ERASMUS SCHOOL OF ECONOMICS

Moving Along Together

Forecasting co-movements with macroeconomic and financial variables

Willem G.J. Kers

356136

Supervisor: Prof. dr. D.J. van Dijk

Bachelor thesis Econometrics and Operations Research

June 30th 2014

Abstract

This study examines co-movement of three assets, i.e. stocks, bonds and commodities, in combination with macroeconomic and financial variables. I use forecast combinations, with a pre-selection based on Least Angle Regression, two factor based models, principal component analysis and partial least squares, and regimes switching models to investigate the predictability of co-movements. This is done on the Fisher and a custom transformation of the realised correlation. The main finding are that interest rates, spreads and bond market factors are important for Stock-Bond co-movement, macroeconomic factors are important for Commodity related co-movements and forecasts made with a custom transformation are more accurate than if the fisher transformation was used.

Keywords: Co-movement, Fisher-transformation, Forecast Combinations, Regime Switch, Factor based models

Content

1 Introduction

Co-movement of asset returns is, next to the volatility of assets, one of the most important determinants for evaluating asset classes e.g. stocks and bonds, portfolio management and hedging (Campbell & Ammer, 1993; Kwan, 1996; Ilmanen, 2003; Baele, Bekaert & Inghelbrecht, 2010; Chui & Yang, 2012**;** Piljak, 2013; Zhang, Zhang Wang & Zhang, 2013; Aslanidis & Christiansen, 2014; Zhou, 2014). Co-movement of assets is the tendency of two assets to move parallel with each other, and it can be measured by either the correlation or the covariance. In the vast econometric literature about co-movement, a great deal of attention is either paid to co-movement within asset classes or across countries, whereas literature about co-movement across different asset classes, including commodities, is scarce. Next to that, one can notice that research lags to capture enough information to give good accurate forecasts of co-movements of asset returns, most forecasts can only give a moving average, instead of being able to forecast the short periods of very high and very low dependence (Baele et al, 2010). This means that further research in co-movements is a welcome topic in the econometric literature.

Co-movement of assets is important for investors who pursue the maximisation of the expected portfolio return, under the simultaneous restriction of minimising their risk. There is a certain trade-off between expected return and risk, depending on the preferences of an investor, and for optimising an investor's portfolio an accurate forecast of the co-movement of assets is needed (Ghysels, Santa-Clara & Valkanov, 2005). Due to the increase in stock market uncertainty and the recent financial crises, there has been a growing interest in volatility and also for the co-movement of assets as an input for asset allocation to hedge a portfolio against other assets, in order to minimise the exposure to risk.
Co-movement is also important for policymakers, to see if there is spill-over between markets and then they can take measures to stabilize the financial system (Zhang, Zhang, Wang & Zhang, 2013).

The aim of this research is to examine whether the dependence of different asset classes, stocks bonds and commodities, can be modelled by using macroeconomic and financial variables, wherein a model-free measure of dependence is used, namely the realised correlation. The interesting question is, which variables are the main determinants of the co-movements? The dataset of Christiansen et al. (2012) is used which contains 38 macroeconomic and financial variables covering monthly observations in the period from January 1983 to December 2010. These predictor variables can be classified in several subclasses: "equity market variables and risk factors", "interest rates, spreads and bond market factors”, “foreign exchange variables and risk factors”, “liquidity and credit risk variables” and “macroeconomic variables”.

To achieve the goal of the research, three types of forecasting techniques are used. First, forecast combinations, this method uses simple models to forecast and it turns out that the combinations of these forecasts are quite accurate (Timmermann, 2006). Second, factor based models are a promising method to forecast in a data rich environment, Principal Components Analysis (PCA) captures most of the variance of the variables into factors, using this technique on preselected variables sounds promising. Partial Least Squares (PLS) in contradiction to PCA already keeps track of the variable one wants to explain, so therefore both methods are used. Third, regime switching models are used; they can capture regime specific information, which enables a model to behave differently in two regimes.
Next to these forecasting techniques, two different data transformations of the realised correlation are looked at, the fisher transformation and a transformation were the natural logarithm is taken over the realised correlation plus one divided by two. These two data transformations might give more accurate forecasts and it can give more robustness. All forecast models are constructed with a moving window of 5 and 10 years, starting with forecasting in January 1993.

Baele, Bekaert and Inghelbrecht (2010) found, by constructing a dynamic factor model and a regime switching model that largely liquidity factors contribute in explaining the co-movement of stock-bond returns, but also that macroeconomic factors do not contribute much in explaining the co-movement of stock-bond returns. Christiansen and Ronaldo (2007) researched the impact of news for stock-bond correlation, they found that macroeconomic announcements do have an impact on the short term (daily) correlation; they also state that the co-movement of stock-bond returns, is mostly stated by some stylized facts. Aslanidis and Christiansen (2014) found that it is difficult to forecast the correlation of the stock-bond return by macroeconomic variables when there was a high positive correlation, so they suggest future research on this issue. Piljak (2013) found that macroeconomic factors are important for different bond returns co-movements; this may suggest that these factors are important for the co-movement of bonds and other assets. In addition to this, it is interesting to look at commodities, because commodities can be a profitable alternative and they have a low correlation with bonds and stocks, therefore further research is needed for co-movement of other assets than stocks and bonds, such as commodities (Silvennoinen & Thorp, 2013; Zhou, 2014). Zhou (2014) states that even though periods with high risk are rare and have a low chance of happening, this possibility needs to be taken into account when constructing a portfolio.

Statically speaking the forecast combination model performs best and from an economic perspective the autoregressive model with macroeconomic and financial variables (ARX(1)) using the bond bull-market indicator as a regime switching models, performs best. The result of this research provide convincing evidence that other transformations than the fisher transformation are useful to forecast realised correlation.

This research is organized as follows. Chapter 2 describes the data which is used to perform this research. In Chapter 3 the methodology used is discussed. Chapter 4 gives the results of the used methodology both statistically and economically. Finally, in Chapter 5 the conclusion is presented.

2 Data

In this Chapter the data is described, it starts with a main description and the construction of the data in Section 2.1. In addition to this, two data transformations are used in order to make better forecasts, this is elaborated in Section 2.2.

2.1 data description

In this research the dataset from Christiansen et al. (2012) will be used. It contains the daily returns of the S&P-500 (Stock), 10-year Treasury note future contracts (Bond), traded on the Chicago Board of Trade (CBOT) and Standard & Poor's GSCI Commodity Index (Commodity), starting from January 1983 till December 2010. In order to get the 336 monthly realized correlations between two assets, the realised covariance is dived by the square root of the realised variances of the two assets, so the realized correlations between asset *i* and *j* in month *t* is

$$Realised\ Correlation\ RC_{i,j;t} == \frac{\sum_{\tau=1}^{M_t} r_{i;t;\tau} \cdot r_{j;t;\tau}}{\sqrt{\sum_{\tau=1}^{M_t} r_{i;t;\tau}^2 \cdot \sum_{\tau=1}^{M_t} r_{j;t;\tau}^2}} \quad with \quad t = 1, \dots, 336$$

In this definition for the realised correlation, $r_{i;t;\tau}$ is the τ^{th} daily continuously compounded return in month *t* for asset *i* and M_t is the number of trading days in month *t*. Correlation is a statistical measure for the simultaneous change in asset returns for two given assets. Correlation is a relative measure of co-movement, whereas covariance is an absolute measure of co-movement. So for interpretation and for robustness it is better to use the realised correlation instead of the realised covariance. The realised correlation between the three different assets can are shown in Figure 2.1.

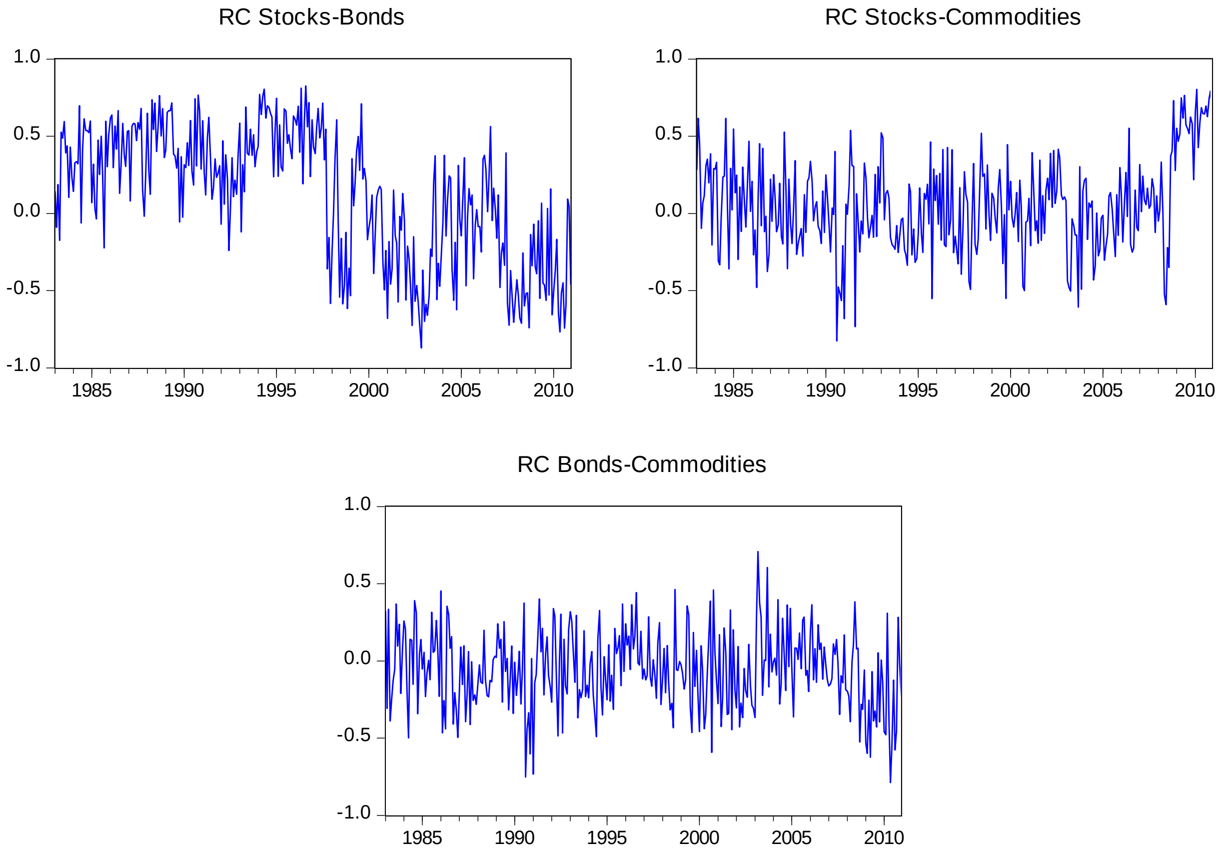

Figure 2.1 Realised Correlation of the three assets returns; stocks bonds and commodities, in the period starting in January 1983 till December 2010.

