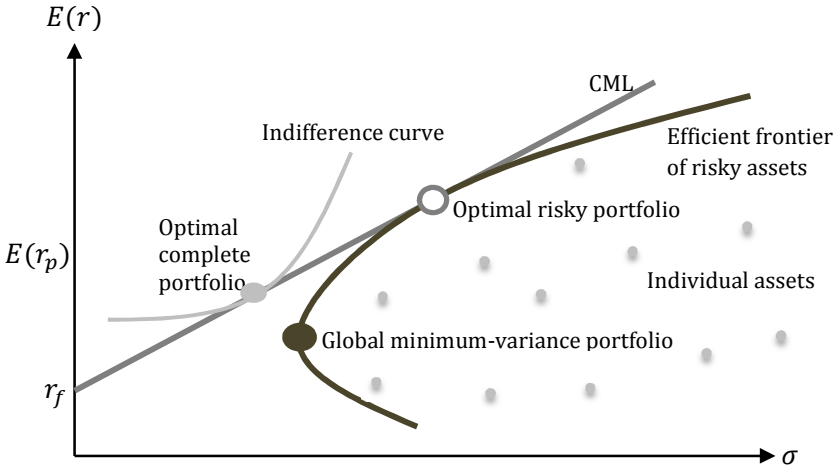


Figure (2.3.1)

3. Previous literature

The vast majority of the literature on how correlations vary over time is focused on the international stock markets, and how correlations vary conditional on extreme returns. In this section these findings are presented, along with an extensive cross-asset class correlation study done by Coaker (2006). To support the case study, an overview of some literature on passive vs. active portfolio management, performance evaluation and momentum strategy is also be presented, and together the results from these papers are used to put this thesis into perspective.

3.1 International stock markets correlation

Longin and Solnik (1995) investigated the correlation between international stock markets during the years 1960 – 1990, using monthly excess return data and found that correlations had generally increased over time and also that they tended to increase in times of high volatility. This acted as the basis for their next paper: Longin and Solnik (2001), where they apply a bivariate framework to study the US stock market separately against four international stock markets during the period 1959 – 1996. They find that correlations are dependent on market trends and not market volatility per se, and conclude that *correlation increases during bear markets, but not during bull markets.* To reach this conclusion the extreme value theory (EVT)[1] is used to study the dependence structure of the different equity indices and estimate the conditional correlation on increasing, pre-determined threshold levels over a multivariate return distribution. These threshold levels are determined as ±X percentage points away from the empirical mean for each country. Using their approach, as the threshold levels increases, the correlation of large returns should asymptotically go to zero. They show that correlation of large negative returns does not converge to zero, but tend to increase with the threshold level, while for positive returns the correlation decreases and converges to zero as the threshold levels increases. Thus, the assumption of multivariate normality can be rejected when returns are negative, but not when returns are positive. This provides evidence that correlation increases during financial stress.

Campbell, Koedjick and Kofman (2002) reached a different conclusion and state that even if correlation is time-varying, it does not imply that correlations depend on the size of market movements, and that correlation studies conditional on size, such as Longin and Solnik (2001) presented above, along with Ramchand and Susmel (1998), Boyer, et al. (1997) and Lorethan and English (2000) will all suffer from a theoretical estimation bias. This bias will arise from the choice

[1] For more information on EVT, see Tawn (1988)

of extreme returns, (i.e. the nature of the conditioning on the size of the joint return) but also on the assumed underlying joint return distribution. Boyer et al. and Lorethan and English condition their correlation estimates on one component of the bivariate return distribution, and then estimate the truncated conditional correlation for bivariate return observations in the cases where one of the returns exceed a certain threshold level. Campbell et al (2002) criticise this approach, arguing that truncating a joint return distribution with constant correlation leads to a downward bias for increasing threshold levels, with the implication of an increase in how often the assumption of constant correlation can be rejected. Longin and Solnik's (1995 and 2001) methodology is slightly different as they only consider the cases where *both* return series exceed *pre-determined* threshold levels, creating a "quadrant" of relevant return observations. When moving further into the bivariate tail, the conditional correlations will as previously discussed converge to zero. However, Campbell et al (2002) claim that this approach gives rise to a theoretical bias similar to that of Boyer et al. and Lorethan and English.

Instead of adjusting the conditioned correlation estimates for this theoretical bias (from either a truncated or quadrant conditioning approach) Campbell et al (2002) take a portfolio managers viewpoint and condition their correlation measure in a way consistent with the portfolio Value-at-risk (VaR). As described by Linsmeier and Pearson (2000), VaR is a statistical measure of possible portfolio losses resulting from 'normal' market movements, such that the correlation estimates are conditioned on portfolio returns falling below a pre-specified worst-case portfolio quantile, instead of being conditioned on the returns on either one or both assets falling below a particular threshold level. Through the VaR methodology, estimations can be made on the probability of a portfolio's return falling below a threshold VaR-return with a specified confidence level. If constant correlation is assumed over the joint return distribution, the probability of the portfolio return falling below the VaR-level equals the weighted average of the individual asset's probability of falling below the same VaR-level. As confidence level increases, return moves further into the tails (of the joint portfolio distribution), and the VaR increases. If at the same time, the correlation between the assets' return were to increase – the portfolios VaR will exceed the weighted average VaR of the individual assets, and the correlation changes can be proved. Using the same equity markets as Longin and Solnik (2001), with more frequent sampling but during a shorter time period, May 1990 – December 1999, Linsmeier and Pearson (2000) observe an increase in the conditional quantile correlation during *both bull markets and bear markets*. This goes against the findings

of Longin and Solnik (2001) who could only observe an increased correlation in bear markets. This indicates that diversification benefits erode when they are needed the most.

3.2 Stock markets' correlation with bond markets

Coaker (2006) studies the volatility of correlation and its implications for asset allocation decisions by analysing 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), using monthly return data. He also analyses the diversification benefits in years when the S&P 500 declines. He finds that the correlation of investment grade corporate bonds with the S&P 500 varies distinctly over time, but that they have provided high diversification benefits. In all of the eight years within the sample where the S&P 500 declined, the bonds earned positive returns, with a 35-year correlation of 0.23 and a high of 0.57 for any 5-year period. During the lifetime of the high yield index used, the correlation between high yield bonds and the S&P 500 is 0.50, and out of the four times the S&P 500 has declined the high yield bonds have declined three times. The correlation between the S&P 500 and high yield bonds is generally stronger and less volatile over time than the correlation between the S&P 500 and investment grade bonds, indicating that there are greater diversification benefits from investment grade than high yield bonds. This conclusion is consistent with the findings of Reilly and Wright (2001) who conclude that there are even stronger correlations between high yield bonds and the S&P 500 than between high yield and investment grade bond markets.

Following Reilly and Wright (2001) and Coaker (2006) it is shown that investment grade bonds is a better source for diversification that high yield bonds. This might be explained by the phenomenon "Flight-to-quality" as studied by Baur and Lucey (2010), which is the flow from stocks into investment grade bonds when there is turmoil in the financial markets. However the researchers only studied short periods of up to 20 trading days following a stock market downturn (an example being the September 11th terrorist attacks). Together the research implies a potential benefit from diversification from the bond markets.

3.3 Stock markets' correlation with other asset classes

In the paper by Coaker (2006) the correlation between the S&P 500 and natural resources[2] was 0.49 or less for all 5-year periods, and negative in 17 out of the past 35 years, with a 35-year correlation of 0.01. Natural resources earned positive returns in six out of eight years when the S&P declined.

[2] Goldman Sachs Commodity Index, (weighted on the basis of liquidity and world market production), http://www.goldmansachs.com/what-we-do/securities/products-and-business-groups/products/gsci/ collected 2013-03-15

Büyükşahin et al (2008) use simple rolling correlations along with a dynamic conditional correlation (DCC) methodology as developed by Engel (2002) to examine the correlation between the same commodity index as above in three different sub-periods depending on trading volumes and economic conditions. The sub-periods are: May 1992 – June 1997, June 1997 – May 2003 and June 2003 – November 2008. No correlation trends could be found by either the simple rolling correlation method or by the DCC method. Furthermore they use a methodology similar to that of Longin and Solnik (2001) to analyse stock and commodity linkages when returns on the respective indices both take values in a given tail of their respective distributions. From 1991 to May 2008, correlations are negative in the joint lower tail, highlighting the diversification benefits of commodities. However, when including the returns from the summer and fall of 2008, correlations are positive in both the upper and lower tail. This indicates that the diversification benefits of commodities decreases during financial distress.

3.4 Active vs. passive portfolio management and performance evaluation

William F. Sharpe (1991) discusses the arithmetic of active management and argues that the return on actively managed portfolios must on average equal the passive portfolio; that is the market portfolio. This statement can also be scaled down to a particular asset class. The logic is very simple, and at first two investor types are classified: 'Passive' that hold the market portfolio, and 'Active' whose holdings differ from the market portfolio. Over any specified time period, the market return must equal the weighted average return on all securities in the market, and as the passive investor will obtain precisely that return, it is impossible for active investors in aggregate to deviate from the market return. As the first two returns are the same, the third must be also. That leads to his first assertion: "Before costs, the return on the average actively managed dollar will equal the return on the average passively managed dollar". This directly implies his second assertion: "After costs, the return on the average actively managed dollar will be less than the return on the average passively managed dollar". Furthermore he suggests that the best way to evaluate the performance of an active portfolio is by comparing it with a feasible passive alternative.

In another paper, Sharpe and Perold (1995) examines and compares a set of dynamic strategies for asset allocation: 'Buy-and-Hold', 'Constant-Mix', 'Constant proportion portfolio insurance' and 'Option based portfolio insurance'. This thesis shall focus on the first two strategies. A 'Buy-and Hold' strategy is a passive strategy characterized by an initial mix of assets that are bought and held without rebalancing, in contrast to the 'Constant-Mix' strategy that is active in the sense that it maintains the same proportion of assets over time. Each strategy's performance is

evaluated in the case of flat markets, bull/bear markets and in the case of volatile/less volatile markets. A 'Constant-Mix' strategy implies selling assets as they appreciate in value, and buying them as they depreciate, to keep the ratios constant over time. In volatile markets without any trend, this strategy will outperform as it takes advantage of "selling high and buying low". However if there is a bull or a bear market, the 'Buy-and-Hold' strategy will be more successful as reversals are small and relatively infrequent, and the marginal buy or sell calls in the 'Constant-Mix' portfolio will often turn out to be poorly timed. Which strategy is then the best? The answer is that no strategy can be said to the best for everyone, as it depends on the strategy's expected payoff compared with the investor's risk tolerance and expectations.

There is much literature on what the appropriate performance evaluation measure is for predicting portfolio returns: Zakamouline & Koekebakker (2009) acknowledge the common use of the Sharpe ratio based on the Mean-Variance theory (as presented in Section 2), but also state that it is a valid *prediction measure* only when there can be an accurate measurement of the standard deviation of returns, together with a normal return distribution. It is further discussed how different research replaces the standard deviation with other measures of the portfolios risk, such as downside deviation or the concept of VaR. Another example is Forinelli et al (2008) who use different performance measures accounting for non-normality in returns in order to find the optimal measure to *predict returns*.

For the purpose of the case study: It is not intended to prove the prediction ability of the Sharpe ratio on portfolio performance, but instead how different portfolios have performed according to the Sharpe ratio over time. Hence, the Sharpe ratio will not be complemented by other performance measures. Further there is a distinction made whether the portfolios are 'Active' or 'Passive', with all 'Active' portfolios being of the nature 'Constant-Mix' following Sharpe and Perold (1995).

3.5 Momentum in asset returns

Following the paper by Debondt and Thaler (1985) discussing the stock markets overreaction to new information, Jagadeesh and Titman (1993) used stock market data to document strong momentum effects, for example as the winners in the past 6 months outperformed the market by an average cumulative return of 9.5 % p.a. between the years 1965 – 1989. Three years later, Fama and French (1996) found support for the fact that short-term winners tend to outperform the market. An extension of this that is highly relevant to the case study are the results of Blitz and Vliet (2008) who investigate momentum effects in terms of returns and Sharpe ratios across asset classes. It is

claimed that the application of momentum to global tactical asset allocation across 12 asset classes (including US investment grade and high yield bonds) delivers statistically significant abnormal returns. It is also shown that a 12 minus 1 month momentum strategy (investing in the best performing portfolios in the past 12 months excluding the most recent) yields on average a return of 7.9 % p.a. This approach resembles that of the active portfolio in the case study, which is presented in greater detail in Section 6.4.

4. Data

The data consist of a stock market index, indices for investment grade and high yield bonds, the price of WTI-Crude Oil and gold. The data set starts in 1986 or at the inception of the particular index, ranging through the beginning of 2013. As an index is used to proxy the stock and bond markets, transaction costs are not included.

4.1 Stock market

As a proxy for the stock market, the S&P 500 index is chosen. First published in 1958, the S&P 500 is a broad, value-weighted stock index consisting of the 500 largest publicly traded companies in the US and is the most widely used benchmark of stock market performance in the industry[3]. This index is preferred above a world index such as MSCI-World since the study is focused on the US market. The study uses monthly return data, collected from WRDS.

In order to conduct a robustness test, two additional stock indices are used: the Nasdaq Composite that consists of over 3000 companies traded on the NASDAQ stock exchange, and the MSCI-US Investable that consists of 2500 stocks representing 98 % of market capitalisation in the US.[4] These two indices were chosen over Dow Jones Industrial Average (DJIA) since they are both value-weighted, compared to the DJIA that is a price-weighted index only containing 30 stocks. Both indices was collected from Bloomberg.

4.2 Bond markets

The bond indices presented below represent a broad bond portfolio and are replicable, either through buying the bonds directly or through an Exchange-Traded-Fund (ETF). This data was collected from the St. Louis Federal Reserve, and a more comprehensive description of these indices is presented below:

(i) Merrill Lynch US Corp Master Total Return Index Value (MLIG)

Used as proxy for investment grade bonds in the US market. The index includes corporate debt, treasuries, agency issued debt and asset backed securities. The maturities of the bonds are mixed, providing monthly observations for the total returns in the period 1985 – 2013.

(ii) Merrill Lynch High Yield Master II (MLHY)

[3] (DeMarzo, 2009)
[4] http://www.msci.com/products/indices/country_and_regional/domestic_equity_indices/us/definitions.html, collected 2013-05-01

Consists of corporate debt issued in the US with a credit rating from Moody's/S&P lower than Baa1/BB+ or Ba1/BBB+. It is an index used by the St. Louis Federal Reserve as benchmark for the high yield bond market providing monthly returns in the period 1985 – 2013.

4.3 Commodities markets

There is a wide range of natural resources actively traded in the financial markets, and this study uses two of the commodities most commonly traded: WTI-Crude Oil and gold. These are chosen due to their high relative weights in the Goldman Sachs Commodity Index (GSCI) that is frequently used to proxy the commodities market, and since gold is the main focus for one of the world's largest ETFs. Investments in these assets can be either physical or non-physical via futures contracts or ETFs. This data was collected from Bloomberg.

4.4 Other data

For the purpose of this study, the following data is used in order to investigate the drivers behind the changes in correlation:

(i) Citigroup Liquidity index

A measurement of market liquidity: the higher the value, the less liquidity on the market. The measurement takes values between 0 and 1, and the formula behind the index is found in the Appendix. This index was collected from Bloomberg.

(ii) S&P 500 Volatility Index (The VIX index)

The VIX index is based on implied volatility of the S&P 500, or more specifically the risk neutral expectation of the S&P 500 variance over the next 30 days. The measure is quoted as annualized standard deviations, and the data was collected from WRDS.

(iii) Risk-free interest rate

In order to accurately calculate the Sharpe ratios in the case study, a proxy for the risk-free interest rate was collected from WRDS under the database: "Fama-French Factor's" and it is the annual return rate on a three-month T-Bill.

4.5 Crises definitions

In order to study how correlation varies with the onset of crises, the following crises definitions are used:

(i) Dotcom crisis

This is defined as the bear market from late March in 2000 until the S&P 500 recovered in October 2002. More specifically: *24 March 2000 – 9 October 2002*.

(ii) Subprime crisis

This period is considered to start in mid-summer 2007 as the subprime crisis begins to unfold and financial institutions and companies around the world begin to default. The crisis period is defined to last until mid-2009, when the stock market showed signs of recovery. More specifically: *1 August 2007 – 30 June 2009*.

(iii) Sovereign debt crisis

This period is considered to start when Greece is downgraded to junk bond status by Standard and Poor's during June 2011. The period is for this thesis defined as *30 June 2011 – 31 Dec 2012*.

To supplement the periods above, the following pre- and post-crisis periods are defined in order to study the actual effect when the crises hit. These periods are defined to have approximately the same duration as the crises periods.

i) Pre Dotcom crisis
1 January 1998- 24 Mars 2000

ii) Post Dotcom crisis
9 October 2002- 31 December 2004

iii) Pre subprime crisis
1 January 2005 -30 June 2007

iv) Post subprime crisis
30 June 2009- 30 June 2011

5. Hypotheses

This thesis uses a top down approach, where the correlation stability in returns on the S&P 500 and the bond indices and the return on the S&P 500 and the commodities are first analysed over the entire sample period, 1986 – 2013, to determine whether the first hypothesis can be rejected:

Hypothesis 1: The correlation in returns between the stock market and the specified asset classes is constant through 1986 – 2013.

Following a rejection of Hypothesis 1, a closer examination is made of the stability of this correlation during periods of crisis, as defined in Section 4.5.

Hypothesis 2: The correlation in returns between the stock market and the specified asset classes is not affected over crisis periods.

Following Hypothesis 2, the Dotcom and Subprime-crises will be analysed in more detail in order to investigate if any of the factors defined in Section 4.4 can explain potential changes in correlation during times of crisis. This leads to the next hypothesis:

Hypothesis 3: The correlation in returns between the stock market and the specified asset classes is not affected by market liquidity or changes in market volatility.

These three hypotheses are followed by a case study, which aims to quantify the actual benefits of cross-asset class diversification during the period 1987 – 2012. As specified, an increase in the correlation of asset returns will directly increases the risk of the portfolio. From Section 2.1 it follows that an investor's objective is to maximize his Sharpe ratio (slope of the CAL) that is returns in relation to risk. If the return correlations were constant, the Sharpe ratio of different portfolios would be predictable, and therefore it would be possible to see a clear pattern on when to rebalance the portfolio. The case study will evaluate the performance of the individual asset classes compared to a set of active portfolios in terms of their yearly, realized Sharpe ratios, in order to quantify the historical diversification benefits of the different assets over time in general, and during crises in particular.

Case study: Evaluate the historical cross-asset class diversification benefits over time in general and during crises in particular, in terms of the portfolios Sharpe ratios.

6. Methodology

In this section, how the different hypotheses are tested and how the case study is performed is presented in greater detail. To get a better understanding of how the different regressions are run, a description will first be presented of the way in which autocorrelation amongst the error terms was resolved.

6.1 Newey-West standard errors

As will be presented later in this section, moving and rolling estimation windows are used for the return correlations, which give rise to the problem of autocorrelation, that is that the correlation in period N is affected by the correlation in period N-1. A method to reduce this effect was developed by Newey and West (1987), which uses a positive, semi-definite, heteroskedasticity and autocorrelation-consistent covariance matrix to reduce the autocorrelation from an ordinary-least-square (OLS) regression. The OLS-regression rests on several assumptions, which can be partially resolved by using this alternative approach. The Newey-West standard errors are calculated dependant on a choice of maximum lag, which is calculated from a distributed lag of the OLS-residuals, and this is chosen to match the actual window length when performing the tests. The use of Newey-West standard errors will be robust to arbitrary departures from homoskedasticity, which is one underlying assumption in OLS-regressions. This will in fact bring higher standard errors to the regressions; however the results will be more reliable.

6.2 Testing for constant correlation over time, 1986 – 2012

Zivot and Wang (2003) discuss the common use of rolling analysis of time-series data, and assert that if parameters are truly constant, that the estimates over a fixed size rolling window should then not be too different. This method is used by Coaker (2006) to study correlation volatility over time, and will be used in this study. Another method discussed as common in the analysis of financial time-series data in particular is the use of a moving window (or moving average window), where the window is symmetric around the particular observation, and where the estimate is the aggregate correlation within the window. To reach a stronger conclusion, both non-overlapping rolling windows of 12 months, as used by Coaker (2006), and moving window correlation estimations are graphed and analysed. As the size of the window has a strong impact of the results, particularly in the moving window correlation estimations, three different window sizes are used: 6, 24 and 60 months, to highlight the differences; however the main focus will be on the 24 month window.

In order to quantify these results further, the following regression with Newey-West standard errors is run with the correlation between the stock market return and asset returns (X) as the dependent variable, and yearly dummy variables covering the entire time-series, to see if there are certain periods that more strongly affects the correlation:

$$\rho_{Stock\ market;X} = \alpha + \beta_1 * Dummy1 + \beta_2 * Dummy2 + \cdots + \varepsilon \quad (6.2.1)$$

If the correlation is constant, no individual dummy would provide more significant results than another. The regression is run with correlation values from a 13 months moving window, which is 6 months before and after each individual observation. Thus, the lag specified was 6 months.

All regressions in this thesis are run with a window and lag as specified above.

6.3 Testing if the correlations are unaffected during crises periods

A regression with Newey-West standard errors is run with correlation as the dependent variable on three clustered dummy variables: A 'Crisis' dummy consisting of the observations during a specified crisis, and similarly the periods before and after crises periods are grouped into the dummy variables: "Pre Crisis" and "Post crisis", respectively. This regression provides the first insight into how the different asset classes return correlations changes with the onset of crises, and what asset classes appears to be more affected than others. The regression below is run for all asset returns correlations with the return on the stock market:

$$\rho_{Stock\ market;X} = \alpha + \beta_1 * Pre\ Crisis + \beta_2 * Crisis + \beta_3 * Post\ Crisis + \varepsilon \quad (6.3.1)$$

As the particular crises are studied in more detail, a regression with Newey-West standard errors is run similar to 6.3.1 but without grouping the periods. Following this regression, it can be highlighted if any particular periods more strongly affect the correlation in returns between the stock market and the asset classes. The regression is specified as:

$$\rho_{Stock\ market;X} = \alpha + \beta_1 * Pre\ Dotcom + \beta_2 * Dotcom + \beta_3 * Post\ dotcom + \beta_4 * Pre\ Subprime + \beta_5 * Subprime + \beta_6 * PostSubprime + \beta_7 * Sovereign + \varepsilon \quad (6.3.2)$$

The regression is accompanied by a graphical illustration of the moving window correlations during the time before, during and after the specific crises, to illustrate if the correlation remains at a certain level throughout the crisis periods.

6.4 Testing if the correlations are unaffected by market factors

In line with the methodology presented for testing Hypotheses 1 and 2, a regression is run with Newey-West standard errors holding the correlation between the stock market and asset returns as the dependent variable, and the monthly change in the parameters from Section 4.4 as the explanatory variables.

The liquidity level is calculated as the moving average over the same window as the moving correlation, that are using 6 months before each observation and 6 months after. The changes in volatility is calculated in two steps, first by creating a moving average of volatility using the same window as above, and then by creating return by dividing observation N with observation N-1. This methodology solves the problem of comparing a spot price with a moving average, as only moving averages are compared. It is also emphasized that this approach might result in regression coefficients above 1 or below -1, seen in β_1 and β_2 below, but given the small number on the Liquidity level and the change in volatility, the correlation will always remain in the range of -1 to 1. The regression is specified as:

$$\rho_{Stock\ market;X} = \alpha + \beta_1 * Liquidity + \beta_2 * \Delta\, Volatility + \varepsilon \qquad (6.4.1)$$

6.5 Case study: Assessing the benefits of diversification

The aim of this study is to show what asset classes have provided the best diversification benefits over the 25 year period 1985 – 2012. As shown in Section 2, the correlation between assets ultimately determines the risk of the portfolio, and if investors are assumed to act rationally, they are only concerned about return in relation to risk. The Sharpe ratio measures this relationship, and is chosen to evaluate the performance of the set of portfolios, to understand which portfolios that provided the best return in relation to risk on a yearly basis. The results are analysed through the perspective of the results from Hypothesis 1 – 3, to conclude the actual diversification benefits from diversification as correlation changes over time, and during particular crisis periods. This measure was chosen based on the assumption of investors' rationality (above), and it is one of the measures used by Blitz and Vliet (2008) to evaluate the performance of momentum strategies across asset classes.

This study compares the performance of a portfolio that is actively rebalanced every year, based on the combination of asset classes that performed the best in the previous year, which is a

modified but still similar approach to that of Blitz and Vliet (2008), with the following set of passive [P] and active 'Constant-Mix' [CM] portfolios, classified on the basis of Sharpe and Perold (1995):

i) Diversified portfolio with equal weights (20%) in stocks, investment grade and high yield bonds, oil and gold [CM]
ii) Bond portfolio (50 % in investment grade/high yield bond portfolio respectively) [CM]
iii) Stock portfolio (100 % in the S&P 500) [P]
iv) Stock and bond portfolio (50 % in the Stock and Bond portfolio respectively) [CM]
v) Investment grade bond portfolio (100 %) [P]
vi) High yield bond portfolio (100 %) [P]
vii) Gold portfolio (100 %) [P]
viii) Oil portfolio (100 %) [P]
ix) Average optimal portfolio (34 % in the investment grade/high yield bond portfolios respectively, 9 % in the stock portfolio and 12 % in the Gold and Oil portfolios respectively) [CM]

The case study is carried out in Excel, and uses the monthly return data as specified in Sections 4.1, 4.2 and 4.3. As Sharpe ratios are evaluated on a yearly basis, the monthly return is compounded to get the yearly returns from each asset class, and a covariance matrix is constructed on a yearly basis, based on the return data in each year (that is 25 matrices in total). The study starts out by finding the optimal weights in each asset class every year to produce the highest possible annual Sharpe ratio. For this purpose, a second 'weighted covariance matrix' is set up for each year, based on the former covariance matrix, and the weights in each asset class. The sum of this weighted covariance matrix is the portfolio variance, and the standard deviation is the square root of the portfolio variance. The return of the portfolio is the simple weighted average of the asset returns, calculated from the yearly returns and the weights in each asset class. As the Sharpe ratio uses excess returns, the average risk-free rate was calculated on a yearly basis (specified in Section 4.4), and subtracted from the portfolio return, thus creating portfolio excess returns on a yearly basis. The Sharpe ratio is calculated by dividing this portfolio excess return with its standard deviation. To find the optimal portfolio, the Solver function is used to maximize the Sharpe ratio directly, by changing the portfolio weights, as they ultimately determine both the standard deviation and return on the portfolio. A constraint was

put on the weights to be in the range of 0 % – 100 %, and that the total weights had to sum up to 100 %, thus implementing a short-sale and borrowing constraint for the portfolio.

To find the Sharpe ratios of portfolios: i, ii, iv and ix, the same procedure with a weighted covariance matrix is constructed on a yearly basis, however holding the weights in each asset class fixed (hence a 'Constant-Mix portfolio). The sum of the covariance matrices constitutes the variance on each portfolio, and the Sharpe ratio is similarly the weighted average of the yearly returns less the average yearly risk-free rate, divided by the square root of the portfolio variance.

The Sharpe ratios for portfolios ii, iii, v, vi, vii) and viii, is the yearly excess returns, divided by the yearly standard deviations of returns.

To measure the performance of the active portfolio rebalanced each year based on the optimal portfolio, a weighted covariance matrix is set up for each year, using the weights from year N-1, and the excess return is calculated using the same optimal weights from year N-1, and the return and risk-free rate in year N.

As the study is performed on a yearly basis, there is a need to define entire years as crisis periods, as well as pre- and post-crisis periods, in order to analyse how the Sharpe ratios are affected over the crises cycles. The new, broader definitions are presented below:

a) Pre Dotcom: 1998 and 1999
b) Dotcom crisis: 2000, 2001and 2002
c) Post Dotcom: 2003 and 2004
d) Pre Subprime: 2005 and 2006
e) Subprime crisis: 2007 and 2008
f) Post Subprime: 2009 and 2010
g) Sovereign debt crisis: 2011 and 2012

In order to illustrate the best diversification benefits, the monthly return on the portfolios with the highest Sharpe ratios during the specific crises are graphed.

6.6 Robustness test

In order to conduct a robustness test of the study, Hypotheses 2 and 3 was re-tested with new proxies for the stock market. As the study takes the viewpoint of an equity investor, it is determined whether the results are robust in the sense that the same result would apply to a broader set of equity investors, e.g. using alternative stock indices. The new proxies for the stock market are

described in Section 4.1. All other data remain the same, as does the methodology in testing the hypotheses.

6.7 Problematization

The first obvious problem with the methodology described above is that of autocorrelation. This problem is tackled as described in Section 6.1 by the use of Newey-West standard errors. However the problem is not completely resolved. There also exist some problems with endogeneity since there might be a number of parameters in the error term of especially the liquidity and volatility data. It can also be assumed that a lot of other factors correlate with these two parameters in times of crisis.

The choice of Sharpe ratio as the risk-adjusted return measure for the purpose of the case study can also be questioned, and several other measures exist, such as the Treynor ratio and the Modigliani risk-adjusted performance framework (RAP). Sharpe ratio was chosen over the Treynor ratio since the latter only takes into account market risk (β). The RAP-framework has some advantages over the Sharpe ratio, mainly that it quantifies the risk-adjusted return as percentages, however it was rejected since the Sharpe ratio has a stronger connection with the theoretical framework presented. Furthermore, the RAP-framework is partially derived from the Sharpe ratio.

Another criticism of the Sharpe ratio is the scepticism of the existence of a risk-free rate. However, finance theory relies on the existence of a risk-free rate and this problem will always be present no matter which risk-adjusted measure that is chosen.

7. Results

This section will present the results obtained for the hypotheses and the case study. The discussion and interpretation of these findings will be presented in Section 8. An initial illustration of the returns on the different asset classes from 1986 to 2013 is shown in Figure 1, and it is clear that the stock market outperformed the other asset classes in terms of returns during the 1990s, losing some of this outperformance during the 2000s.

7.1 Constant correlation test results

Following the calculation of three different moving correlation windows, the graphical results of the 24 month correlation window between the stock and bond markets and the stock and commodities markets are presented in Figures 2 and 4 respectively. The rolling 12 month correlation windows in question are presented in Figures 3 and 5 respectively. The graphs match up well; the main difference is that the rolling windows show sharper swings due to fewer observations. Graphical illustrations of the results from the 6 and 60 month moving window can be found in the Appendix.

The correlation between the stock- and high yield bond markets diverges in correlation from the stock- and investment grade bond markets in the 2000s, exhibiting consistently higher levels of correlation. From this graphical illustration, it appears as if the correlation between the stock and bond markets is not particularly stable over time.