In Figure 2.1 can be seen that however the realised correlation is quite volatile, it follows kind of a pattern. The stock-bond realised correlation stays mainly positive till 1997, during the Asian crisis, and becomes mainly negative and more volatile afterwards. During the credit-crisis in 2008 a time with a fairly negative stock-bond RC is noticed.

The stock-commodity RC has two remarkable periods, first it has a strong negative correlation in the end of 1990 and the beginning of 1991, which might be caused by the recession in the early 1990s in the US. Second the years after the credit crisis in 2008, since then the stock-commodity RC has mainly been going up.

The bond-commodity realised correlation is, more than the other two, symmetric around zero and has lower peaks. It has no clear periods of positive or negative correlation, but there is, just like in the stock-commodity graph, a negative peak in the end of the 1990 and beginning of 1991, which might be the result of the recession in the US. After 2007 the RC tends to go down, but it keeps having the positive peaks.

The realised return (RR) and the natural logarithm of the realised variance (RV) of the three assets may have explanatory power over the realised correlations and therefore added to the dataset.

$$RR_{i;t} = \sum_{\tau=1}^{M_t} r_{i;t;\tau} \qquad RV_{i;t} = \ln \sum_{\tau=1}^{M_t} r_{i;t;\tau}^2 \qquad with \quad t = 1, \dots, 336$$

Where $RR_{i;t}$ and $RV_{i;t}$ are respectively the realized return and the natural logarithm of the realized variance of asset *i* in month t, $r_{i;t;\tau}$ is the τ^{th} daily continuously compounded return in month t for asset *i* and M_t is the number of trading days in month t.

There are 38 macroeconomic and financial variables from Christiansen et al. (2012) and are shown in Appendix A. These variables are used as explanatory variables to model the realised correlations, as these variables may explain a lot of the correlations between assets. They can be classified in five categories: *1. Equity market variables and risk factors 2. Interest rates, spreads and bond market factors 3. Foreign exchange variables and risk factors 4. Liquidity and credit risk variables 5. Macroeconomic variables.*

2.2 data transformation

The realized correlation is per definition between -1 and 1, in order to lose the restriction on the range, the Fisher transformation is used. This transformation results in a distribution closer to normality and it also gives a simpler time series, i.e. it gets rid of the negative peaks and it becomes smoother (Johnson, Kotz & Balakhrishnan, 1994).

$$Fisher(RC_{i,j;t}) = \frac{1}{2}\ln\left(\frac{1 + RC_{i,j;t}}{1 - RC_{i,j;t}}\right) \quad with \quad t = 1, \dots, 336$$

where $RC_{i,j;t}$ is the realized correlations between asset *i* and *j* in month *t*. The main statistics of these correlation series are shown in Table 2.1.

Fisher(RC)	RC $_{\text{Stock-Bond}}$	RC $_{\text{Stock-Commodity}}$	RC $_{\text{Bond-Commodity}}$
Mean	0,14	0,06	-0,07
Std. Dev.	0,50	0,34	0,28
Skewness	-0,36	0,21	-0,18
Kurtosis	2,42	3,79	3,52
JB P-value	0,00	0,00	0,06
AC(1)	0,68	0,41	0,10

Table 2.1 Descriptive statistics of the fisher transformation of the realized correlation (Fisher(RC)), for the sample period January 1983 until December 2010

Note: **The reported statistics in the table include the mean, standard deviation, skewness, kurtosis, Jarque-Bera (JB) and the first order autocorrelation coefficients (AC).**

From table 2.1 can be seen that the Stock-Bond RC and Stock-Commodity have positive mean and that the mean Bond-Commodity RC is slightly negative. The standard deviation of the Stock-Bond RC is quite high compared to the other two. By looking at the Jarque-Bera P-value, only the Bond-commodity RC is similar to a normal distribution according to the Jarque-Bera test. Only the Stock-Bond and the Stock-Commodity RC have a quite strong autocorrelation, in contradiction to the Bond-Commodity RC autocorrelation, which is quite low.

The peaks of the realized correlation are hard to predict, in order to make the time series a bit smoother, taking the natural logarithm would help. Next to the Fisher transformation, another data transformation is used, it could be that a simple transformation already helps to make the variable more predictable, but because the data contains also negative values it is not possible to take the natural logarithm, the following 'Custom' transformation could be helpful.

$$Custom(RC_{i,j;t}) = \ln\left(\frac{RC_{i,j;t}+1}{2}\right) \quad with \quad t = 1, \dots, 336$$

where $RC_{i,j;t}$ is the realized correlations between asset *i* and *j* in month *t*. The main statistics of this transformation are given in Table 2.2.

Custom(RC)	**RC Stock-Bond**	**RC Stock-Commodity**	**RC Bond-Commodity**
Mean	-0,80	-0,68	-0,69
Std. Dev.	0,31	0,49	0,32
Skewness	-1,05	-1,20	-1,14
Kurtosis	5,19	3,86	6,10
JB P-value	0,00	0,00	0,00
AC(1)	0,67	0,30	0,12

Table 2.2 Descriptive statistics for transformation of the realized correlation (Custom(RC)), for the sample period January 1983 until December 2010

Note: **The reported statistics in the table include the mean, standard deviation, skewness, kurtosis, Jarque-Bera (JB) and the first order autocorrelation coefficients (AC)**

This transformation does look less attractive than the fisher transformation, because none of the variables is following a normal distribution. The time series is now much smoother, it got rid of its high peaks in the graph; however this cannot be seen in the table 2.2.

All variables were tested for a unit root using the Augmented Dickey-Fuller (ADF) test. The null-hypothesis of the ADF test is that there is a unit root in the data ($\varphi = 1$), and the alternative hypothesis is that there is not a unit root ($\varphi < 1$). Where φ is the coefficient of y_{t-1}.

$$y_t = \alpha + \varphi y_{t-1} + \varepsilon_t$$

Here y_t denotes the variables to be tested for a unit root, the variables which need to be tested are both transformations of the RCs, the realised variances and returns of the different assets and the 38 macroeconomic and financial variables. The results of this test are shown in Appendix B. A unit root is found in the in the Fisher(RC) and in some of the 38 macroeconomic and financial variables, these are corrected for the unit root by taking the first differences. Christiansen et al. (2012) already adjusted the relevant variables for seasonality.

3 Methods

This Chapter is organised as follows, first, a method for pre-selection the variables is discussed. For some models a pre-selection of the 38 macroeconomic and financial variables is needed, this is done by the ranking method Least Angle Regression (LARS), this method is discussed in Chapter 3.1. Second the technique of forecast combinations is discussed in Section 3.2. Third, two types of factor based models are discussed: Principal Component Analysis (PCA) and Partial Least Squares (PLS) respectively in Section 3.3.1 and 3.3.2. Fourth, Section 3.4 describes the usage of regimes switching models, these regimes switching models make use of the other models constructed. Fifth, three types of benchmark models are constructed in Section 3.5. Finally, the best model can be examined statistically and economically in Sections 3.6 and 3.7, the most important macroeconomic and financial variables can be derived from these models. To all the constructed models an autoregressive term is added as well as a lag of the realised variance ($RV_{i;t-1}$) and realised return ($RR_{i;t-1}$) of the assets. This may result in better models, because earlier research has shown that correlation differs in times of economic expansions and contraction (Zhou, 2014). All models are made with a 5 and 10 year moving window, and are used to make 1-month-ahead forecasts, starting in January 1993 till December 2010.

3.1 Forecast Combinations

First, forecast combinations are made of forecasts of 'simple' models, based on Timmermann (2006). These are models with all possible combinations of a subset of the 38 macroeconomic and financial variables. Because making combinations of all the 38 variables would lead to 2^{38} models, a subset of the best 18 variables is needed to keep it computable. To determine the 'best' variables in the subset, the Least Angle Regression (LARS) method (elaborated in Section 3.3) is used to give a ranking to the 38 variables (Bai & Ng, 2008; Cakmakli & Van Dijk, 2013). The forecast combinations are made using the mean as a weighting scheme, because this method performs relatively well compared to difficult schemes (Chan, Stock and Watson, 1999; Timmermann, 2006).

For each time window a subset of the *k* = 38 macroeconomic and financial variables is selected using the LARS method, resulting in the most relevant variables for explaining the volatility at the specific time interval (Bai & Ng, 2008). Then, to each of the regression models a variable from the selection is either added or not; for a forecast combination model with 18 variables this results in a total of 2^p = 2^{18} = 262.144 models. To each of these models an autoregressive term will also be added, since this carries a lot of information on the current observation. In addition a lag of the realised variance ($RV_{i;t-1}$) and realised return ($RR_{i;t-1}$) of the assets will be added as well, this may result in better models, because earlier research has shown that correlation differs in times of economic expansions and contraction (Zhou, 2014). Each model *m* is then specified as

$$y_t = \alpha_m + \beta_m y_{t-1} + \sum_{i=1}^{k} I(i)\gamma_{i,m}x_i + \varepsilon_{t,m} \text{ with m } = 1, \dots 2^p \qquad (1)$$

Here is $I(i)$ an indicator function taking value one when *xi* is included in model *m*, and zero otherwise. γ is a 1 x *p* vector, containing the OLS regression coefficients of *xi*. The 38 financial and macro economical variable are represented in *xi* with *i = 1, … , 38*. To get one forecast, the forecasts of all the models are combined by taking the mean over the forecasts.

3.2 Factor based models

The second and third model are two factor based models, i.e. principle component analysis (PCA) factor model and partial least squares (PLS) factor model. PCA is a useful technique to transform a high number of possible correlated variables into a smaller number of factors. The advantage of PLS over PCA is that it takes into account the correlation with the variable one wants to explain. To make the PCA factor model more reliable, PCA is performed on the 'best' 18 of the 38 variables, determined by LARS (elaborated in Section 3.3).

The optimal number of factors in both factor models will be determined by the information criterion used by Bay and Ng (2002) and Groen and Kapetanios (2008), the minimum number of factors is set to one.

$$\min_j IC_j = \ln(\sigma_\epsilon^2) + j\left(\frac{(k+T)\ln(\min(T,k))}{kT}\right) \quad j = 1, \dots, k \qquad (2)$$

In which σ_ϵ^2 is the squared of the standard error of estimated model; with *j* the number of factors in the model, assuming the factors sorted in order of importance; with *k* the maximum number of factors, which is 38, the number of variables.