The correlation between the stock- and commodities markets exhibits a higher rate of variability than the stock- and bond market, and also a generally lower level of correlation. As in the case of the stock- and bond markets correlation, it supports a rejection of the hypothesis that correlation is in fact constant over time.

These graphical illustrations of a non-stable correlation are supported by the descriptive statistics in Table 1, which exhibit a high level of variance in the correlation coefficients, with maximum levels of correlation being very high for all assets, and also strongly negative levels of correlation as a minimum.

Running regression 6.2.1 with Newey-West standard errors shows that some years have significantly stronger explanatory effects than others on each of the correlations, significant on a 5 % level, as presented in Table 2.

This test together with the graphical investigation leads us to reject Hypothesis 1 and to conclude that correlation is neither constant nor stable over time.

7.2 The effect of crises periods on correlation

As correlation was proven to vary significantly over time, the focus is now shifted towards correlation changes in times of crisis. The results from Regression 6.3.1 with Newey-West standard errors that included the three clustered dummy variables: 'Crisis', 'Pre-crisis' and 'Post-crisis' are presented in Table 3. The stock market correlation with investment grade bonds remains at low levels over the crises, and it even shows that correlation will decrease in times of crises, and in the post-crisis period, that the correlation decreases even further, as the investment grade bonds do not follow the stock market in the bull market recovery following the crises. This is illustrated in Figure 1. All results from the investment grade bond market are significant at the 1 % level.

The high yield bond market will becomes increasingly correlated with the stock market during times of crisis, however the significance is lower (17 %). In times after crises the correlation declines, but at a level that is not as statistically significant. However, this presents a pattern that suggests that during crises the correlation increases as the returns on both the high yield bond- and stock market are negative. Thus a difference between the bond markets, where investment grade bond correlation decreases with the stock market during and after crises is observed, whereas the high yield bond correlation appears to increase during crises.

WTI-Crude Oil shows little to no significance in explaining correlation differences over periods of crisis, whereas gold decreases its correlation with the stock market during crises; however this is only significant at the 15 % level.

Table 4 shows the regression results from regression 6.3.2 and provides more detailed information for the specific crises. Around the Dotcom crisis the correlation between the stock market and investment grade bonds decreases during the actual crisis period, a result that is significant even below the 1 % level. This is also visualised in Figure 6. Around the Subprime crisis, the correlation increases slightly, but it remains at low levels throughout the crisis cycle. Figure 8 shows how the correlation decreases in the beginning of the crisis, before it increases towards the end of the period, decreasing again after the crisis.

The high yield bond market shows different results, with a strong increase in correlation during both the Subprime and Sovereign debt crisis, as there is a strong increase in correlation, significant at the 1 % level in both cases, as displayed in Table 4. Figure 8 shows how there is an aggregate increase in correlation during the Subprime crisis.

Gold shows a strong decrease in correlation during the Sovereign debt crisis which is significant below the 1 % level. During the Subprime crisis the correlation also decreases, however at

a less significant level, 16 %. Figure 9 shows how the correlation between gold and the stock market trends downwards going into the Subprime crisis, and how the correlation seems to increase after the crisis.

The changes in correlation during times of crisis for WTI-Crude Oil and the stock market shows a lack of significance in Table 4, and from Figure 7 and Figure 9 no clear trend can be observed.

From these results, we reject Hypothesis 2 in the sense that correlation is unaffected during crises for investment grade and high yield bonds as well as gold. For WTI-Crude Oil, we cannot reject Hypothesis 2.

7.3 The effect of market parameters on correlation

Following the results for Hypothesis 2, it is shown that investment grade bonds decreased its correlation with the stock market during and after the Dotcom crisis, and resisted the increase in correlation during the Subprime crisis that high yield bonds experienced. Gold decreased in correlation with the stock market during the Subprime and Sovereign debt crises, and these results lead us to focus Hypothesis 3 towards those two asset classes, to understand why there have been diversification benefits from investment grade bonds and gold.

The results from regression 6.4.1 are presented in Table 5. During the Dotcom crisis the liquidity level has a significant effect on the correlation between the stock market and both asset classes; however the effect is much stronger on investment grade bonds. This indicates that as liquidity is reduced in the market, the correlation decreases, and following Hypothesis 2 it is seen that the correlation decreases between the stock market and investment grade bonds during the Dotcom crisis.

The changes in volatility do not have any explanatory effects during the same crisis. During the Subprime crisis the dominant effect stems from the changes in the market volatility level, and as the volatility increases in the market, the correlation decreases between the stock market and the asset classes, the effect being higher for gold than for investment grade bonds. This decrease in market liquidity (or the increase in the liquidity premium) positively affects the investment grade bond market's correlation with the stock market during this crisis, and the opposite is true for the correlation between gold and the stock market.

From these results, we reject Hypothesis 3 as both liquidity and changes in volatility significantly affects the correlation during crisis periods; however there are differences in the effects between the different crises.

7.4 Case study results

Following the rejection of Hypothesis 2 for all asset classes apart from WTI-Crude Oil, the focus now shifts towards the actual benefits of diversification during the 25 year-period 1987 – 2012 in order to understand whether there is a direct effect on investment management from changes in correlation. At first the summary statistics are presented, before getting into how the optimal portfolio varies in composition. It is then explored how the different portfolios performed at the onset of crises in general and during the specific crises in particular.

7.4.1 Summary statistics

If an investor could perfectly anticipate changes in the financial markets and then position himself accordingly, it would be possible to achieve the optimal Sharpe ratio each year. The descriptive statistics of all portfolios are presented in Table 6, the yearly Sharpe ratios of all portfolios are presented in Table 7 and the yearly composition of the optimal Sharpe ratio is presented in Table 8. The optimal portfolio under short-sale and borrowing constraints shows an average Sharpe ratio of 3.16. The portfolio rebalanced each year along the optimal weights in the previous year yields an average Sharpe ratio of 0.86, which is similar to the passive portfolio that holds a diversified set of assets that averaged a ratio of 0.85. However, the variation in the diversified portfolio is the lowest of all portfolios. It is also shown that the average optimal portfolio is a diversified portfolio, with holdings in each of the different asset classes, however with the lowest holdings in the Stock portfolio.

The highest Sharpe ratios among the passive portfolios is found in the bond markets, where the high yield portfolio yielded the highest Sharpe ratios on average (1.50), but with a high variation. The investment grade portfolio proved to be much safer, and still provided Sharpe ratios on average above 1.0 (1.04). The equally weighted bond portfolio performed well, with the safety from the investment grade bonds limiting the downside, and the high yield bonds providing higher upsides, yielding an average Sharpe ratio of 1.30.

The stock market had a good decade in the 1990s, (1.53) but crashed rather hard in the 2000s (0.17) resulting in an average Sharpe ratio of 0.77. For the broad equity investor, it is proven that there are strong gains to be made by investing 50 % of the portfolio's value in the bond portfolio: this strategy still outperformed the strong stock market in the 1990s, and landed much softer in the 2000s, yielding Sharpe ratios of 1.73 and 0.62 respectively, for an average of 1.07.

Commodities had the lowest Sharpe ratios on average, much due to the high standard deviation in the returns. Gold had a particularly bad decade in the 1990s, but recovered in the 2000s,

with Sharpe ratios of –0.84 and 0.91 respectively, for the lowest average of 0.04. Oil performed second worst, with an average Sharpe ratio of 0.27 over the sample period.

7.4.2 The portfolios' performance during crises in general

As the case study was carried out on a yearly basis, the crisis definitions follow the specification in Section 6.4. In the pre-crisis periods, the best performing portfolio was the diverse and passive portfolio, with equal weights in all of the five asset classes. The investment grade bonds perform rather badly during the pre-crisis periods, and the only two portfolios with a negative Sharpe ratio are the investment grade bonds and the equally weighted bond portfolio. This however changes dramatically with the onset of an actual crisis period, where the relative performance of the portfolios changes substantially. The results show that the worst performer in pre-crisis periods becomes the best performer during crisis periods, as the investment grade bonds perform the best, with the high average Sharpe ratio of 1.35 (comparing this with the average stock performance with a ratio of –0.67, puts this ratio into perspective). Thus, there appears to be a lagging effect from the bad performance of the bond market into the stock market. The second best performance is shown in the one-year rebalancing portfolio; however this is due to the large holding of investment grade bonds during the Dotcom crisis in the optimal portfolio (see Table 8).

In post-crisis periods, the high yield bonds are the best performer, with a very high average Sharpe ratio of 3.19, followed by the average optimal portfolio and the equally weighted bond portfolio. Noticeable is the fact that all portfolios in the study show Sharpe ratios above 1.0 during this recovery period.

7.4.3 Diversification benefits during the Dotcom crisis

In the two-year period before the Dotcom crisis, both the investment grade and high yield bond markets were underperforming compared to the stock market. During the crisis period, this relationship is reversed and the investment grade bond market is the best performer. This is consistent with the results from Hypothesis 2, that the correlation decreased between the stock market and investment grade bonds. Hence, this correlation decrease is proven to directly affect the performance of the portfolios. As was also shown in the results for Hypothesis 2, the high yield bond market correlation with the stock market increases during a crisis, which holds true also in this study as the Sharpe ratios remain below 0. This shows that investment grade bonds were the best possible diversification during the Dotcom crisis in terms of reward-to-risk. The period after the crisis is a time where the high yield bond market takes off, even more than the stock market, again in

line with earlier tests, and the Sharpe ratio of the investment grade bonds decline, however still being at positive levels. The commodities markets show a decline in performance during the crisis period, indicating that the diversification benefits were not as good as in the case of investment grade bonds. The monthly returns during the Dotcom crisis for investment grade bonds, gold and the stock market are illustrated in Figure 10. The volatility in returns of investment grade bonds is shown to be much lower than for gold during this crisis.

7.4.4 Diversification benefits during the Subprime crisis

Before the crisis, the best performance is found in the equally weighted and diversified portfolio and the average optimal portfolio. The high yield bond market also performed well. The pattern previously mentioned, with negative Sharpe ratios on investment grade bonds in pre-crisis periods, also holds true for the Subprime crisis. Although during the actual crisis, the performance of investment grade bonds increased, however there was still a slightly negative Sharpe ratio (-0.16) as the correlation with the stock market did not decrease as much as during the Dotcom crisis, which is consistent with the findings of Hypothesis 2. Following Hypothesis 2, the best performer should be gold, as the correlation was shown to decrease during the Subprime crisis, something that proves to hold, with an average Sharpe ratio of 1.05. The worst performing portfolios are the stock- and high yield bond portfolio, findings that are also consistent with the results from Hypothesis 2, highlighting an important connection between the two asset classes. The only portfolios that show positive Sharpe ratios during this crisis are the commodities and diversified portfolios. The period after the Subprime crisis is characterized by high and positive Sharpe ratios across all portfolios (all above 1.0). The monthly returns during the Subprime crisis for investment grade bonds, gold and the stock market are illustrated in Figure 11. Even though gold had the higher Sharpe ratio during this crisis, the volatility in returns on investment grade bonds were still lower than for gold.

This Case study supports the findings in Hypothesis 2, and highlights the importance of correlation changes on investment management. Investment grade bonds provided the best diversification during the Dotcom crisis, and also performed better than the stock market during the Subprime crisis. Gold provided the best diversification benefits during the Subprime crisis, and it can be concluded that a strategy that rebalances on a yearly basis on the best performance in the previous year is not an appropriate strategy from a diversification standpoint.

7.5 Robustness test results

As this study investigates the time-varying correlation between the stock market and the bond/commodities markets to assess the benefits of cross-asset class diversification, the proxy for the stock market was altered from the S&P 500 to the Nasdaq composite index and the MSCI-US Investable index, to test the robustness of the results presented in Sections 7.2 and 7.3.

Table 11 shows the MSCI-US Investable index's correlation with the other asset classes at the onset of a crisis, and it is shown that high yield bonds show a stronger, more significant increase in correlation during crises. The investment grade bonds show a stronger negative change in correlation with the period following crises, and a significant negative change during crises. Thus the use of the MSCI-US Investable index amplifies the results from the bond markets. This is however not the case for commodities, where oil is not at all significant, and gold shows a less significant decrease in correlation during crises than with the S&P 500, significant at the 21 % level. Analysing the crises in more detail as in Table 13, the results shows a general support for the earlier findings.

Using the Nasdaq composite index as the stock market proxy, Table 12 also shows that high yield bonds increase in correlation with the stock market during crises in general, but for investment grade bonds it only shows significant decreases in correlation in the period after crises. However when studying Figure 16, there is a clear downwards trend in correlation between investment grade bonds and the stock market, even if the regression results are less significant than with other stock market proxies. Table 14 shows the results from regression 6.3.2, which is in line with previous results. The graphical illustrations show that the results from the robustness test are in line with the findings from Hypothesis 2.

The robustness test of Hypothesis 3 is presented in Table 15, wherein it is possible to see that the chosen market factors have the same effect when using both the Nasdaq composite index and the MSCI-US Investable index as when the S&P 500 is used. The same coefficients are significant and they have similar values. This will strengthen the conclusions in the analysis as well as the presented results.

8. Analysis

In this Section, the results presented in Section 7 are analysed and discussed. The aim is to put the findings from this thesis into perspective by connecting the results with previous literature, and to discuss the implications for investment management, as well as suggesting areas for further research.

At first this study aimed to challenge the assumption of the MPT that correlation is constant over time. This was proven to be wrong by the first tests where it was possible to see that correlations vary distinctly over time; volatility can be observed both graphically and from the regression results. This supports the findings of Coaker (2006), and as correlation does vary over time, this brings both opportunities and significant risks to investors. If correlation between asset classes were constant, it would be possible to hold an optimal risky portfolio. It proves that it can be profitable to diversify and it could be crucial in times of crisis, but the question remains as to how?

It was shown with statistical significance that investment grade bonds have provided good diversification benefits in times of crises, as correlation between the stock market and investment grade bonds tends to decrease during crises, as proven by the regression results in Table 3 and Figures 6 and 8. This indicates that there is a "flight-to-quality" effect as described in the findings of Baur and Lucey (2010). This is the nature of investment grade bonds: they provide a smaller predictable return every year compared to stocks and they are subject to different risks (see Figures 10 and 11). It was also shown with statistical significance that correlation kept decreasing in the period after the crisis; this could reflect that as confidence returns to the financial markets, there is a reversed flight-to-quality effect, leading to a sell-off in the safer bond markets, and a return to riskier assets.

Gold shows a decrease in correlation with the stock market during the Subprime and Sovereign Debt crises, indicating that gold is still considered a safe investment when the financial markets are unstable. Büyükşahin et al (2008) concluded that diversification benefits from commodities eroded during the Subprime crisis, however they did not study the individual commodities, but instead a broad commodity index. It might well be that gold is a good diversification in times of severe financial crises, but commodities in general are not.

It is concluded that the high yield bond market provides a weak alternative for diversification, as it tends to increase its correlation with the stock market in times of crises, particularly seen for the Subprime and Sovereign debt crises, which is line with Coaker (2006) and Reilly and Wright (2001). However it can be seen in the case study that high yield bonds provide a good alternative for equity investors, as it has outperformed the stock market in terms of higher

Sharpe ratios during the chosen time span. However it is important to take transaction costs and market access into account when it comes to the high yield bond market. Access to the market can be difficult, but it has been more accessible due to a number of ETFs in recent years. However this is something that further studies needs to examine.

The next part of the study investigated if changes in any of the market factors liquidity and/or volatility had any explanatory effects on the correlation between the stock market and the investment grade bonds, and the correlation between the stock market and gold. This is interesting as they reflect the climate of the financial markets and might provide an indication for investors when it is time to rebalance their portfolios. During the Dotcom crisis the liquidity premium affected the correlation between the stock- and investment grade bond market negatively, which supports the "flight-to-safety" effect, however this effect was slightly reversed during the Subprime crisis, as it became slightly positive. As previously discussed, this should be due to the different nature of the Subprime crisis as compared to the Dotcom crisis. The change in volatility levels had little impact during the Dotcom crisis; however it is the dominant factor during the Subprime crisis, where volatility reached unprecedented levels. This negatively affects both assets' correlations with the stock market. The negative asset correlations indicates a flight to safety since the return on the chosen assets stay positive due to higher demand, however the effect appears to come from volatility, and not as much from liquidity.

In an attempt to quantify the actual benefits of diversification over the past 25 years, a case study was conducted that compared the Sharpe ratio of an all-equity investor with the Sharpe ratio for a set of diverse active 'Constant-Mix' portfolios, passive portfolios and an active portfolio that rebalances every year according to previous year's optimal portfolio. The choice of the Sharpe ratio was based on its sound theoretical framework, linking returns to risk effectively determined by the assets' correlation, its common usage in the industry and as it was used by Blitz and Vliet (2008), whose results were key in motivating our research.

The price for an all-equity investor to ignore diversification has been high, as the Sharpe ratio for that portfolio is significantly lower on average than any diversified portfolio or an all-bond portfolio. This study shows that the highest average Sharpe ratios occurred for the bond portfolios, and it confirms the finding that investment grade bonds provide high diversification benefits, as it is the optimal portfolio during the Dotcom crisis, and one of the best portfolios during the Subprime crisis. Another interesting finding on investment grade bonds is that they performed worst in the period *before* crises: this could imply that the bond market is an indicator that the stock market is

about to tumble, however this is an area this study does not address and may indeed be due to several factors. One possible explanation is that interest levels tend to be higher before crises in order to cool down the economy, but this is an area which we strongly recommend further research.

The high yield bond portfolio was the best performer on average, but it also had the highest variability and its strong correlation with the stock market lead to its worst performance occurring during crises periods: thus it is not a good alternative for diversification, but given the on average high Sharpe ratios it remains an interesting investment alternative.

Gold proved to be the best diversification vehicle during the Subprime crisis, with a Sharpe ratio far exceeding its average over the 25-year period. On average, the performance of the commodities is lowest, mainly due to high standard deviations in their returns. The benefits from diversifying into gold during the Subprime crisis could be due to the nature of the crisis as such; it was not only a stock market crash, the entire financial system was threatened. As the financial system is threatened, this is bound to affect the bond market, but not necessarily gold (or other physical assets). Even though commodities on their own do not have attractive Sharpe ratios, a risk-averse investor would still have benefitted from diversifying into commodities, as the variability is the lowest in the portfolios that was the most diversified across all the asset classes.

Perhaps surprisingly, the overall performance of the equally diversified portfolio did not match those of the bond portfolios, even though variability was less. The actively rebalanced portfolio based on last year's optimal portfolio performed rather poorly compared to the others, and when taking transaction costs into account, this would have been a costly strategy, not providing the returns one might have expected following the reasoning behind momentum strategies, especially drawing from Blitz and Vliet (2008), who found a significant momentum effect in cross-asset class investments. However, they used actual returns to rank the highest yielding assets, whether this portfolio selected the assets that created the optimal Sharpe ratio, and there is apparently a big discrepancy between these two methods.

Figure 10 and Figure 11 challenges the notion of gold as a safe diversification alternative during times of crisis. It shows that even if gold were to have positive returns, the volatility would be quite high resulting in a lower Sharpe ratio on average compared to investment grade bonds. An investor therefore has an alternative in times of crisis, to choose an absolute return that is more frequently the case with investment grade bonds or choose speculation on higher returns with gold. Investment grade bonds often results in higher Sharpe ratios, but it all comes down to the investor's risk aversion.

9. Conclusion

This thesis provides evidence that correlation varies distinctly over time, and that different asset classes are affected differently over the crisis cycle. Investment grade bonds decreases in correlation with the stock market during periods of crisis in general, and the case study proves that these correlation changes can be directly translated into diversification benefits, given the high relative Sharpe ratios provided by an investment grade bond portfolio during a crisis. Gold is shown to decrease its correlation with the stock market under severe financial crises such as the Subprime crisis, and consequently it provided the best diversification benefits in terms of Sharpe ratios during that crisis. It is however concluded that the volatility in returns from gold is much higher than that of investment grade bonds during crises. Furthermore it supports previous research regarding the correlation increases between the stock market and high yield bonds during crises; this is supported by the case study where the high yield bond- and stock portfolios were the worst performing portfolios during crises. WTI-Crude Oil was not affected by crises with any statistical significance.

The diversification benefits that arise from investment grade bonds and gold from the changes in correlation are partially due to a "flight-to-safety" effect. It is also shown that a well-diversified portfolio has not benefitted from higher Sharpe ratios than those yielded by the bond markets, but it has had lower variability according to the same study, which is line with the MPT.

9.1 Suggestions for further research

During the case study it was found that the excessive return on the investment grade bond portfolio was negative in the times immediately preceding crisis periods, which might imply that negative investment grade bond returns indicate a future stock market crash, or financial turmoil. This effect is something that was not considered at the commencement of this thesis, thus no further emphasis was put on this particular area. Furthermore, it would be beneficial for the investment- and risk management professions to use economic models without assuming constant correlation, allowing modelling risk and returns in a way that reflects reality. A reality in which correlations are time-varying.