3.2.1 Principal Component Analysis

Principal Component Analysis (PCA) is a useful technique in statistical analysis (Smith, 2002). Richardson (2009) defines PCA as a technique which uses sophisticated underlying mathematical principles to transform a number of possibly correlated variables into factors, a smaller number of variables. Because there are a relatively high number of explanatory variables, it is advantageous for our analysis to put the variables into factors. PCA finds the linear combinations of these macroeconomic and financial variables that are uncorrelated and explain an as large as possible variance of these variables. This reduces the problem form choosing between 38 different variables

into a choice of a number of factors. This results in a model with fewer coefficients to estimate. A drawback of using PCA is that is does not take into account which variable one wants to explain.
In order to cope with that, PCA will be performed on the pre-selected subset of 18 variables by the LARS method, and compare these to the results obtained with the model with all 38 variables. This gives better results, because the fact that PCA does not have a selection mechanism for which explanatory variables are more important to explain the dependent variable.

PCA starts with a dataset in terms of a *T* x *k* matrix X, with T is the sample size and *k* is the number of variables. The matrix X will be transformed into another matrix G, which has dimension *T x k* too. Now for some transformation matrix P the following holds

$$G = PX$$

The rows of P need to be orthogonal to be a new basis for representing the columns of X, which will become the principal components. It is either possible to perform PCA on the covariance or the correlation matrix. PCA is performed on the covariance matrix of the standardised data, which is the same as performing PCA on the correlation matrix, this in order prevent the factors of being wrongly influenced by the nominal value.

The covariance matrix of matrix G can be represented as the following matrix product.

$$C_G = \frac{1}{n-1} GGC_G = \frac{1}{n-1} PSP' \quad where \quad S = XX' = EDE'$$

where S is a *T* x *T*, E is an *T* x *T* orthonormal matrix whose columns are the orthonormal eigenvectors of S and D is a diagonal matrix which has the eigenvectors of S as its entries. The covariance matrix C_G can be written as

$$C_G = \frac{1}{n-1} PSP' = \frac{1}{n-1} E'(EDE')E = \frac{1}{n-1} D$$

Since E is an orthonormal matrix, it holds that $E'E = I$, where I is the *T* x *T* identity matrix. After obtaining the eigenvalues and eigenvectors of $S = XX'$, the eigenvalues are sorted in descending order and are placed in this order on the diagonal of D. Then, the orthonormal matrix E is constructed by placing the associated eigenvectors in the same order to form the columns of E. Now the principal components, i.e. matrix E, are the eigenvectors of the covariance matrix XX', and the rows are the principal components in order of importance.
With this method, information is gathered about the relative importance of each principal component from the variances. The largest variance corresponds to the first principal component, the second largest to the second principal component and so on. The data is organized in the diagonalization stage. The factors which are included in equation (4) are obtained by multiplying the principle components, located in matrix P, with matrix X

$$F^{PCA} = G = PX$$

An autoregressive term will be added to the PCA model, since this may give useful information on the current observation. In addition a lag of the realised variance ($RV_{i;t-1}$) and realised return ($RR_{i;t-1}$) of the assets will be added as well. The factors constructed with PCA can now be used in the following model

$$y_t = \alpha + \beta F_t^{PCA} + \rho y_{t-1} + \varepsilon_t \qquad (3)$$

With F_t^{PCA} being the factors constructed with PCA, the optimal number of factors to include in this model is determined by the information criterion in Equation 2.

3.2.2 Partial Least Squares

Partial Least Squares is a useful technique which can add more information to the factors than a factor model based on PCA.

In order to make it easy to perform PLS, the explanatory variables in X must be standardized and the dependent variable *y* must be demeaned (Groen & Kapetanios, 2008). PLS is constructed iteratively

$$Initialization: \qquad u_t = y_t, \qquad v_{i,t} = x_{i,t}, \qquad j = 1, \qquad with\; i = 1, \dots, k$$

Here *j* is the current constructed number of factors. The maximum number of factors to construct is *k* = 38. The variable weights ($w_{i,j}$) are constructed by taking the covariance between u_t and $v_{i,t}$ for every *i*.

$$w_{i,j} = Cov(u_t, v_{i,t})$$

The first factor ($f_{1,t}$) can now be constructed by $w_1'v_t$. Then u_t and $v_{i,t}$ are regressed on $f_{1,t}$ and the residuals of these regressions $\tilde{u}_t$ and $\tilde{v}_t$ are set as the new u_t and $v_{i,t}$.

To compute the remaining *k-1* factors, *j* is set to *j+1* and the weights ($w_{i,j}$) are then calculated for every *i*. The next factor can be constructed by $w_j'v_t$. Then, u_t and $v_{i,t}$ are regressed on $f_{j,t}$ and their residuals $\tilde{u}_t$ and $\tilde{v}_t$ are set as the new u_t and $v_{i,t}$. This is repeated until all the *k* factors are constructed.

After constructing the factors with PLS, the model looks similar to the model constructed with PCA but with different factors

$$y_t = \alpha + \beta F_t^{PLS} + \rho y_{t-1} + \varepsilon_t \qquad (4)$$

Here, y_t is the realized volatility, F_t a matrix with *k* columns and each column is a factor constructed with PLS.

3.3 Preselecting variables

As was said in the two previous Sections, Section 3.1 and Section 3.2.1, a selection of the best 18 out of 38 variables is needed. This pre-selection is done by using the ranking method Least Angle Regressions (LARS). One could pre-select the variables by simply regressing all separate variables on volatility but this may cause problems because of possibly correlated information in other variables

(Cakmakli & Van Dijk, 2013). Therefore LARS is used, this algorithm gives a ranking to all the 38 variables and by taking the first 18 a pre-selection is made.

The LARS algorithm builds up estimates of $\hat{\mu}$ and $\hat{\beta}$. These estimates are represented as follows

$$\hat{\mu} = X\hat{\beta} \tag{5}$$

With X is the complete data set of all macroeconomic and financial variables, and y contains the realized volatilities. The simple geometric version of the LARS algorithm is elaborated in Figure 3.1. It starts by setting $\hat{\mu}$ and $\hat{\beta}$ equal to zero, starting at point $\hat{\mu}_0$ in Figure 3.1. Then, the variable which is most correlated with volatility, say x_1, is selected. A large step is taken in the direction of this variable until some other variable, x_2, has as much correlation with the current residual(y) as x_1. From this point ($\hat{\mu}_1$), the new angle is taken as the biSection of x_1 and x_2. A new LARS estimate is constructed, say $\hat{\mu}_1$. Then, LARS continues with the new angle until a third variable, x_3, is just as correlated with the current residual as a combination of x_1 and x_2.Then a new angle is raised and after this the LARS method continues recursively.

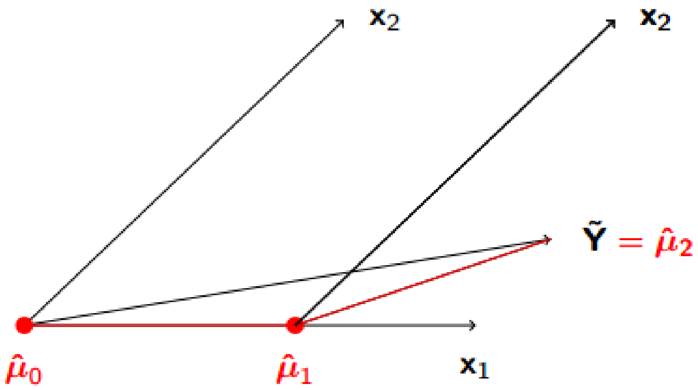

Figure 3.1 Geometric representation of the LARS algorithm with two explanatory variables x_1 and x_2

The LARS algorithm augments $\hat{\mu}_0$ in the direction of x_1, to $\hat{\mu}_1$, which is given by

$$\hat{\mu}_1 = \hat{\mu}_0 + \hat{\gamma}_1 x_1$$

The covariance of $\hat{\mu}$ is given by

$$Cov(\hat{\mu}) = X'(y - \hat{\mu})$$

$\hat{\gamma}_1$ is chosen so that y_2-$\hat{\mu}$ is equally correlated with x_1 and x_2. So y_2-$\hat{\mu}$ bisects the angle between $x_1$and x_2, this results in the following equality

$$c_1(\hat{\mu}_1) = c_2(\hat{\mu}_1)$$

Here $c_1(\hat{\mu}_1)$denotes the covariance of $\hat{\mu}_1$with y_1 and $c_2(\hat{\mu}_1)$denotes the covariance of $\hat{\mu}_1$with y_2. After constructing $\hat{\mu}_1$, the LARS algorithm proceeds with computing

$$\hat{\mu}_2 = \hat{\mu}_1 + \hat{\gamma}_2 u_2$$

where u_2 is the unit bisector which combines x_1 and x_2.

The LARS algorithm is elaborated in the case of two covariates. It continues in the same way with multiple covariates. It stops when all variables are included, resulting in a vector with estimates of all μ´s; $\hat{\beta}$ from Equation (5) can now be estimated by ordinary least squares. Finally, a ranking of the variables can be made by taking the highest absolute values of the $\hat{\beta}$s as the best explaining variables. Now the top 18 variables can be determined, in order to use this for the forecast combinations and for PCA.

3.4 Regime switching models

After making all models and having done the forecasts, a new type of model is introduced. The regime switching models, these models are made, by adding an indicator function (I) to the models form Section 3.1 and 3.2. If the model was $Y = X\beta + \varepsilon$ it becomes

$$Y = \begin{cases} X\beta + \varepsilon & if \quad I = 1 \\ X\beta + \varepsilon & otherwise \end{cases}$$

This gives a model the opportunity to capture two types of behaviour, first in the case the criterion indicated by the indicator functions holds, and the second type of behaviour if it does not hold. This can also be written by the following equation

$$Y = I \cdot X\beta + (1 - I) \cdot X\beta + \eta$$

The function I is the indicator function, which makes the distinction between two types of market behaviour. It is known that correlations behaves differently in bull of bear markets, correlations between stocks and bonds is usually high in times of economic expansion and low in times of economic contraction (Zhou, 2014). Therefore it the indicator functions indicates whether the market is in a bull market or not. A reasonably good indication of a bull market is that the sum of the market return in the last three months is positive. Three months are used in order to give in indication of the tendency of the market, one month would be to uncertain and by taking half a year it would be to rigid and not be able to react to fluctuations. Therefore the sum of the market return of the last quarter is used as an indicator. So three indicators are made, which indicates a bull market in market of stocks, bonds and commodities. This indicator is equal to one if the return of the last three periods of the asset was positive and is zero otherwise. All three regimes are used for the stock-bond, stock-commodity and the bond-commodity realised correlation.