10. Figures and Tables

Figure 1

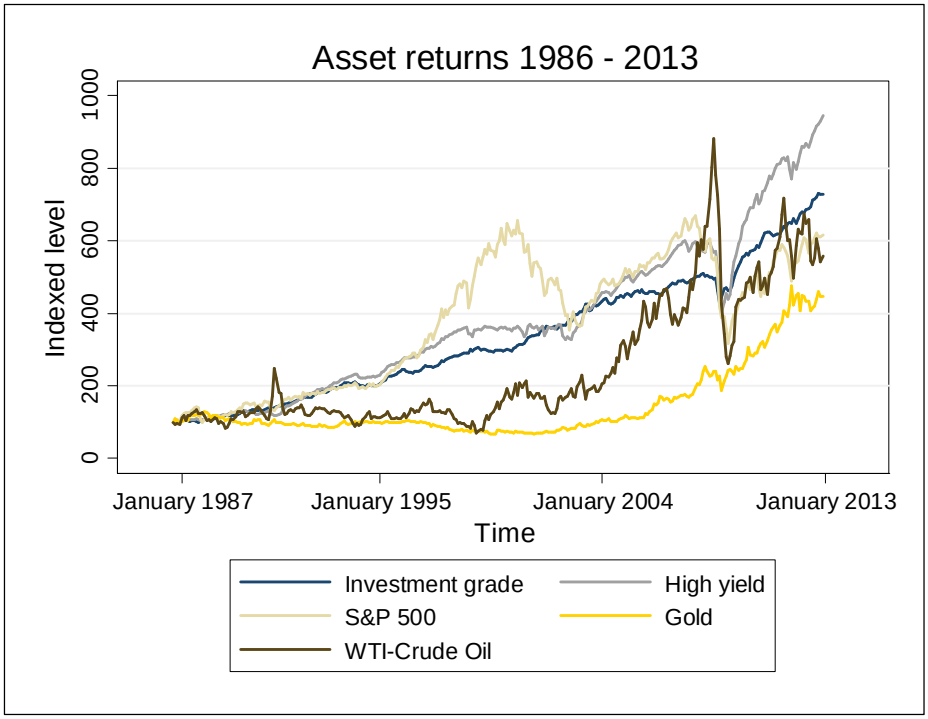


Figure 2

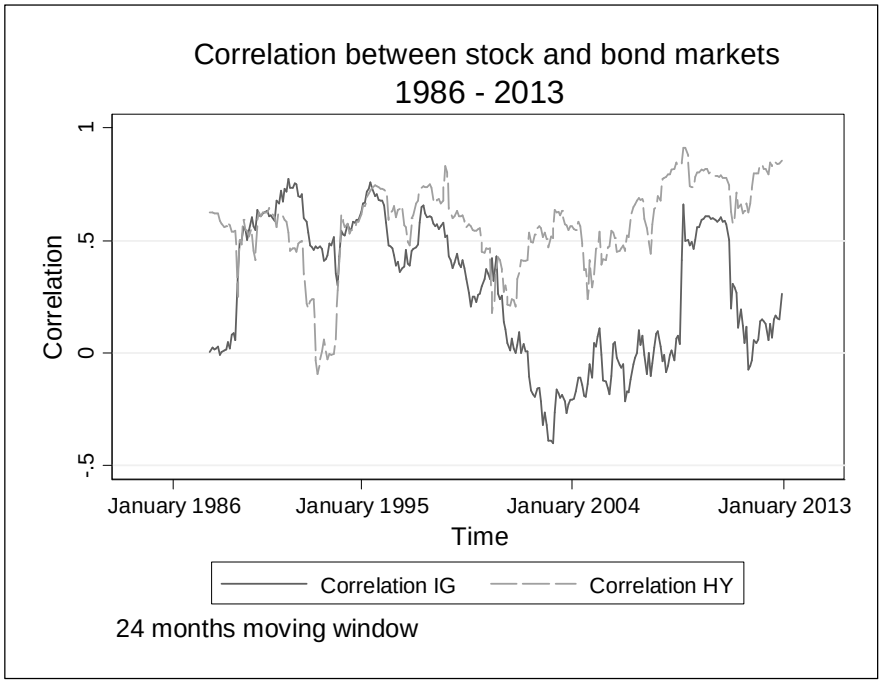


Figure 3

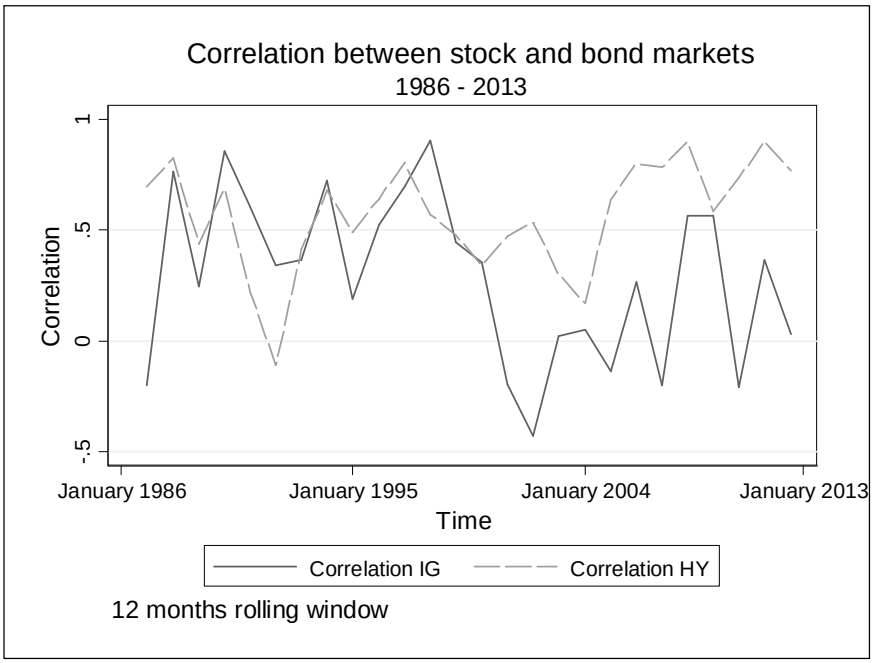


Figure 4

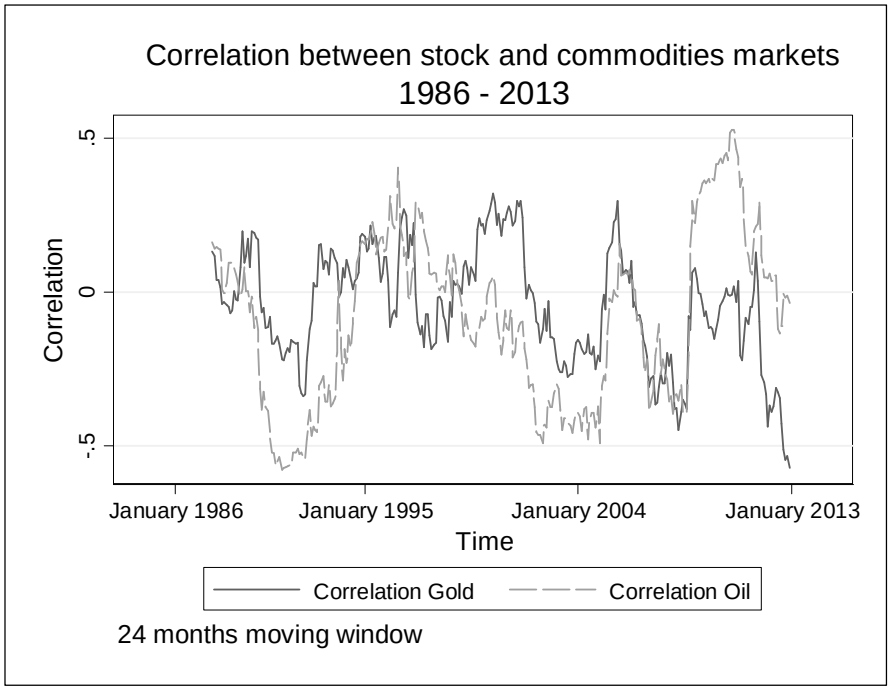


Figure 5

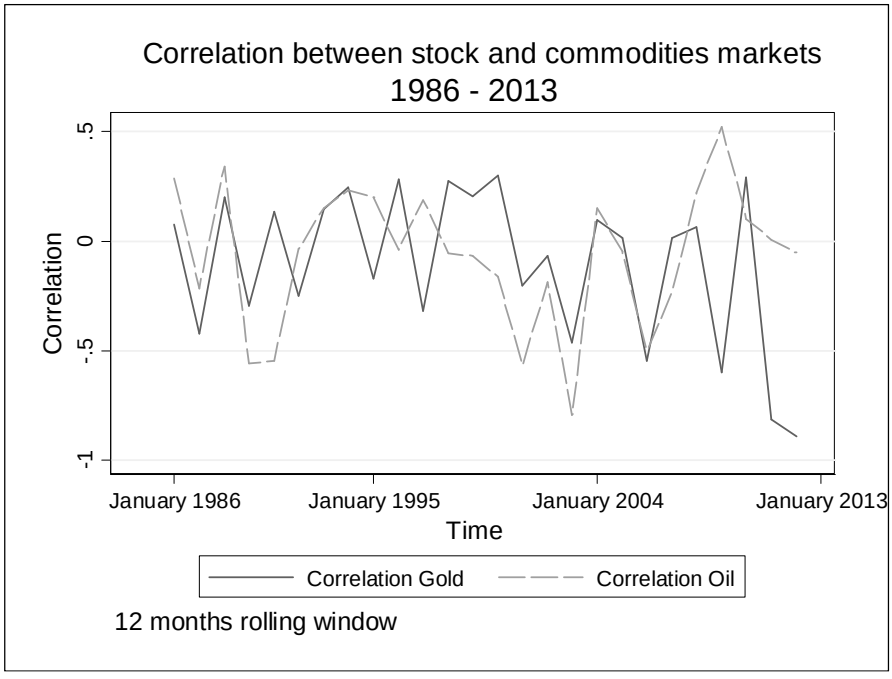


Figure 6

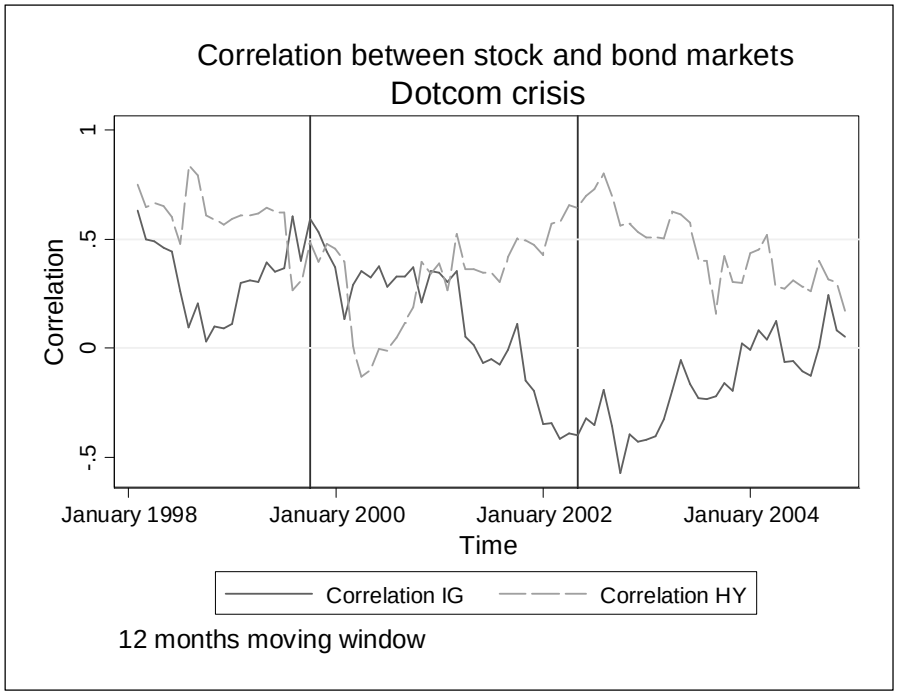


Figure 7

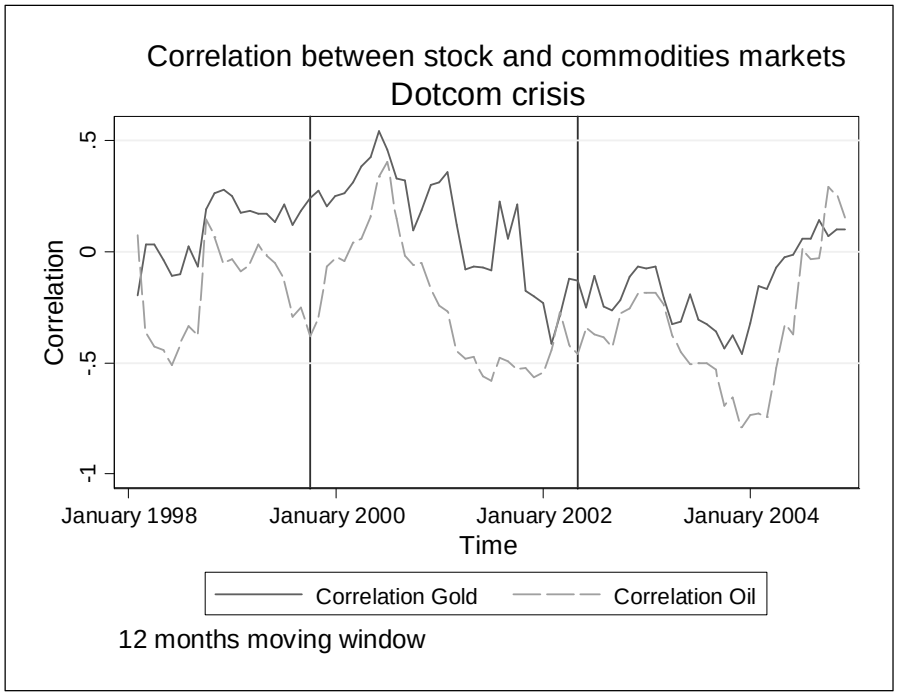


Figure 8

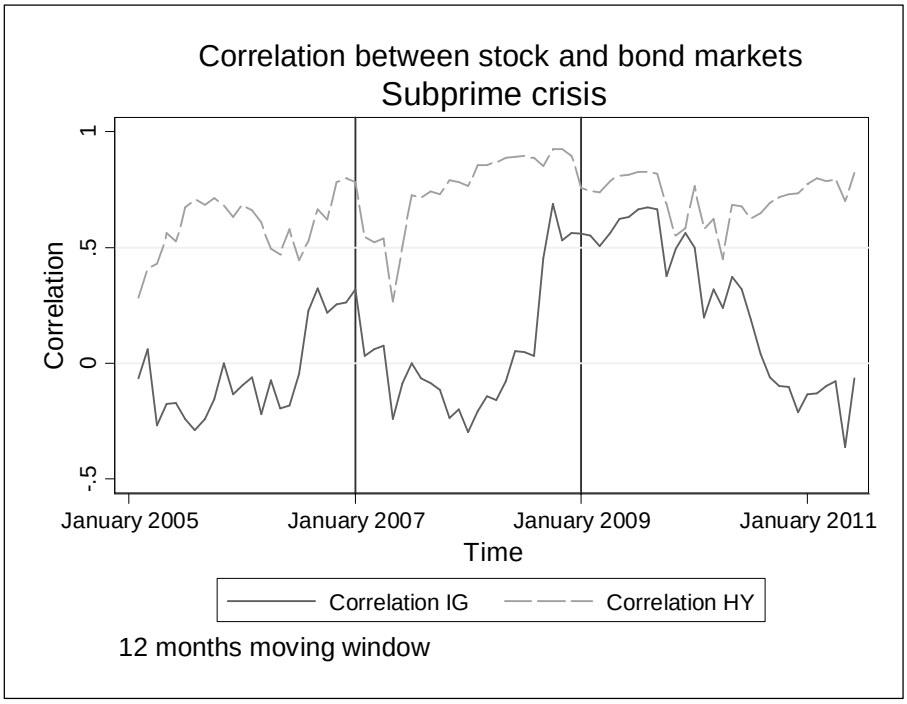


Figure 9

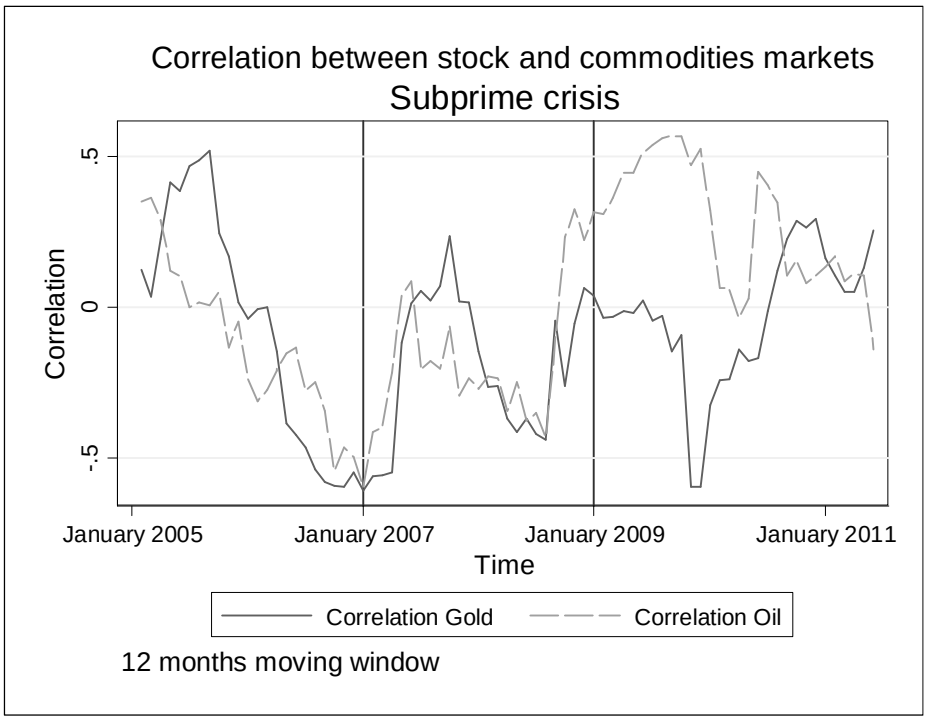


Table 1

Descriptive statistics

	Correlation IG	Correlation HY	Correlation Gold	Correlation Oil
Max	0.8301	0.9246	0.4913	0.5858
Min	-0.4738	-0.2097	-0.8137	-0.7856
Mean	0.2103	0.5666	-0.0513	-0.0722
Std. Dev.	0.3313	0.2431	0.2883	0.3012

Table 2 – (Regression 6.2.1)

Correlation coefficients over time: Yearly basis

	Correlation IG	Correlation HY	Correlation Gold	Correlation Oil
1987	0.0651	0.7058*	0.1163*	0.4108*
1988	0.0496	0.6000*	0.0182*	-0.1281
1989	0.5356*	0.4401*	0.0447*	0.2230*
1990	0.6066*	0.6147*	0.1463*	-0.4665*
1991	0.6709*	0.5563*	-0.4349	-0.5916*
1992	0.6096*	-0.0938*	0.2654*	-0.3271*
1993	0.1477	0.2707*	-0.2077	-0.2126
1994	0.7361*	0.6809*	0.2281*	-0.0137
1995	0.5360*	0.6775*	0.0714*	0.3670*
1996	0.275	0.5290*	0.0129*	0.0792*
1997	0.6793*	0.726	-0.0786*	0.2383*
1998	0.3388	0.6695*	-0.0041*	-0.2121
1999	0.3928	0.5222*	0.1929*	-0.1357
2000	0.3109	0.1423*	0.3214*	0.0663*
2001	0.0535*	0.3994*	0.0505*	-0.4693*
2002	-0.3767*	0.6232*	-0.2047*	-0.3649*
2003	-0.2147*	0.4438*	-0.2873	-0.4680*
2004	0.0229*	0.3335*	-0.0191*	-0.2313
2005	-0.1392*	0.5446*	0.2702*	0.1181*
2006	0.0364	0.6113*	-0.3614	-0.3088*
2007	-0.0442*	0.6381*	-0.1643	-0.2244
2008	0.1251	0.8758	-0.249	-0.1511
2009	0.5735*	0.7465	-0.1294*	0.4689*
2010	0.1425	0.6614*	-0.0108*	0.1736*
2011	-0.0519*	0.8188	-0.156	0.1046*

* Significant at the 5 % level

Table 3 – (Regression 6.3.1)

	Correlation with the onset of crises periods			
	Pre Crisis	Crisis	Post Crisis	_cons
Correlation IG				
Coefficient	-0.3255	-0.3618	-0.4431	0.4665
t-value	(-3.34)	(-3.48)	(-4.00)	-7.46
Confidence level	0%	0%	0%	0%
N-W std.err	0.0975	0.1041	0.1107	0.0626
Correlation HY				
Coefficient	0.0575	0.1328	0.0385	0.5087
t-value	-0.9	-1.39	-0.47	-9.16
Confidence level	37%	17%	64%	0%
N-W std.err	0.0636	0.0954	0.0813	0.0556
Correlation Gold				
Coefficient	-0.013	-0.1451	-0.1042	0.0093
t-value	(-0.11)	(-1.43)	(-1.22)	-0.17
Confidence level	91%	15%	22%	86%
N-W std.err	0.1158	0.1014	0.0855	0.0531
Correlation Oil				
Coefficient	-0.0934	-0.0795	-0.0017	-0.0593
t-value	(-1.00)	(-0.75)	(-0.01)	(-0.81)
Confidence level	32%	45%	99%	42%
N-W std.err	0.0931	0.106	0.1508	0.0731

Table 4 – (Regression 6.3.2)

	Correlation during the specified crises and the periods before/after							
	Pre Dotcom	Dotcom	Post Dotcom	Pre Subprime	Subprime	Post Subprime	Sovereign	_cons
Correlation IG								
Coefficient	-0.1139	-0.4611	-0.6033	-0.5019	-0.2894	-0.2652	-0.2658	0.4679
t-value	(-1.35)	(-3.40)	(-6.46)	(-5.67)	(-1.69)	(-1.71)	(-2.69)	(-7.55)
Confidence level	18%	0%	0%	0%	9%	9%	1%	0%
N-W std.err	0.0842	0.1355	0.0934	0.0885	0.1715	0.155	0.0987	0.062
Correlation HY								
Coefficient	0.058	-0.1266	-0.0921	0.0717	0.3066	0.2035	0.3386	0.5078
t-value	(0.75)	(-1.20)	(-1.28)	(1.12)	(5.09)	(3.33)	(5.62)	(9.25)
Confidence level	45%	23%	20%	26%	0%	0%	0%	0%
N-W std.err	0.0773	0.1052	0.0721	0.0638	0.0603	0.061	0.0602	0.0549
Correlation Gold								
Coefficient	0.1054	0.044	-0.1672	-0.1392	-0.1203	-0.0473	-0.4957	0.0113
t-value	(-1.42)	(0.39)	(-1.9)	(-0.81)	(-1.43)	(-0.45)	(-4.32)	(0.22)
Confidence level	16%	70%	6%	42%	16%	66%	0%	82%
N-W std.err	0.0745	0.1121	0.0878	0.1726	0.0843	0.1061	0.1146	0.0502
Correlation Oil								
Coefficient	-0.0856	-0.2153	-0.2921	-0.0705	0.0277	0.3335	0.0045	-0.0615
t-value	(-1.00)	(-1.69)	(-2.19)	(-0.58)	(0.18)	(3.18)	(0.05)	(-0.86)
Confidence level	32%	9%	3%	56%	86%	0%	96%	39%
N-W std.err	0.0858	0.1274	0.1332	0.121	0.1521	0.1048	0.094	0.0716

Table 5 – (Regression 6.4.1)

Effect of changes in market factors during the specific crises and the periods before/after

	Pre Dotcom	Dotcom	Post Dotcom	Pre Subprime	Subprime	Post Subprime
Correlation IG						
Change in Liquidity level	**-0.2229**	**-0.0718**	**-0.0074**	**-0.8373**	**-0.0456**	**-1.4257**
t-value	-(1.68)	-(1.99)	-(0.39)	-(0.92)	-(2.13)	-(4.03)
Confidence level	10%	6%	70%	37%	5%	0%
N-W std.err	0.1331	0.0361	0.0189	0.9133	0.0214	0.3534
Change in Volatility level	**-0.28**	**-2.359**	**4.109**	**1.419**	**-3.932**	**5.035**
t-value	-(1.92)	-(0.82)	-(2.15)	-(1.25)	-(4.56)	-(2.49)
Confidence level	6%	42%	4%	22%	0%	2%
N-W std.err	0.146	2.885	1.914	1.137	0.862	2.024
_Const	**-0.082**	**0.009**	**0.107**	**-0.032**	**0.292**	**-0.005**
t-value	-(0.67)	-(0.08)	-(1.57)	-(0.46)	-(2.05)	-(0.04)
Confidence level	50%	94%	13%	65%	5%	97%
N-W std.err	0.123	0.114	0.068	0.069	0.143	0.113
Correlation Gold						
Change in Liquidity level	**0.0208**	**-0.0809**	**0.0148**	**5.4158**	**-0.0364**	**1.2275**
t-value	(0.17)	-(2.91)	(0.62)	(2.96)	-(4.2)	(2.56)
Confidence level	87%	1%	54%	1%	0%	2%
N-W std.err	0.1231	0.0277	0.0241	1.829	0.0087	0.4803
Change in Volatility level	**-2.4829**	**-3.5744**	**5.0346**	**-0.7021**	**-1.8662**	**-2.2466**
t-value	-(2.79)	-(1.56)	(2.49)	-(0.27)	-(2.41)	-(1.93)
Confidence level	1%	13%	2%	79%	3%	7%
N-W std.err	0.8898	2.2911	2.0244	2.6334	0.7749	1.1666
_Const	**0.129**	**0.0661**	**-0.005**	**-0.2363**	**-0.0496**	**-0.0162**
t-value	(3.55)	(0.76)	-(0.04)	-(1.59)	-(1.12)	-(0.23)
Confidence level	0%	46%	97%	12%	27%	82%
N-W std.err	0.0363	0.0873	0.1132	0.1485	0.0441	0.0693