3.5 Benchmark models

Three benchmark models are constructed, a random walk model, a simple autoregressive (AR (1)) model and an autoregressive model with some macroeconomic and financial variables, ARX (1). These benchmarks need to be beaten by the other models, otherwise it would be wiser just to use these simple models.

The first benchmark model is the random walk model. This model is one of the simplest models there exists, namely

$$y_t = y_{t-1} + \varepsilon_t$$

The forecast for the next period is simply the value of the last period.

The second benchmark model is the autoregressive model (AR(1)). This is a model with a constant and one autoregressive (AR) term. The first AR term is included, since there is a large first order autocorrelation in the volatilities for all asset classes as stated in Chapter 2. This model is slightly more advanced than the random walk model, and should be harder to beat by the constructed models. The AR(1) model is described as follows

$$y_t = \alpha + \beta y_{t-1} + \varepsilon_t$$

Finally the third benchmark model, the autoregressive model with macroeconomic and financial variables (ARX(1)), is introduced. This is an AR(1) model with 18 variables x_i. The macroeconomic and financial variables in the model are the highest-ranked variables which have been selected by the LARS method. So the ARX(1) is described as follows

$$y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{p} c_i x_i + \varepsilon_t$$

It could be possible that one of the x_i is not significant, but it is still included in the model. This is done to make it more comparable with our constructed models, which also use the same p financial and macroeconomic variables in their model specification.

3.6 Statistic interpretation

The statistical evaluation of the forecasts will be done by analyzing the accuracy, efficiency and unbiasedness. The mean squared prediction error (MSPE) and the mean absolute prediction error (MAE) will be examined for the accuracy.

$$MSPE = \frac{1}{n}\sum_{t=1}^{n} \varepsilon_t^2 \qquad\qquad MAE = \frac{1}{n}\sum_{t=1}^{n} |\varepsilon_t|$$

For comparing MSPE of the forecasts with the random walk model easily, the out-of-sample R^2 is used. The out-of-sample R^2 is defined by

$$R^2{}_{model\,x} = 1 - \frac{MSPE_{model\,x}}{MSPE_{Random\,Walk\,model}}$$

One can see that an out-of-sample R^2 which is higher than 1, corresponds with a higher performance in terms of accuracy than the random walk model.

To be able to compare the accuracy of the models, the Diebold-Mariano test will be used. The Diebold Mariano test makes it is possible to determine if the differences in the prediction errors are statistically significant. The null hypothesis of this test is that the sample mean of the difference in squared prediction errors of two different models *i,j* is not significantly larger than zero.

$$DM = \frac{\bar{d}}{\sqrt{\frac{V(d_{t+1})}{n}}} \approx N(0,1)$$

$$with\ d_{t+1} = e^2{}_{i,t+1|t} - e^2{}_{j,t+1|t} \qquad and \quad V(d_{t+1}) = \frac{1}{n-1}\sum_{t=1}^{n}(d_{t+1} - \bar{d})^2$$

Where $\bar{d}$ is the sample mean of d_{t+1} and n is the number of forecasts which is equal to 216. With a significance level of 5 percent, the critical value of this one-sided test is equal to 1.645. Tot test for efficient forecasts, the Mincer-Zarnowitz regression test is used.

$$y_{t+1} = \beta_0 + \beta_1 \hat{y}_{t+1|t} + \eta_{t+1}$$

The null hypothesis in this test is β_0 = 0 and β_1 = 1, an F-test is performed to test the null hypothesis. The underlying idea is that it should not be possible to forecast the forecast errors, based on the info at the time the forecast is made. Finally, unbiasedness is checked by testing if the forecast error significantly differs from zero.

3.7 Economic interpretation

Next to the statistical evaluation, it is interesting to see the economic practice of this research by looking at an investor with the possibility of investing in risk free T-bond rate and the three assets: stocks, bonds and commodities. Constructing an optimal portfolio can be done by making use of the preferences of an investor and of the forecasts of the realised correlations (RC), the realised returns (RR) and realised variances (RV). For the forecasts of the RC, the forecasts of the models from the previous Sections are used. A forecast for the RR is made by taking the average of the last 5 or 10 years, depending on the forecast window. A forecast for the RV is made by making use of the economically best performing forecast of the RV, which is a PCA factor model with the best 18 macroeconomic and financial variables selected by LARS, made by Holtrop, Kers, Mourer and Verkuijlen (2014), who use the same data to predict the RV. The economic evaluation is done by making use of the utility function of a fictive investor.

$$\max_{\boldsymbol{w}_{t+1}} \ E(r_{p,t+1}) - \frac{1}{2}\gamma Var(r_{p,t+1}) \qquad (?)$$

Where $\boldsymbol{w}_{t+1}$ is a 3x1 vector with the three investment weights of stocks, bonds and commodities; γ is the risk aversion rate of the investor and $r_{p,t+1}$ is the portfolio return and is given by

$$r_{p,t+1} = \begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \begin{bmatrix} r_{s,t+1} \\ r_{b,t+1} \\ r_{c,t+1} \end{bmatrix} - \begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \begin{bmatrix} r_{f,t+1} \\ r_{f,t+1} \\ r_{f,t+1} \end{bmatrix} + r_{f,t+1}$$

$$= \boldsymbol{w}'_{t+1}\boldsymbol{a}_{t+1} + r_{f,t+1} - \boldsymbol{w}'_{t+1}\boldsymbol{c}_{t+1}$$

In this formula $\boldsymbol{a}_{t+1}$ is a 3x1 vector with the expected returns of stocks, bonds and commodities; $r_{f,t+1}$ is the expected return on the risk free T-bond and $\boldsymbol{c}_{t+1}$ is a 3x1 vector with the $r_{f,t+1}$ on all three spots. The variance of the portfolio is

$$Var(r_{p,t+1}) = \boldsymbol{w}'_{t+1}\boldsymbol{\Sigma}_{t+1}\boldsymbol{w}_{t+1}$$

In which $\boldsymbol{\Sigma}_{t+1}$ is the expected covariance matrix of the returns of the three assets. It is assumed that the risk-free bond return for time *t+1* is already known at time *t* and this return is assumed independent from the three asset classes. This gives, by optimizing equation (?) the following optimal portfolio weights

$$\boldsymbol{w}^*_{t+1} = \frac{1}{\gamma}\boldsymbol{\Sigma}^{-1}_{t+1}(\boldsymbol{a}_{t+1} - \boldsymbol{c}_{t+1}) \qquad (?)$$

In which $\boldsymbol{\Sigma}^{-1}_{t+1}$ is the inverse of the expected covariance matrix, the expected covariance matrix needs to be positive definite to be invertible, it turned out like that. Two cases are considered; first, the weights are bounded between zero and one. These weights imply that short selling and lending are not allowed. In the second case, short selling and lending are permitted. Transaction costs are neglected. To evaluate what an investor is willing to pay for using the RC forecasts of this paper, the maximum performance fee is calculated. To be able to do this, a quadratic utility function is assumed (West, Edison & Cho, 1993). The average utility is given by

$$\bar{U} = \frac{W}{n}\sum_{t=0}^{n-1}\left(R_{p,t+1} - \frac{1}{2}\frac{\gamma}{(1+\gamma)}R^2_{p,t+1}\right) \qquad with\ R_{p,t+1} = 1 + r_{p,t+1}$$

Here *W* is defined as the wealth to be invested and *n* is the number of time periods where the investing is analyzed. In order to calculate the maximum performance fee, the utility of a strategy arising from the forecast of the constructed models (*strategy a*) needs to be compared with an unsophisticated buy-and-hold strategy (*strategy b*). The buy-and-hold strategy consists of either only investing in the risk-free t-bonds, only investing equally in the three markets, or in an equally weighted combination of the four.

$$\sum_{t=0}^{n-1}\left(\left(R^a_{p,t+1} - \Delta\right) - \frac{1}{2}\frac{\gamma}{(1+\gamma)}\left(R^a_{p,t+1} - \Delta\right)^2\right) = \sum_{t=0}^{n-1}\left(R^b_{p,t+1} - \frac{1}{2}\frac{\gamma}{(1+\gamma)}\left(R^b_{p,t+1}\right)^2\right)$$

From this equation the delta can be calculated, which is a fraction of the wealth that the investor is maximally willing to pay for this information.

4 Results

In Chapter 3 the methodology for the construction of all models and forecasts and for the statistical and economical evaluation are described. The results will be shown in this chapter; to begin with, in Section 4.1 the statistical results will be shown by statistically evaluating the forecast, by means of the unbiasedness, accuracy and the efficiency. For the three types of forecasts, i.e. forecasts combinations, factor based model-forecasts and regime switching model-forecasts, a selection of the results are presented in depth, for readability, the remaining results are given in the appendices. Then the models are compared with each other and with the benchmark models by means of their relative accuracy. In addition to the statistical results, Section 4.2 will elaborate on the results of the economic interpretation of the forecasts made in this paper.

The tables and graphs which will be shown in Section 4.1, are about the Stock-Bond realised correlation. The tables and graphs of the forecasts of the other realised correlations are shown in the appendices, as referred to in the text.

4.1 Statistic evaluation

In this section the forecasts of the models will be statistically evaluated, as described in Section 3.6. The following table shows the result of the forecast of the Stock-Bond realised correlation, where the Fisher transformation was used to transform the RC.

	Model	MSPE	MAE	Unbiasedness	Mincer-Zarnowitz F-statistic	Out-of-sample R^2
	Random Walk	0,119	0,275	0,164	*18,835	1,000
	AR(1)	0,105	0,253	*3,640	*7,010	0,877
	Forecast Combinations	0,102	0,247	*3,752	*9,030	0,858
	ARX(1)	0,127	0,273	*3,522	*17,133	1,068
	PCA	0,107	0,253	*3,692	*8,093	0,899
	PLS	0,108	0,255	*4,282	*10,401	0,907
I1	AR(1)	0,114	0,270	*3,614	*8,163	0,960
I1	Forecast Combinations	0,121	0,268	*3,244	*12,731	1,011
I1	ARX(1)	0,185	0,318	*2,921	*41,183	*1,555
I1	PCA	0,121	0,273	*3,600	*10,018	1,015
I1	PLS	0,119	0,272	*4,155	*11,736	1,000

Table 4.1 Statistic evaluation of the forecast of the Stock-Bond realised correlation. The Fisher transformation was used to transform the RC, the models were estimated with a 10 year moving window and the forecasts are made from January 1993 till December 2010.