From this page follows the Case study results

Table 6

Descriptive statistics Sharpe ratios

	Optimal	1 year rebalance	Diverse and passive	Stock	Equal bond	IG	HY	Stock and Bond	Gold	Oil	Average optimal
Average	3.16	0.86	0.85	0.77	1.31	1.04	1.50	1.07	0.04	0.27	1.23
90's Average	3.54	0.90	0.73	1.53	1.63	0.94	2.06	1.73	-0.84	-0.07	1.26
00's Average	3.15	1.23	1.06	0.17	1.27	1.24	1.32	0.62	0.91	0.51	1.41
Max	7.45	4.40	3.75	6.35	5.60	3.35	6.62	6.80	2.70	2.49	4.40
Min	0.11	-2.17	-2.28	-1.95	-2.05	-2.27	-2.17	-1.63	-2.29	-1.77	-1.33
Std.Dev.	2.07	1.63	1.36	1.56	2.10	1.47	2.39	1.78	1.27	1.21	1.52
Nr of negative	0	8	7	6	8	6	10	7	13	11	8
Nr above 1.0	21	13	12	12	12	13	13	13	7	7	15

Table 7

Sharpe ratio of the different portfolios:

Year	Optimal	1 year rebalance	Diverse and passive	Stock	Equal bond	IG	HY	Stock and Bond	Gold	Oil	Average optimal
1988	1.84	-1.41	-0.1	1.22	0.89	0.18	1.84	1.18	-1.41	-0.1	0.1
1989	0.97	-2.17	0.18	0.41	-0.92	0.48	-2.17	0.11	-0.84	0.9	-0.26
1990	0.55	0.41	0.09	0.04	-0.42	0.52	-0.83	-0.09	-0.76	0.34	-0.07
1991	7.45	1.19	0.36	1.71	5.6	2.51	4.6	2.15	-1.54	-1.21	3.36
1992	4.02	3.26	1.21	1.02	3.29	2.36	3.77	2.22	-1.09	-0.11	2.49
1993	6.63	3.67	0.78	1.51	4.49	2.43	6.62	2.57	0.97	-1.77	2
1994	0.87	-1.31	-0.01	-0.32	-1.44	-1.41	-1.3	-0.7	-0.79	0.87	-0.51
1995	6.85	0.27	2.65	6.35	4.43	3.35	4.83	6.8	-0.92	0.27	3.27
1996	2.43	1.42	1.47	1.82	0.39	-0.42	1.93	1.62	-1.44	1.1	1.19
1997	2.42	1.43	-0.8	1.42	1.9	1.34	2.42	1.57	-2.29	-1.67	-0.1
1998	1.66	-0.26	-0.24	1.33	0.14	0.98	-0.26	1.19	-0.37	-1	-0.32
1999	2.52	-1.1	1.79	0.41	-2.05	-2.27	-1.2	0	-0.23	2.47	1.31
2000	1.62	-0.13	-0.36	-0.47	0.16	1.62	-0.49	-0.35	-1.04	-0.03	-0.21
2001	1.22	1.22	-2.28	-1.1	-0.04	1.22	-0.5	-0.99	-0.13	-1.26	-1.29
2002	3.7	1.65	1.34	-1.26	0.49	1.65	-0.09	-0.94	1.74	1.76	1.36
2003	5.57	1.55	2.4	1.84	2.99	1.13	4.46	3.8	1.21	0.1	3.02
2004	2.09	1.34	1.28	0.41	1.5	0.8	2.05	1	0.29	1	1.51
2005	2.95	0.49	2.39	0.72	-0.07	-0.52	0.29	0.53	1.12	1.34	2.26
2006	3.51	0.81	0.71	1.37	1.26	-0.05	2.93	1.49	0.93	-0.18	0.96
2007	2.3	-0.55	1.91	-0.77	-0.54	0.4	-0.85	-0.79	1.98	2.02	1.6
2008	0.11	-0.59	-1.42	-1.95	-0.98	-0.72	-1.01	-1.63	0.11	-1.09	-1.33
2009	5.92	1.26	3.75	1.48	4.09	3.34	4	2.42	1.26	2.49	4.4
2010	5.04	4.4	2.18	1.06	2.5	1.9	2.24	1.46	2.7	0.55	2.71
2011	2.69	1.52	0.87	0.12	1.09	2.08	0.53	0.42	0.38	0.27	1.35
2012	4.19	3.04	1.07	0.75	4.05	3.22	3.58	1.61	1.24	-0.32	1.98

Table 8

	Composition of the optimal portfolio				
Year	Stocks	IG	HY	Gold	Oil
1988	0%	0%	100%	0%	0%
1989	0%	61%	0%	0%	39%
1990	13%	73%	2%	4%	9%
1991	0%	30%	57%	3%	10%
1992	11%	0%	82%	0%	7%
1993	0%	0%	100%	0%	0%
1994	0%	0%	0%	0%	100%
1995	50%	28%	14%	8%	0%
1996	10%	0%	83%	0%	7%
1997	0%	0%	100%	0%	0%
1998	20%	92%	0%	0%	0%
1999	37%	0%	0%	0%	63%
2000	0%	100%	0%	0%	0%
2001	0%	100%	0%	0%	0%
2002	4%	70%	0%	21%	4%
2003	40%	1%	43%	6%	10%
2004	0%	0%	98%	0%	2%
2005	20%	50%	0%	19%	11%
2006	0%	0%	94%	6%	0%
2007	0%	0%	0%	65%	35%
2008	0%	0%	0%	100%	0%
2009	0%	53%	24%	23%	0%
2010	2%	69%	0%	26%	4%
2011	8%	80%	0%	12%	0%
2012	0%	43%	54%	0%	3%
Average	9%	34%	34%	12%	12%

* The average portfolio weights act as the basis in the Average optimal portfolio [CM]

Table 9

	Sharpe ratios during the onset of crises		
	Pre Crisis	Crisis	Post Crisis
Optimal portfolio	2.5	2.26	4.66
1 year rebalance	-0.28	0.88	2.14
Diverse and passive	1.04	0.16	2.4
Stock	0.59	-0.67	1.2
Equal weight bond	-0.3	0.6	2.77
IG	-0.24	1.35	1.79
HY	0.15	0.17	3.19
Stock and Bond	0.47	-0.38	2.17
Gold	0.58	0.61	1.37
Oil	0.83	0.19	1.04
Average optimal	0.88	0.49	2.91

Table 10

	Average Sharpe ratios conditioned on the specified crises periods						
	Pre Dotcom	Dotcom	Post Dotcom	Pre Subprime	Subprime	Post Subprime	Sovereign
Optimal	2.09	2.18	3.83	3.23	1.2	5.48	3.44
1 year rebalance	-0.68	0.91	1.45	0.65	-0.57	2.83	2.28
Diverse and passive	0.78	-0.43	1.84	1.55	0.25	2.96	0.97
Stock	0.87	-0.94	1.13	1.05	-1.36	1.27	0.44
Equal bond	-0.96	0.2	2.25	0.59	-0.76	3.29	2.57
IG	-0.65	1.5	0.96	-0.29	-0.16	2.62	2.65
HY	-0.73	-0.36	3.26	1.61	-0.93	3.12	2.05
Stock and Bond	0.6	-0.76	2.4	1.01	-1.21	1.94	1.01
Gold	-0.3	0.19	0.75	1.03	1.05	1.98	0.81
Oil	0.73	0.16	0.55	0.58	0.46	1.52	-0.03
Average optimal	0.49	-0.05	2.27	1.61	0.13	3.56	1.67
Average	0.2	0.24	1.88	1.15	-0.17	2.78	1.62
Average excl. Optimal	0.01	0.04	1.68	0.94	-0.31	2.51	1.44

Figure 10

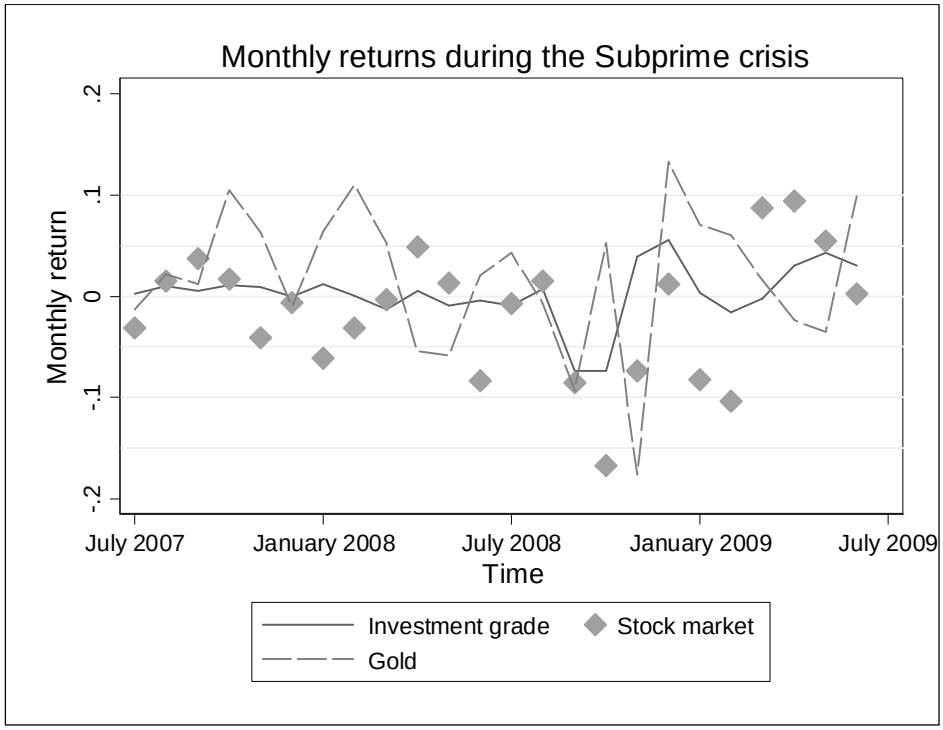
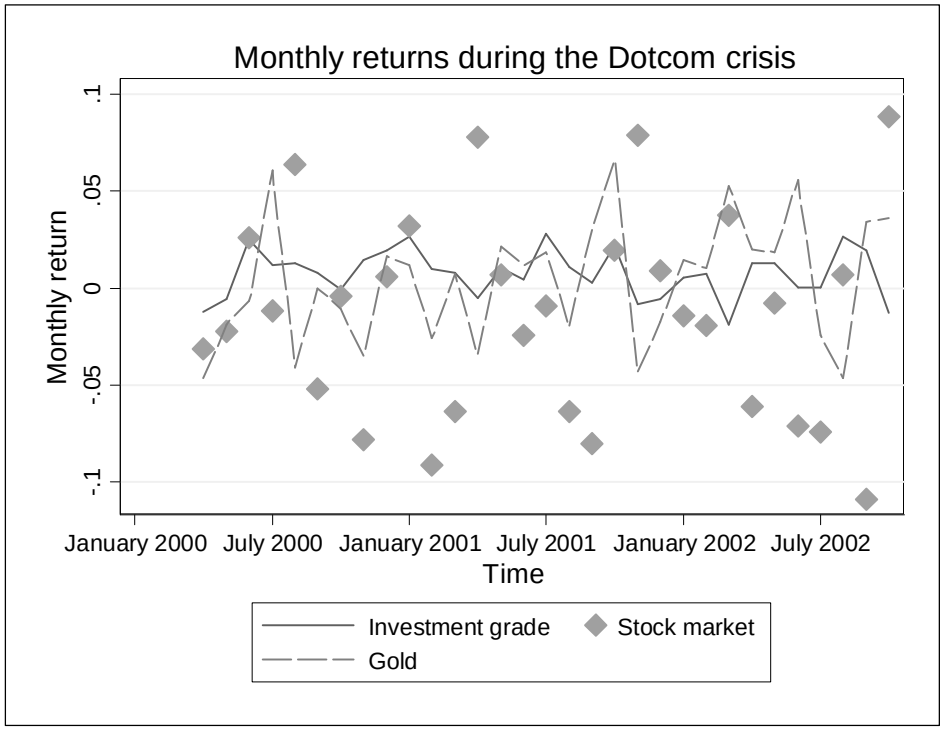


Figure 11



From this page follows the Robustness test results

Table 11

Correlation changes during the onset of crises:
MSCI US Investable index used as a proxy for the stock market

	Pre Crisis	Crisis	Post Crisis	_cons
Correlation IG				
Coefficient	-0.2677	-0.2861	-0.3833	0.4081
t-value	(-2.32)	(-2.38)	(-2.95)	(4.63)
Confidence level	2%	2%	0%	0%
N-W std.err	0.1155	0.1202	0.1300	0.0881
Correlation HY				
Coefficient	0.0478	0.1558	0.0282	0.5363
t-value	(0.71)	(1.85)	(0.32)	(8.59)
Confidence level	47%	6%	75%	0%
N-W std.err	0.0669	0.084	0.0879	0.0624
Correlation Gold				
Coefficient	-0.0067	-0.1254	-0.0882	-0.0136
t-value	(-0.06)	(-1.24)	(-1.01)	(-0.23)
Confidence level	95%	21%	31%	82%
N-W std.err	0.1158	0.1008	0.0871	0.0603
Correlation Oil				
Coefficient	-0.0884	-0.0632	0.0004	-0.0605
t-value	(-0.73)	(-0.49)	(0.00)	(-0.57)
Confidence level	46%	62%	100%	57%
N-W std.err	0.1204	0.1282	0.1742	0.1068

Table 12

Correlation changes during the onset of crises:
Nasdaq Composite index used as a proxy for the stock market

	Pre Crisis	Crisis	Post Crisis	_cons
Correlation IG				
Coefficient	-0.0696	-0.1135	-0.3464	0.2592
t-value	(-0.59)	(-1.08)	(-2.92)	(-3.51)
Confidence level	56%	28%	0%	0%
N-W std.err	0.118	0.1046	0.1185	0.0739
Correlation HY				
Coefficient	0.0783	0.2165	0.0258	0.4673
t-value	(1.23)	(3.11)	(0.24)	(8.21)
Confidence level	22%	0%	81%	0%
N-W std.err	0.0639	0.0696	0.1077	0.0569
Correlation Gold				
Coefficient	0.0054	-0.1082	0.0205	-0.0384
t-value	(0.05)	(-1.26)	(0.27)	(0.91)
Confidence level	96%	21%	79%	36%
N-W std.err	0.1007	0.0856	0.0768	0.0421
Correlation Oil				
Coefficient	-0.0773	0.0421	0.1527	-0.1755
t-value	(-0.79)	(0.38)	(0.98)	(-2.27)
Confidence level	43%	70%	33%	2%
N-W std.err	0.0981	0.1105	0.1564	0.0772

Table 13

Correlation during crises: MSCI US Investable as proxy for the stock market

	Pre Dotcom	Dotcom	Post Dotcom	Pre Subprime	Subprime	Post Subprime	Sovereign	_cons
Correlation IG								
Coefficient	-0.0492	-0.3539	-0.5361	-0.4637	-0.2244	-0.2178	-0.2578	0.4081
t-value	(-0.48)	(-2.1)	(-4.79)	(-4.56)	(-1.21)	(-1.27)	(-2.06)	(4.59)
Confidence level	63%	4%	0%	0%	23%	21%	4%	0%
N-W std.err	0.1027	0.1683	0.1118	0.1016	0.1855	0.1722	0.1249	0.0889
Correlation HY								
Coefficient	0.0434	-0.0532	-0.1174	0.0516	0.2917	0.1859	0.3021	0.5363
t-value	(0.58)	(0.63)	(1.37)	(0.72)	(4.35)	(2.79)	(4.41)	(8.52)
Confidence level	57%	53%	17%	47%	0%	1%	0%	0%
N-W std.err	0.0754	0.0851	0.0856	0.0713	0.0671	0.0667	0.0685	0.0629
Correlation Gold								
Coefficient	0.1216	0.0651	-0.1574	-0.1217	-0.0952	-0.0133	-0.4269	-0.0136
t-value	(1.59)	(0.62)	(-1.73)	(-0.69)	(-1.03)	(-0.12)	(-3.35)	(-0.22)
Confidence level	11%	54%	9%	49%	31%	91%	0%	82%
N-W std.err	0.766	0.1056	0.091	0.1757	0.0928	0.1118	0.1273	0.0608
Correlation Oil								
Coefficient	-0.0808	-0.1768	-0.3028	-0.0952	-0.0137	0.3288	0.1297	-0.0605
t-value	(-0.70)	(-1.12)	(-1.88)	(-0.64)	(-0.08)	(2.49)	(0.11)	(-0.56)
Confidence level	49%	26%	6%	52%	94%	1%	91%	58%
N-W std.err	0.1161	0.1572	0.1612	0.148	0.1797	0.132	0.1182	0.1077

Table 14

Correlation during crises: Nasdaq composite index as proxy for the stock market

	Pre Dotcom	Dotcom	Post Dotcom	Pre Subprime	Subprime	Post Subprime	Sovereign	_cons
Correlation IG								
Coefficient	0.1793	-0.1646	-0.5216	-0.2929	-0.0751	-0.1565	-0.0833	0.2592
t-value	(-1.78)	(-1.12)	(-6.10)	(-3.12)	(-0.48)	(-1.01)	(-0.62)	(3.48)
Confidence level	8%	26%	0%	0%	63%	32%	54%	0%
N-W std.err	0.1006	0.1463	0.0855	0.0939	0.1549	0.1555	0.1347	0.0744
Correlation HY								
Coefficient	0.1211	0.0921	-0.1818	0.0399	0.2666	0.2507	0.3372	0.4673
t-value	(1.81)	(1.38)	(-1.68)	(0.56)	(3.64)	(3.91)	(4.4)	(8.16)
Confidence level	7%	17%	9%	58%	0%	0%	0%	0%
N-W std.err	0.067	0.0669	0.108	0.0715	0.0733	0.0641	0.0767	0.0573
Correlation Gold								
Coefficient	0.0148	0.0755	-0.0968	-0.0031	-0.0653	0.1475	-0.4138	-0.0384
t-value	(0.32)	(1.53)	(-1.39)	(-0.02)	(-0.72)	(1.73)	(-3.60)	(-0.91)
Confidence level	75%	13%	17%	99%	47%	9%	0%	37%
N-W std.err	0.0459	0.0493	0.0696	0.1791	0.091	0.0853	0.115	0.0423
Correlation Oil								
Coefficient	-0.0617	-0.0763	-0.1421	-0.0913	0.1620	0.4721	0.0781	-0.1755
t-value	(-0.75)	(-0.48)	(-1.03)	(-0.66)	(0.96)	(3.84)	(0.87)	(-2.26)
Confidence level	46%	63%	30%	51%	34%	0%	39%	3%
N-W std.err	0.0827	0.1577	0.1378	0.1393	0.1685	0.123	0.0897	0.0777

Table 15

	Effect in crises of market parameters on correlation, robustness test					
	Dotcom (S&P 500)	Dotcom (Nasdaq)	Dotcom (MSCI)	Subprime (S&P 500)	Subprime (Nasdaq)	Subprime (MSCI)
Correlation IG						
Liquidity level	**-1.2380**	**-1.2561**	**-1.4373**	**0.5110**	**0.2658**	**0.5120**
t-value	-(8.72)	-(7.32)	-(7.93)	(3.23)	(1.60)	(3.18)
Confidence level	0%	0%	0%	0%	13%	0%
N-W std.err	0.1420	0.1717	0.1813	0.1583	0.1662	0.1609
Change in Volatility level	**0.0640**	**1.3798**	**0.3685**	**-1.6483**	**-2.6703**	**1.7575**
t-value	(0.04)	(0.75)	(0.21)	-(2.23)	-(3.36)	-(2.35)
Confidence level	97%	46%	84%	4%	0%	3%
N-W std.err	1.488	1.8332	1.774	0.739	0.7946	0.749
_Const	**0.3076**	**0.3889**	**0.4011**	**0.0534**	**0.1657**	**0.0611**
t-value	(5.81)	(5.70)	(5.89)	(0.49)	(1.46)	(0.56)
Confidence level	0%	0%	0%	63%	16%	58%
N-W std.err	0.0530	0.0682	0.0681	0.1080	0.1135	0.1093
Correlation Gold						
Liquidity level	**-1.0106**	**-0.1815**	**-0.8769**	**-0.1750**	**0.0065**	**-0.1579**
t-value	-(6.16)	-(3.03)	-(6.36)	-(1.94)	(0.09)	-(1.71)
Confidence level	0%	1%	0%	7%	93%	10%
N-W std.err	0.1640	0.0599	0.1380	0.0900	0.0757	0.0921
Change in Volatility level	**-0.3949**	**-0.7976**	**-0.7051**	**-2.2980**	**-2.8744**	**-2.4064**
t-value	-(0.23)	-(0.50)	-(0.40)	-(4.26)	-(6.05)	-(4.29)
Confidence level	82%	62%	70%	0%	0%	0%
N-W std.err	1.6952	1.5821	1.7791	0.5393	0.4749	0.5609
_Const	**0.3046**	**0.0879**	**0.2708**	**0.0076**	**-0.0317**	**0.0050**
t-value	(5.89)	(3.96)	(7.42)	(0.16)	-(0.79)	(0.11)
Confidence level	0%	0%	0%	88%	44%	92%
N-W std.err	0.0517	0.0222	0.0365	0.0484	0.0403	0.0474