Note: **The I1 in bold means that this is a Regime Switching model with Indicator 1 (Stock bull-market indicator), see Section 3.4 for details. The accuracy is shown by the mean squared prediction error (MSPE) and the mean absolute prediction error (MAE), the unbiasedness is given by t-statistics where the null hypothesis is that the forecast is unbiased and the efficiency is displayed by the Mincer Zarnowitz F-statistic, where the null hypothesis is that the forecast is efficient. The out-of-sample R^2 is a comparison of the MSPE, each model is compared with the Random Walk model. If the out-of-sample R^2 has a *, it indicates that the Diebold-Mariano test was rejected, which means a significant difference in accuracy.**

Table 4.1 shows that the predictions made with Forecast combinations have the lowest out-of-sample R^2, and therefore also the lowest MSPE. However this model has the lowest MSPE, it is not

* denotes the rejection of the null hypothesis for a significance level of 5 percent.

significantly better than the other models, which can be seen by the result of the Diebold-Mariano (DM) test, shown in Appendix C. Because of the fact that the DM test is not significant, the forecasts made with the other models, even though they have a slightly higher MSPE, they are not performing significantly worse. All of the forecasts made when making use of the Fisher transformation, are neither unbiased nor efficient, except the random walk model has unbiased forecasts.

Table 4.1 also shows results of the Regime Switching models with indicator 1 (Stock bull-market indicator), even though Zhou (2014) suggest that Regime Switching model can contribute to forecasts of co-movements, this is not the case with this specific kind of indicators. Especially when the ARX(1) is used in a Regime Switching model, it performs significantly worse in terms of accuracy compared to the other models model. The results of the other Regime Switching models are similar to this result, with one with indicator 1.

A complete table of Table 4.1 can be found in Appendix D, which includes statistic results of all models for all three RC: Stock-Bond, Stock-Commodity and Bond-Commodity, for the Fisher transformation.

The following table shows much different results in terms of unbiasedness and efficiency, when making use of a custom transformation of the RC, instead of the Fisher transformation.

	Model	MSPE	MAE	Unbiasedness	Mincer-Zarnowitz F-statistic	Out-of-sample R^2
	Random Walk	0,119	0,275	0,164	*18,835	1,000
	AR(1)	0,097	0,246	1,218	0,854	*0,812
	Forecast Combinations	0,091	0,236	1,250	1,266	*0,761
	ARX(1)	0,138	0,275	1,929	*15,742	1,160
	PCA	0,097	0,244	1,252	1,293	*0,814
	PLS	0,095	0,241	1,618	1,617	*0,800
I1	AR(1)	0,115	0,262	1,514	3,640	0,966
I1	Forecast Combinations	0,109	0,254	0,930	5,248	0,916
I1	ARX(1)	0,233	0,326	1,283	54,629	* 1,954
I1	PCA	0,117	0,264	1,499	4,653	0,978
I1	PLS	0,113	0,261	1,785	4,230	0,945

Table 4.2 Statistic evaluation of the forecast of the Stock-Bond realised correlation. The Custom transformation was used to transform the RC, the models were estimated with a 10 year moving window and the forecasts are made from January 1993 till December 2010.

Note: **The I1 in bold means that this is a Regime Switching model with Indicator 1 (Stock bull-market indicator), see Section 3.4 for details. The accuracy is shown by the mean squared prediction error (MSPE) and the mean absolute prediction error (MAE), the unbiasedness is given by t-statistics where the null hypothesis is that the forecast is unbiased and the efficiency is displayed by the Mincer Zarnowitz F-statistic, where the null hypothesis is that the forecast is**

* denotes the rejection of the null hypothesis for a significance level of 5 percent.

efficient. The out-of-sample R^2 is a comparison of the MSPE, each model is compared with the Random Walk model. If the out-of-sample R^2 has a *, it indicates that the Diebold-Mariano test was rejected, which means a significant difference in accuracy.

From Table 4.2 can be derived that most forecasts made, by making use of a custom transformation, are unbiased and efficient. Also more forecasts are now significant better in accuracy than the random walk model, which was not the case when the fisher transformation was used. The forecasts of the random walk do, by construction, not differ when making use of data transformation, therefore the results are the same as well. The AR(1) model, forecast combinations, the PCA factor model and the PLS factor model are all four unbiased, efficient and are significant more accurate than the random walk model. These four forecasts are even significantly better than nearly all forecasts made by making use of the Fisher transformation, which can be seen by the result of the Diebold-Mariano (DM) test, shown in Appendix C. By looking at the out-of-sample R^2, forecast combinations would be the most accurate, but it does not differ significantly with the other three well performing models.

One cloud say that the out-of-sample R^2 of most of the forecasts of the regime switching models are slightly lower than they were when making use of the fisher transformation, but this is not significant. The ARX(1) with indicator 1 is still performing badly in terms of accuracy.

A complete table of Table 4.2 can be found in Appendix E, which includes statistic results of all models for all three RC: Stock-Bond, Stock-Commodity and Bond-Commodity, for the custom transformation.

From table 4.1 and 4.2 can be seen that the forecasts made with Forecast Combinations give the lowest MSPE. Figure 4.1 gives a moving window of the development of the MSPE.

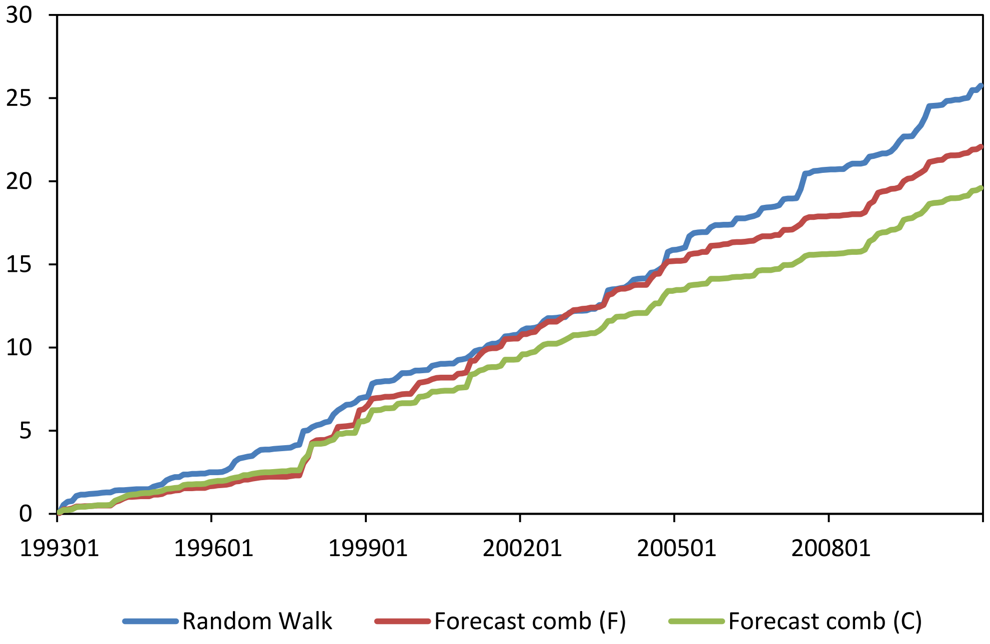

Figure 4.1 Moving window of the sum of the squared prediction error (SSPE) of forecasts made from: a random walk model, forecast combinations with use of the Fisher transformation (F) and forecasts combinations with use of custom transformation (C). For an exact specification of transformation types, see Section 2.2.

Note: **The moving SSPE is calculated by taking the aggregate sum over the squared forecasts errors.**

One can see from Figure 4.1 that the Forecast Combinations with the Custom transformation perform, in terms of accuracy, much better than the Random Walk model. From 1993 till the beginning of 1998 is the Forecast combinations with the Fisher transformation slightly lower, but afterwards the Forecast Combinations with the Fisher transformation even reaches the same values as the Random Walk model.

Forecast Combinations perform quite well, the forecasting technique makes use of a pre-selection method, the LARS method. Table 4.3 shows the 3 most selected macroeconomic and financial variables for being in the selection were the forecast combination were preformed on.

Stock-Bond RC		Stock-Commodity RC		Bond-Commodity RC	
Relative Bond Rate	0,986	**Capacity Utilization**	0,921	**Chicago PM Business Barometer**	0,917
T-Bill Rate, Level	0,824	**Industrial Production Growth, Monthly**	0,912	**Capacity Utilization**	0,875
M1 Growth, Yearly	0,815	**T-Bill Rate**	0,847	**Dividend Price Ratio**	0,861

Table 4.3 Fraction of a macroeconomic or financial variable of being selected by LARS, for the Fisher transformation

Note: **A full list of the macroeconomic and financial variables with their main specifications can be found in Appendix A. A full table of Table 4.4 can be found in Appendix E.**

Figure 4.3 shows that the Relative Bond rate is most important for the Stock-Bond realised correlation. Most of the main variables are from the second category: *Interest rates, spreads and bond market factors.* For the Stock-Commodity realised correlation the capacity utilization, the monthly industrial production growth and the T-Bill rate play an important role. The majority of important variables are from the fifth category: *Macroeconomic variables*. This was to be expected because of the fact that commodities are more related to the macro economy. The Bond-Commodity realised correlation is mainly indicated by the Chicago Business Barometer, the Capacity Utilization and the Dividend Price Ratio. Most of the main variables are from the fifth category: *Macroeconomic variables*. For the same reasons as for the Stock-Commodity RC, this was to be expected.

4.2 Economic evaluation

In this section the different forecasts are evaluated economically, as described in Section 3.7. Table 4.4 shows how the forecast of the models can be used in an economic context,

		Mean	STD	Portfolio weights restriction $\in [0, 1]$				
100% Risk Free		0,03	0,01					
100% Stocks		0,65	4,38					
100% Bonds		0,08	2,01					
100% Commodities		0,54	6,38					
25% in every asset		0,38	2,13					
Model		**Mean**	**STD**	**ΔRiskFree**	**ΔStock**	**ΔBond**	**ΔCom**	**Δ25**
REAL		0,70	6,40	-87	-64	-52	15	-84
Random Walk		0,65	6,45	-94	-71	-59	8	-91
Fisher transformation								
AR(1)		0,72	6,40	-85	-62	-50	17	-82
Forecast Combinations		0,71	6,75	-101	-78	-66	2	-98
ARX(1)		0,86	6,64	-81	-58	-47	21	-78
PCA		0,74	6,39	-83	-60	-48	19	-80
PLS		0,74	6,47	-85	-62	-51	17	-82
AR(1)	**I2**	0,71	6,43	-87	-64	-53	15	-84
Forecast Combinations	**I2**	0,86	6,32	-68	-44	-33	34	-65
ARX(1)	**I2**	1,30	6,07	-13	10	21	88	-10
Custom transformation								
AR(1)		0,70	6,43	-88	-65	-53	14	-85
Forecast Combinations		0,67	6,98	-116	-92	-81	-12	-113
ARX(1)		0,85	6,92	-95	-71	-60	8	-92
PCA		0,70	6,42	-88	-65	-53	14	-85
PLS		0,70	6,51	-92	-69	-57	10	-89
AR(1)	**I2**	0,66	6,52	-97	-73	-62	6	-93
Forecast Combinations	**I2**	0,80	6,39	-77	-53	-42	25	-73
ARX(1)	**I2**	1,08	5,93	-30	-7	4	71	-27

Table 4.4 Economic evaluation of the realised correlation forecasts of the constructed models and the benchmark models, in which the forecasts of the realised correlations are used to construct an optimal portfolio, consisting of stocks, bonds, commodities and risk free government bonds.

Note: **Mean and STD are respectively the average and the standard deviation of the portfolio return, displayed in monthly percentages. ΔRiskFree, ΔStock, ΔBond, ΔCom and Δ25 are the performance fees an investor is willing to pay extra to use these models instead of a standard strategies, displayed in basis points. These five strategies are 100% in risk free government bonds, 100% in stocks, 100% in bonds, 100% in commodities and 25% in every asset including the risk free government bonds. The 'real' model is the economic evaluation where the optimal weights were constructed with the real values for the realised correlation. The weights of an investor are bounded between 0 and 1. The I2 in bold means that this is a Regime Switching model with Indicator 2 (Bond bull-market indicator), see Section 3.4 for details.**

From table 4.4 can be seen that all strategies give have a quite low mean and a high standard deviation, only the risk free strategy standard deviation is in proportion to its mean. This is partly because the mean and standard deviation are displayed in monthly percentages, but is mainly caused by the fact that for the determination of the optimal portfolio weights quite inaccurate forecasts of the expected return are used. This table is still useful for comparing the relative economic value of the different models, because the same forecast is used for every model. For this very same reason, most of the deltas contain negative values, which would be resolved by using better forecasts for the expected return on the assets. Some models even perform slightly better than if the Real values of the realised correlation were used, which is a bit odd, which might be just 'luck' of the forecast.

By comparing the different forecasts, it can be noticed that the ARX(1) with a regime switching model of indicator 2 performs economically best, because it has the highest delta compared to the others models. It is interesting that this model performs so well economically, even though it did not performs outstandingly in the statistic evaluation. Also the Forecast Combinations with a Regime Switching model is performing reasonable. However it is performing quite well in combination with at regime switching model, Forecast Combinations scores worst without a Regime Switching model. The factor models perform approximately as good as the AR(1) model. When there was a clear difference for the two data transformations in the statistic interpretation, this is not the case for the economic interpretation, in the sense that it cannot be seen clearly which transformation gives better results.
A complete table of Table 4.4 can be found in Appendix G, which includes the economic evaluation of both restrictions on portfolios weights for all models for the Fisher and the custom transformation.

5 Conclusion

This research forecasted co-movements of stocks, bonds and commodities, with the use of macroeconomic and financial variables. This is done by different forecasting techniques on two data transformations on the realised correlation, which is a measure of co-movement. These techniques consisted of forecasts combinations, two factor based approaches and regime switching models.

Some drivers behind the co-movements were derived. These forecasts were evaluated both statically and economically.

The economic evaluation shows that the autoregressive model with macroeconomic and financial variables, with regime switching on an indicator of a bond-bull market (ARX(1), with indicator 2) performs best. If an investor would use this model to construct her portfolio, she would get the most utility based on her risk-averse preference.
This in contradiction to the statistic evaluation, where forecast combinations turned out to be the best performing model, but also other models such a simple autoregressive model (AR(1)) or the factor based models PCA and PLS do not perform worse than the forecast combinations. The statistic evaluation does show that forecasts made with the custom transformation from this paper, performs significantly better than forecasts made with the fisher transformation. For the Stock-Bond realised correlation, Interest rates, spreads and bond market factors are important, such as the relative bond rate. For the Stock-Commodity and Bond-Commodity realised correlation Macroeconomic variables are important, such as capacity utilization and industrial production growth.

Overall realised correlation is difficult to predict, therefore still further research is needed. A different data transformation is recommended in order to increase predictability. Regime switching models is a promising method for forecasting realised correlation, different regimes can be used, and an option could be to use the most important macroeconomic or financial variables of the realised correlations of stocks, bonds and commodities.

References

Aslanidis, N. and C. Christiansen (2014), Quantiles of the realized stock–bond correlation and links to the macroeconomy, *Journal of Empirical Finance*. Advance online publication

Baele, L., G. Bekaert, and K. Inghelbrecht (2010), The determinants of stock and bond return comovements. *Review of Financial Studies,* 23, 2374-2428.

Bai, J. and S. Ng (2002), Determining the Number of Factors in Approximate Factor Models, *Econometrica,* 70, 191-221.

Bai, J. and S. Ng (2008), Forecasting Economic Time Series Using Targeted Predictors, *Journal of Econometrics*, 146, 304-317.

Cakmakli, C. and D. Van Dijk (2013), Getting the Most out of Macroeconomic Information for Predicting Excess Stock Returns, to be published.

Campbell, J. Y., and J. Ammer (1993), What moves the stock and bond markets? A variance decomposition for long-term asset returns. *Journal of Finance*, 48, 3-37.

Chan, Y. L., Stock, J. H. and Watson, M. W. (1999). A Dynamic Factor Model Framework for Forecast Combination, *Spanish Economic Review,* 1, 91-121.

Christiansen, C. and A. Ranaldo (2007), Realized bond—stock correlation: Macroeconomic announcement effects. *Journal of Futures Markets,* 27, 439-469.

Christiansen, C., M. Schmeling and A. Schrimpf (2012), A comprehensive look at financial volatility prediction by economic variables, *Journal of Applied Econometrics,* 27, 956-977.

Chui, C. M. and J. Yang (2012), Extreme correlation of stock and bond futures markets: International evidence. *Financial Review,* 47, 565-587.

Ghysels, E., P. Santa-Clara and R. Valkanov (2005), There is a risk-return trade-off after all. *Journal of Financial Economics,* 76, 509-548.

Groen, J. J., and G. Kapetanios (2008). Revisiting Useful Approaches to Data-rich Macroeconomic Forecasting, *Federal Reserve Bank of New York Staff Reports,* 327, 1-56.

Holtrop, N., W, Kers, F. Mourer, M. Verkuijlen (2014). Volatility's next top driver: forecasting volatility with macroeconomic and financial variables. Not yet published.

Ilmanen, A. (2003), Stock-bond correlations, *Journal of Fixed Income*, 13, 55-66

Johnson, N. L., S. Kotz and N. Balakrishnan (1994), Continuous univariate distributions, New York, NY: John Wiley & Sons.

Kwan, S. H. (1996), Firm-specific information and the correlation between individual stocks and bonds. *Journal of Financial Economics,* 40, 63-80.

Piljak, V. (2013), Bond markets co-movement dynamics and macroeconomic factors: Evidence from emerging and frontier markets. *Emerging Markets Review,* 17, 29-43.

Silvennoinen, A., and S. Thorp (2013), Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions & Money,* 24, 42-65.

Timmermann, A. (2006), Forecast Combinations, *Handbook of Economic Forecasting,* 1, 135-196.

Zhang, J., D. Zhang, J. Wang, and Y. Zhang (2013), Volatility spillovers between equity and bond markets: Evidence from G7 and BRICS. *Romanian Journal of Economic Forecasting,* 16, 205-217.

Zhou, Y. (2014), Modeling the joint dynamics of risk-neutral stock index and bond yield volatilities. *Journal of Banking & Finance,* 38, 216-228.

Appendix

Appendix A

Variable	Abbrev.	Mean	Std.	Skew.	Kurt.	AC(1)
A. Equity Market Variables and Risk Factors						
1 Dividend Price Ratio (Log)*	D-P	0.28	4.58	0.77	6.44	0.06
2 Earnings Price Ratio (Log)	E-P	-3.02	0.43	-1.31	6.49	0.98
3 US Market Excess Return	MKT	0.59	4.57	-0.91	5.77	0.10
4 Size Factor	SMB	0.12	3.23	0.81	11.44	-0.03
5 Value Factor	HML	0.35	3.15	0.05	5.54	0.14
6 Short Term Reversal Factor	STR	0.37	3.44	0.17	8.34	-0.02
7 S&P500 Turnover	TURN	0.01	0.16	-0.07	3.38	-0.51
8 Return MSCI World	MSCI	0.73	4.26	-1.20	6.44	0.13
B. Interest Rates, Spreads and Bond Market Factors						
9 T-Bill Rate (Level)*	T-B	-0.23	2.32	0.95	5.12	0.48
10 Rel. T-Bill Rate	RTB	-0.18	0.86	-0.30	2.85	0.95
11 Long Term Bond Return	LTR	0.81	2.97	0.20	4.78	0.02
12 Rel. Bond Rate	RBR	-0.18	0.63	-0.36	4.49	0.87
13 Term Spread*	T-S	-0.01	33.77	0.34	3.67	0.08
14 Cochrane Piazzesi Factor	C-P	1.22	1.56	0.41	3.34	0.90
C. FX Variables and Risk Factors						
15 Dollar Risk Factor	DOL	0.12	2.19	-0.34	4.02	0.12
16 Carry Trade Factor	C-T	0.05	2.58	-0.69	4.38	0.18
17 Average Forward Discount	AFD	0.18	0.19	0.87	7.83	0.75
D. Liquidity and Credit Risk Variables						
18 Default Spread	DEF	0.11	0.43	2.48	12.3	0.94
19 FX Average Bid-ask Spread	BAS	1.43	5.00	1.92	7.46	0.88
20 Pastor-Stambaugh Liquidity Factor	PS	-0.28	6.83	-1.76	10.49	0.00
21 TED Spread	TED	0.07	0.00	1.78	8.67	0.81
E. Macroeconomic Variables						
22 Inflation Rate, Monthly	INFM	0.24	0.31	-1.38	11.31	0.47
23 Inflation Rate, Yearly	INFA	2.91	1.26	-0.48	4.41	0.95
24 Industrial Production Growth, Monthly	IPM	0.20	0.66	-1.32	10.18	0.23
25 Industrial Production Growth, Yearly*	IPA	0.27	9.52	0.29	6.96	0.28
26 Housing Starts	H-S	-2.20	24.9	-0.04	4.52	0.79
27 M1 Growth, Monthly	M1M	0.40	0.79	1.51	13.79	0.18
28 M1 Growth, Yearly	M1A	4.81	4.98	0.29	2.31	0.98
29 Orders, Monthly	ORDM	0.11	1.78	0.00	3.15	-0.19
30 Orders, Yearly	ORDA	1.20	6.93	-1.51	8.49	0.93
31 Return CRB Spot	CRB	0.25	2.74	-1.76	17.62	0.25
32 Capacity Utilization	CAP	0.02	0.66	-1.07	8.95	0.25
33 Employment Growth	EMPL	0.11	0.19	-0.37	7.40	0.65
34 Consumer Sentiment	SENT	0.01	4.70	0.07	5.66	0.00
35 Consumer Confidence	CONF	0.02	8.25	-0.29	9.94	0.07
36 Diffusion Index	DIFF	8.68	16.91	-0.64	3.57	0.83
37 Chicago PM Business Barometer	PMBB	55.15	7.33	-0.37	3.37	0.88
38 ISM PMI	PMI	52.08	5.35	-0.39	3.77	0.93