Figure 12

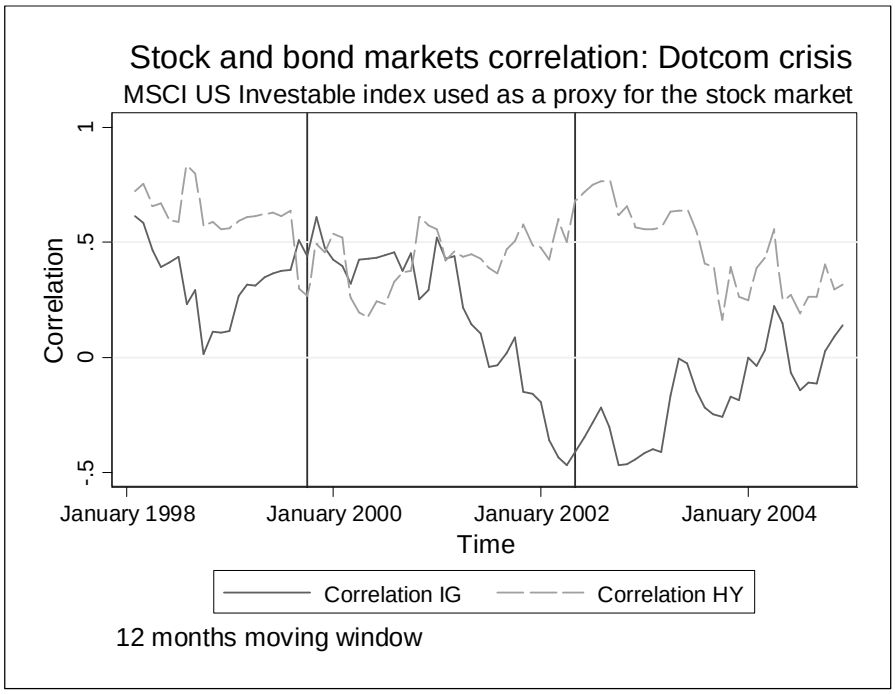


Figure 13

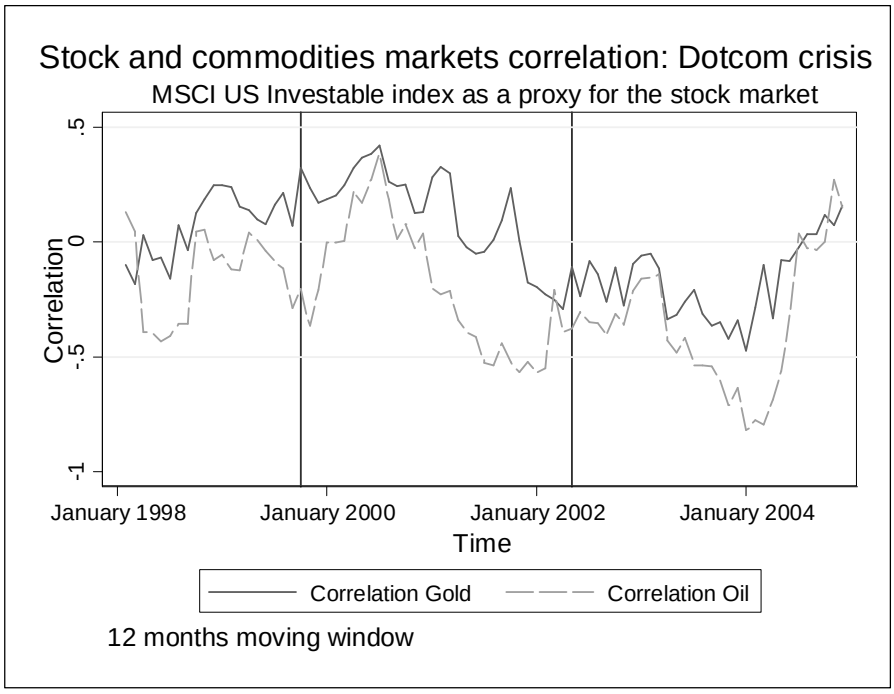


Figure 14

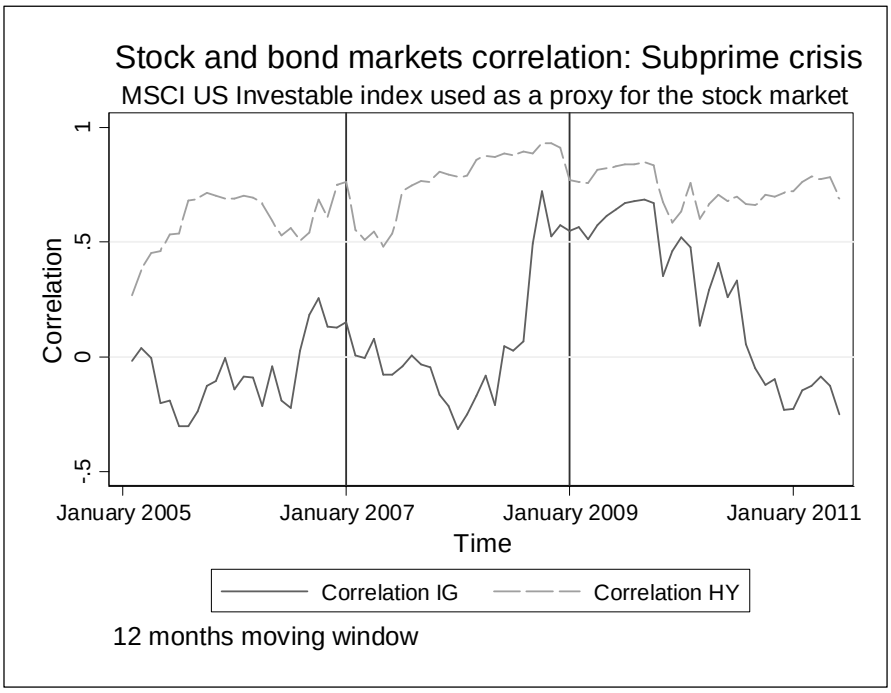


Figure 15

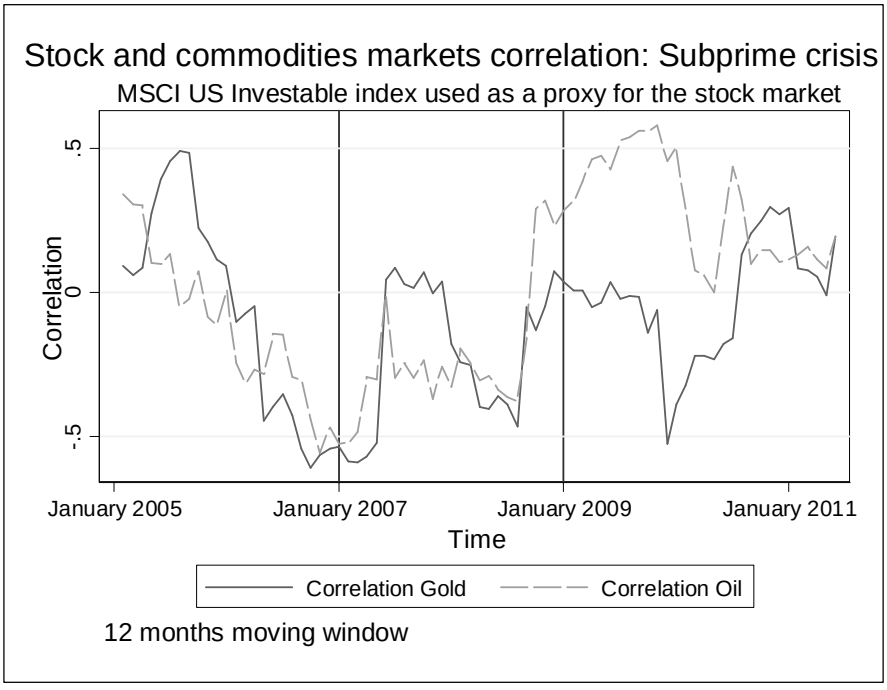


Figure 16

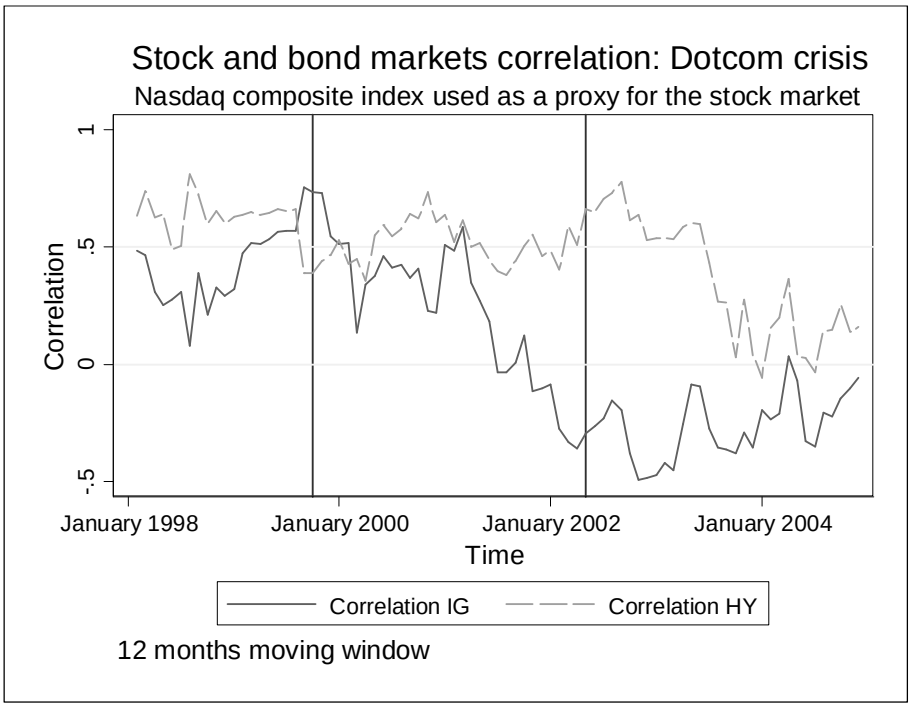


Figure 17

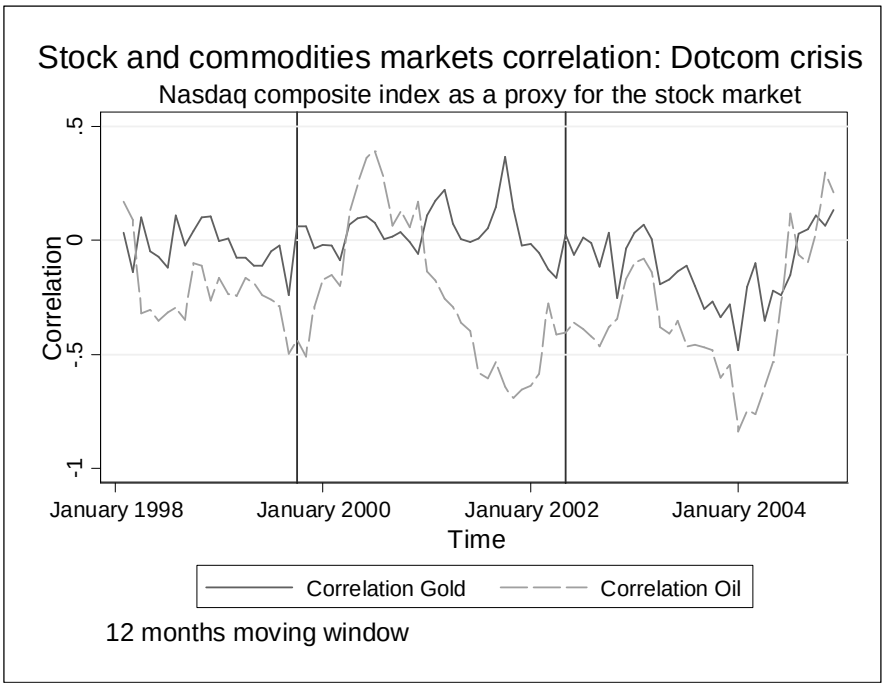


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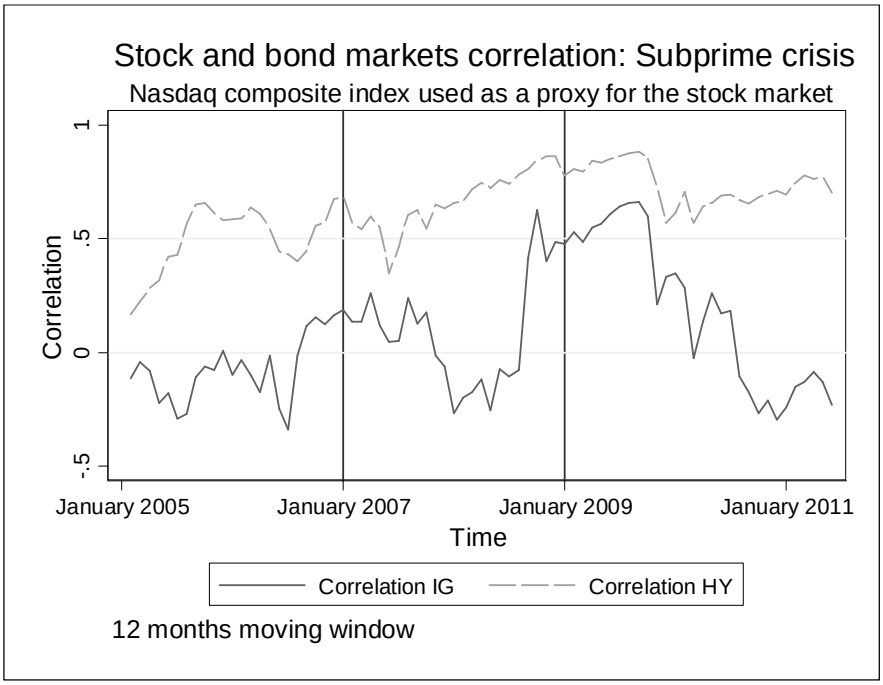
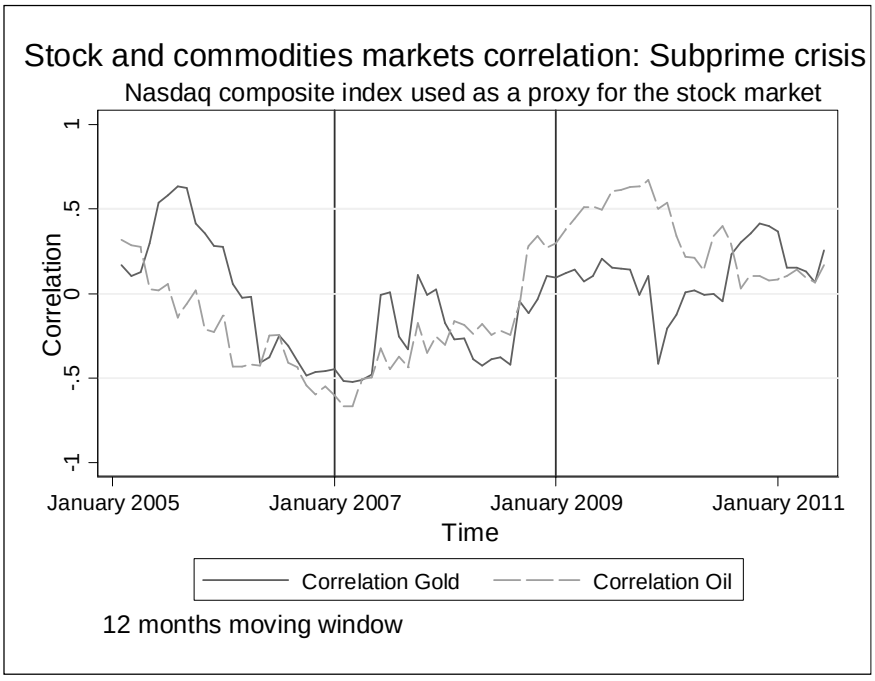


Figure 19



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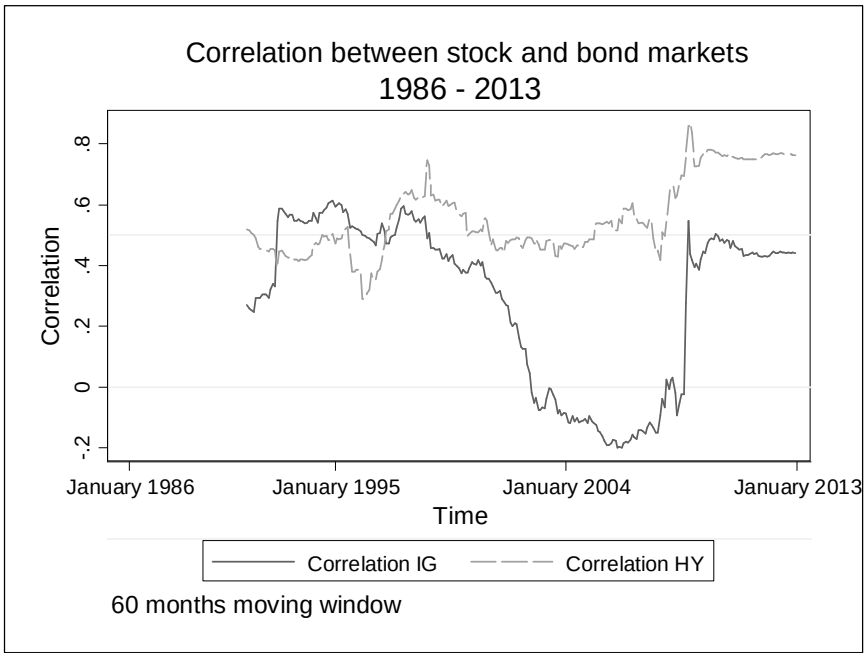
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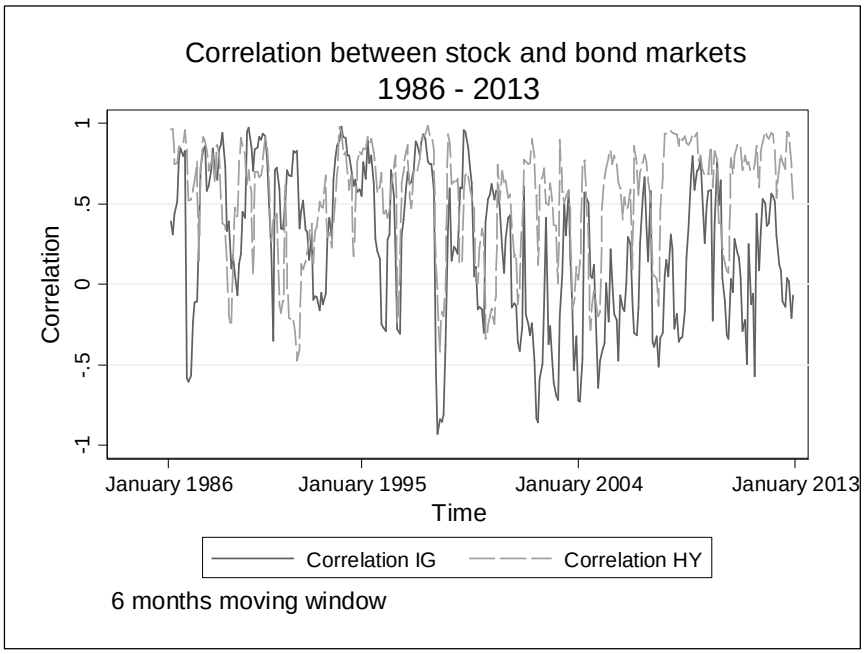
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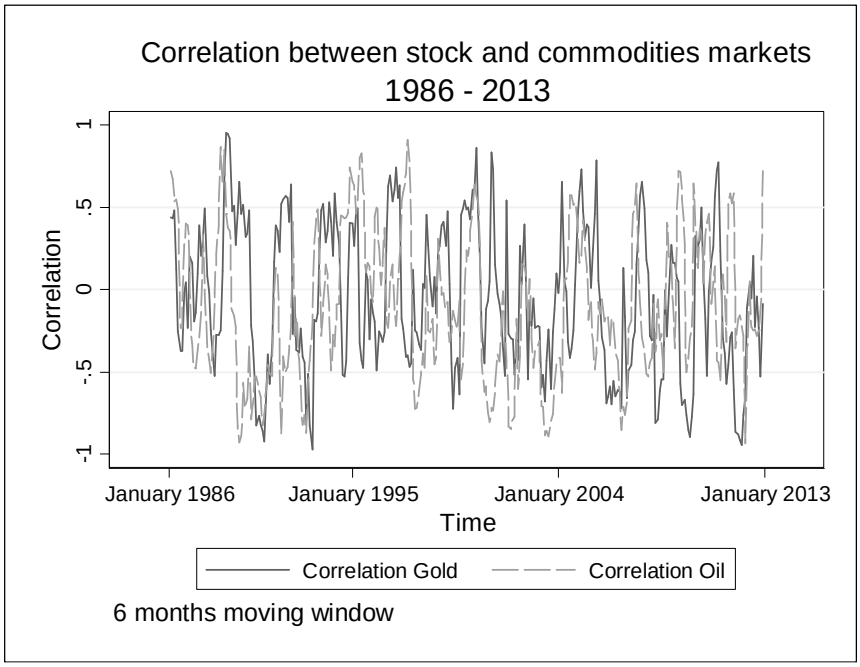
Appendix

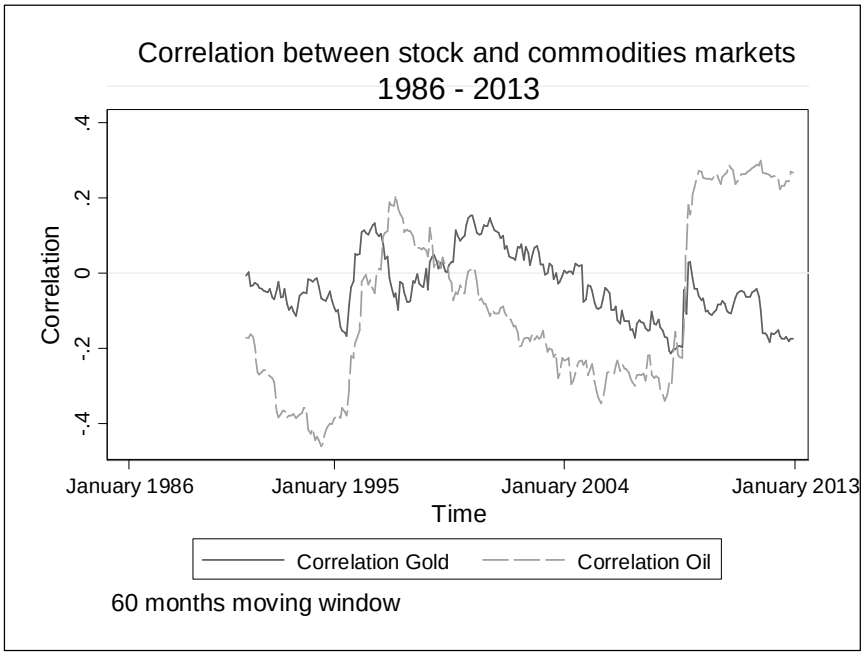
Below follows some additional figures and equations which is not included in the results section, but which support the claims and findings of this thesis.

Different moving windows that supports the use of 24 months in the results:









Calculation of the Citigroup Liquidity index:

$$\left[\left[0.2 \cdot \frac{(Swaption\ price)}{200.7} - \frac{Rate\ Swaps}{0.68} + \frac{Swap\ Spreads}{22} + \frac{IG_{CDS}index}{57.71} + \frac{VIX\ Futures}{11.30}\right] - 1.2074\right]$$