Note: **The table shows the summary statistics for the macro-finance predictive variables. The reported statistics include the mean, standard deviation (Std.), Skewness (Skew.), Kurtosis (Kurt.), as well as the first order autocorrelation coefficient (AC(1)). An asterisk (*) denotes that the variable is changed from Christianssen et al. (2012), corrected for a unit root.**

Appendix B Unit root test:

Augmented Dickey-Fuller tests on macro-economic and financial variables

variable	p-value	variable	p-value	variable	p-value	variable	p-value
BAS	0,0109	E-P	0,0147	STR	0,0000	LTR	0,0000
PS	0,0000	MKT	0,0000	TURN	0,0000	RBR	0,0000
PMI	0,0003	SMB	0,0000	MSCI	0,0000	T-S	0,1197*
DEF	0,0018	HML	0,0000	T-B	0,6382*	C-P	0,0011
D-P	0,4046*	HMLFX	0,0000	RTB	0,0003	DOL	0,0000
AFD	0,0000	IPGA	0,0743*	ORDA	0,0352	CONF	0,0000
TED	0,0000	H-S	0,0006	CRB	0,0000	DIFF	0,0004
INFM	0,0000	M1M	0,0000	CAP	0,0000	PMBB	0,0048
INFA	0,0253	M1A	0,0400	EMPL	0,0237		
IPM	0,0001	ORDM	0,0000	SENT	0,0000		

*denotes presence of unit root with a significance level of 0.05

Appendix C Diebold-Mariano Test

		Stock-Bond RC	Stock-Commodity RC	Bond-Commodity RC
Fisher	**RW**			
	AR	1,63	3,11	4,59
	ForeComb	1,63	2,56	4,58
	ARX	-0,55	-0,47	2,15
	PCA	1,26	3,16	4,45
	PLS	1,15	2,70	3,35
I1	AR	0,45	2,28	3,22
I1	ForeComb	-0,11	0,81	2,42
I1	ARX	-2,74	-2,83	-0,80
I1	PCA	-0,16	1,99	3,11
I1	PLS	0,00	1,73	2,63
I2	AR	0,96	2,05	3,81
I2	ForeComb	0,39	0,28	2,88
I2	ARX	-2,50	-3,45	-0,85
I2	PCA	0,69	1,88	3,38
I2	PLS	0,78	1,58	2,55
I3	AR	1,01	1,97	3,63
I3	ForeComb	0,60	1,00	3,00
I3	ARX	-2,48	-1,40	-0,97
I3	PCA	0,82	1,87	3,23
I3	PLS	0,94	1,39	2,44
Custom	**Transformation**			
	AR	2,72	1,92	4,39
	ForeComb	2,89	1,61	4,32
	ARX	-0,90	-1,56	1,40
	PCA	2,58	1,89	4,24
	PLS	2,81	1,52	2,94
I1	AR	0,24	1,37	2,78
I1	ForeComb	0,75	-0,06	2,65
I1	ARX	-2,55	-4,10	-2,31
I1	PCA	0,16	1,11	2,61
I1	PLS	0,46	0,86	1,64
I2	AR	1,80	0,86	3,65
I2	ForeComb	0,69	-0,69	2,83
I2	ARX	-3,07	-3,04	-0,90
I2	PCA	1,58	0,70	2,29
I2	PLS	0,46	0,86	1,64
I3	AR	1,74	0,82	3,30
I3	ForeComb	1,34	-0,29	2,59
I3	ARX	-2,10	-3,05	-2,25
I3	PCA	1,44	0,58	2,97
I3	PLS	1,87	0,32	1,42

Green indicates a significant better model than the random walk model and red indicates a significant worse model than the random walk model.

Appendix D Statistical evaluation of the forecasts for the Stock-Bond, Stock-Commodity and the Bond-Commodity realised correlation. (Fisher transformation)

Note: The fisher transformation is used as a data transformation, see Section 2.2.

S-B	Model	MSPE	MAE	Unbaisedness	Mincer-Zarnowitz F-statistic	Out-of-sample R2
	RW	0,119	0,275	0,164	18,835	1,000
	AR	0,105	0,253	3,640	7,010	0,877
	ForeComb	0,102	0,247	3,752	9,030	0,858
	ARX	0,127	0,273	3,522	17,133	1,068
	PCA	0,107	0,253	3,692	8,093	0,899
	PLS	0,108	0,255	4,282	10,401	0,907
I1	AR	0,114	0,270	3,614	8,163	0,960
I1	ForeComb	0,121	0,268	3,244	12,731	1,011
I1	ARX	0,185	0,318	2,921	41,183	1,555
I1	PCA	0,121	0,273	3,600	10,018	1,015
I1	PLS	0,119	0,272	4,155	11,736	1,000
I2	AR	0,110	0,261	3,914	8,371	0,922
I2	ForeComb	0,114	0,257	3,338	11,514	0,959
I2	ARX	0,165	0,308	3,059	30,308	1,387
I2	PCA	0,112	0,264	3,964	9,817	0,940
I2	PLS	0,111	0,263	4,316	11,158	0,935
I3	AR	0,110	0,263	3,144	6,811	0,926
I3	ForeComb	0,112	0,260	3,154	10,314	0,941
I3	ARX	0,169	0,315	2,419	28,989	1,418
I3	PCA	0,111	0,258	2,965	7,709	0,935
I3	PLS	0,110	0,256	3,526	8,908	0,923
S-C	**Model**	**MSPE**	**MAE**	**Unbaisedness**	**Mincer-Zarnowitz F-statistic**	**Out-of-sample R2**
	RW	0,101	0,244	-0,121	36,787	1,000
	AR	0,070	0,214	-2,464	3,790	0,691
	ForeComb	0,075	0,220	-2,071	3,030	0,745
	ARX	0,108	0,258	-1,377	30,695	1,066
	PCA	0,070	0,213	-2,414	3,762	0,689
	PLS	0,073	0,220	-2,047	2,413	0,723
I1	AR	0,077	0,224	-2,319	3,228	0,758
I1	ForeComb	0,092	0,243	-1,959	10,953	0,906
I1	ARX	0,154	0,306	-0,471	73,075	1,518
I1	PCA	0,079	0,227	-2,409	4,165	0,780
I1	PLS	0,081	0,231	-2,123	3,561	0,804
I2	AR	0,079	0,227	-2,584	3,515	0,781
I2	ForeComb	0,098	0,250	-2,114	14,819	0,968
I2	ARX	0,164	0,318	-0,929	82,488	1,626
I2	PCA	0,081	0,229	-2,601	3,882	0,796

I2	PLS	0,083	0,235	-1,998	2,951	0,825
I3	AR	0,079	0,220	-1,942	3,020	0,777
I3	ForeComb	0,089	0,230	-1,697	11,323	0,880
I3	ARX	0,125	0,273	-1,050	51,132	1,239
I3	PCA	0,079	0,221	-2,079	3,639	0,785
I3	PLS	0,084	0,229	-1,608	3,800	0,830
B-C	**Model**	**MSPE**	**MAE**	**Unbaisedness**	**Mincer-Zarnowitz F-statistic**	**Out-of-sample R2**
	RW	0,116	0,272	0,086	82,149	1,000
	AR	0,070	0,215	0,259	5,373	0,605
	ForeComb	0,069	0,210	0,811	6,671	0,597
	ARX	0,090	0,240	0,590	40,553	0,780
	PCA	0,070	0,213	0,677	5,145	0,603
	PLS	0,076	0,221	1,192	15,393	0,659
I1	AR	0,081	0,222	0,390	24,558	0,702
I1	ForeComb	0,087	0,230	0,610	33,148	0,754
I1	ARX	0,129	0,276	0,257	102,728	1,115
I1	PCA	0,081	0,225	0,827	24,449	0,705
I1	PLS	0,084	0,228	1,342	27,981	0,726
I2	AR	0,075	0,223	0,845	13,669	0,649
I2	ForeComb	0,083	0,229	1,154	27,728	0,722
I2	ARX	0,129	0,283	0,972	100,092	1,113
I2	PCA	0,077	0,225	1,355	17,025	0,667
I2	PLS	0,082	0,230	1,819	25,615	0,713
I3	AR	0,077	0,219	-0,517	16,713	0,666
I3	ForeComb	0,082	0,228	0,549	25,440	0,710
I3	ARX	0,131	0,293	0,628	103,414	1,130
I3	PCA	0,080	0,224	0,067	22,022	0,693
I3	PLS	0,084	0,228	0,508	28,624	0,729

Statistic evaluation of the forecast of the Stock-Bond, Stock-Commodity and the Bond-Commodity realised correlation. The Fisher transformation was used to transform the RC, the models were estimated with a 10 year moving window and the forecasts are made from January 1993 till December 2010.
Note: **The I1 in bold means that this is a Regime Switching model with Indicator 1 (Stock bull-market indicator), Indicator 2 (Bond bull-market indicator) and indicator 3 (Commodity bull-market indicator), see Section 3.4 for details. The accuracy is shown by the mean squared prediction error (MSPE) and the mean absolute prediction error (MAE), the unbiasedness is given by t-statistics where the null hypothesis is that the forecast is unbiased and the efficiency is displayed by the Mincer Zarnowitz F-statistic, where the null hypothesis is that the forecast is efficient. The out-of-sample R^2 is a comparison of the MSPE, each model is compared with the Random Walk model. If the out-of-sample R^2 has a *, it indicates that the Diebold-Mariano test was rejected, which means a significant difference in accuracy.**
*** denotes the rejection of the null hypothesis for a significance level of 5 percent.**

Appendix E Statistical evaluation of the forecasts for the Stock-Bond, Stock-Commodity and the Bond-Commodity realised correlation. (Custom transformation)

Note: A custom transformation is used as a data transformation, see Section 2.2.

S-B	Model	MSPE	MAE	Unbaisedness	Mincer-Zarnowitz F-statistic	Out-of-sample R2
	RW	0,119	0,275	0,164	18,835	1,000
	AR	0,097	0,246	1,218	0,854	0,812
	ForeComb	0,091	0,236	1,250	1,266	0,761
	ARX	0,138	0,275	1,929	15,742	1,160
	PCA	0,097	0,244	1,252	1,293	0,814
	PLS	0,095	0,241	1,618	1,617	0,800
I1	AR	0,115	0,262	1,514	3,640	0,966
I1	ForeComb	0,109	0,254	0,930	5,248	0,916
I1	ARX	0,233	0,326	1,283	54,629	1,954
I1	PCA	0,117	0,264	1,499	4,653	0,978
I1	PLS	0,113	0,261	1,785	4,230	0,945
I2	AR	0,103	0,256	1,616	1,648	0,865
I2	ForeComb	0,110	0,254	1,483	5,636	0,925
I2	ARX	0,221	0,337	2,796	52,207	1,856
I2	PCA	0,103	0,258	1,677	2,341	0,868
I2	PLS	0,113	0,261	1,785	4,230	0,945
I3	AR	0,104	0,255	0,804	1,724	0,875
I3	ForeComb	0,104	0,251	0,871	4,610	0,874
I3	ARX	0,185	0,314	1,798	37,763	1,549
I3	PCA	0,106	0,256	0,666	3,122	0,888
I3	PLS	0,110	0,256	3,526	8,908	0,923
S-C	**Model**	**MSPE**	**MAE**	**Unbaisedness**	**Mincer-Zarnowitz F-statistic**	**Out-of-sample R2**
	RW	0,101	0,244	-0,121	36,787	1,000
	AR	0,080	0,229	-4,918	13,441	0,793
	ForeComb	0,084	0,234	-3,838	8,928	0,830
	ARX	0,124	0,285	-1,344	50,174	1,228
	PCA	0,080	0,230	-4,754	12,275	0,795
	PLS	0,084	0,238	-4,270	9,372	0,830
I1	AR	0,085	0,234	-4,464	10,435	0,842
I1	ForeComb	0,102	0,254	-3,444	19,161	1,008
I1	ARX	0,214	0,349	-0,246	136,551	2,112
I1	PCA	0,087	0,237	-4,436	10,895	0,865
I1	PLS	0,090	0,245	-4,048	9,868	0,893
I2	AR	0,091	0,244	-4,795	11,792	0,899
I2	ForeComb	0,110	0,267	-3,079	23,795	1,086
I2	ARX	0,293	0,392	0,602	229,594	2,896
I2	PCA	0,093	0,247	-4,624	11,749	0,917

I2	PLS	0,090	0,245	-4,048	9,868	0,893
I3	AR	0,091	0,234	-3,965	10,617	0,895
I3	ForeComb	0,105	0,249	-2,740	23,120	1,040
I3	ARX	0,212	0,333	-0,099	143,704	2,097
I3	PCA	0,093	0,237	-3,915	11,782	0,921
I3	PLS	0,084	0,229	-1,608	3,800	0,830
B-C	**Model**	**MSPE**	**MAE**	**Unbaisedness**	**Mincer-Zarnowitz F-statistic**	**Out-of-sample R2**
	RW	0,116	0,272	0,086	82,149	1,000
	AR	0,071	0,215	-1,658	8,154	0,619
	ForeComb	0,071	0,213	-0,830	8,689	0,612
	ARX	0,098	0,250	-0,236	52,302	0,851
	PCA	0,071	0,214	-1,228	7,077	0,614
	PLS	0,079	0,223	-0,190	20,659	0,687
I1	AR	0,085	0,227	-1,228	32,114	0,733
I1	ForeComb	0,085	0,227	-0,775	30,130	0,738
I1	ARX	0,168	0,309	0,611	165,050	1,458
I1	PCA	0,086	0,230	-0,722	33,070	0,743
I1	PLS	0,094	0,238	0,195	43,777	0,810
I2	AR	0,076	0,223	-0,847	14,981	0,656
I2	ForeComb	0,083	0,230	0,070	27,880	0,721
I2	ARX	0,128	0,290	0,546	99,708	1,110
I2	PCA	0,083	0,228	-0,185	25,845	0,715
I2	PLS	0,094	0,238	0,195	43,777	0,810
I3	AR	0,080	0,225	-2,124	22,122	0,693
I3	ForeComb	0,085	0,230	-0,773	29,930	0,736
I3	ARX	0,194	0,323	0,939	205,008	1,678
I3	PCA	0,082	0,227	-1,371	25,192	0,707
I3	PLS	0,084	0,228	0,508	28,624	0,729

Statistic evaluation of the forecast of the Stock-Bond, Stock-Commodity and the Bond-Commodity realised correlation. The Custom transformation was used to transform the RC, the models were estimated with a 10 year moving window and the forecasts are made from January 1993 till December 2010.

Note: **The I1 in bold means that this is a Regime Switching model with Indicator 1 (Stock bull-market indicator), Indicator 2 (Bond bull-market indicator) and indicator 3 (Commodity bull-market indicator), see Section 3.4 for details. The accuracy is shown by the mean squared prediction error (MSPE) and the mean absolute prediction error (MAE), the unbiasedness is given by t-statistics where the null hypothesis is that the forecast is unbiased and the efficiency is displayed by the Mincer Zarnowitz F-statistic, where the null hypothesis is that the forecast is efficient. The out-of-sample R^2 is a comparison of the MSPE, each model is compared with the Random Walk model. If the out-of-sample R^2 has a *, it indicates that the Diebold-Mariano test was rejected, which means a significant difference in accuracy.**
*** denotes the rejection of the null hypothesis for a significance level of 5 percent.**

Appendix F Percentile of macroeconomic and financial variable being selected by LARS

Note: This variable selection is used for the ARX(1) model, forecast combinations and PCA model.

Stock-Bond RC		Stock-Commodity RC		Bond-Commodity RC		Stock-Bond RC		Stock-Commodity RC		Bond-Commodity RC	
RBR	0,986	CAP	0,921	PMBB	0,917	RBR	0,944	CAP	0,889	DIFF	0,880
T-B	0,824	IPM	0,912	CAP	0,875	T-B	0,898	IPM	0,870	IPM	0,875
M1A	0,815	T-B	0,847	D-P	0,861	T-S	0,829	BAS	0,810	CAP	0,866
D-P	0,801	BAS	0,759	IPM	0,843	DEF	0,792	ORDA	0,796	D-P	0,829
CONF	0,787	ORDA	0,745	E-P	0,833	LTR	0,778	MSCI	0,782	PMBB	0,801
LTR	0,773	E-P	0,685	DIFF	0,833	AFD	0,755	IPGA	0,755	E-P	0,782
T-S	0,759	MSCI	0,685	M1A	0,759	INFA	0,731	T-B	0,722	M1A	0,769
PS	0,759	D-P	0,681	C-P	0,676	M1A	0,718	INFA	0,722	TURN	0,718
BAS	0,713	T-S	0,681	PMI	0,671	D-P	0,704	E-P	0,713	MSCI	0,694
E-P	0,699	IPGA	0,676	TURN	0,657	E-P	0,694	DEF	0,694	LTR	0,662
DEF	0,694	INFA	0,671	LTR	0,653	BAS	0,671	M1A	0,667	RTB	0,616
INFA	0,685	LTR	0,662	RTB	0,625	PS	0,644	TED	0,634	HMLFX	0,602
AFD	0,671	PMBB	0,644	AFD	0,625	RTB	0,634	AFD	0,597	AFD	0,583
MKT	0,616	M1A	0,606	T-B	0,611	CONF	0,593	T-S	0,583	C-P	0,565
RTB	0,611	DEF	0,606	HMLFX	0,606	PMBB	0,588	D-P	0,565	MKT	0,556
CAP	0,565	MKT	0,569	MSCI	0,542	MKT	0,574	M1M	0,523	PMI	0,551
MSCI	0,519	AFD	0,542	T-S	0,542	C-P	0,528	PMI	0,514	T-B	0,546
IPM	0,500	DIFF	0,523	MKT	0,537	CAP	0,509	PMBB	0,495	INFA	0,519
SMB	0,454	M1M	0,514	INFA	0,523	TED	0,500	C-P	0,481	T-S	0,500
PMBB	0,449	PMI	0,509	TED	0,421	MSCI	0,468	PS	0,463	H-S	0,491
C-P	0,444	TED	0,449	M1M	0,417	IPM	0,463	TURN	0,444	CONF	0,435
HML	0,435	RTB	0,444	CONF	0,417	STR	0,444	RTB	0,444	RBR	0,389
M1M	0,407	RBR	0,444	RBR	0,403	HML	0,431	LTR	0,444	PS	0,380
PMI	0,403	C-P	0,421	PS	0,366	SMB	0,417	RBR	0,444	M1M	0,356
TED	0,389	TURN	0,394	H-S	0,361	ORDA	0,412	STR	0,394	ORDM	0,343
STR	0,282	PS	0,352	ORDM	0,333	M1M	0,384	DOL	0,338	SMB	0,338
ORDA	0,282	SENT	0,310	SMB	0,301	PMI	0,356	DIFF	0,329	BAS	0,333
DIFF	0,273	STR	0,292	DEF	0,292	CRB	0,278	H-S	0,324	DEF	0,319
INFM	0,255	DOL	0,292	BAS	0,273	DIFF	0,190	MKT	0,310	TED	0,310
EMPL	0,227	H-S	0,264	DOL	0,245	ORDM	0,176	SENT	0,269	DOL	0,269
ORDM	0,218	HML	0,250	STR	0,194	INFM	0,167	EMPL	0,259	ORDA	0,231
H-S	0,194	HMLFX	0,181	ORDA	0,176	IPGA	0,130	HMLFX	0,241	CRB	0,227
SENT	0,148	SMB	0,157	IPGA	0,157	HMLFX	0,116	HML	0,199	IPGA	0,218
DOL	0,083	EMPL	0,153	CRB	0,153	SENT	0,116	SMB	0,144	EMPL	0,199
HMLFX	0,074	ORDM	0,088	HML	0,148	H-S	0,106	ORDM	0,056	STR	0,111
IPGA	0,074	CONF	0,028	EMPL	0,130	EMPL	0,102	CONF	0,056	HML	0,083
TURN	0,069	INFM	0,023	INFM	0,023	TURN	0,088	INFM	0,014	INFM	0,051
CRB	0,060	CRB	0,019	SENT	0,000	DOL	0,074	CRB	0,014	SENT	0,005

Appendix G Results of the economic interpretation of the different forecasts made in this paper.

	Mean	STD
100% Risk Free	0,28	0,16
100% Stocks	0,65	4,38
100% Bonds	0,08	2,01
100% Commodities	0,54	6,38
25% in every asset	0,38	2,13

	Weights $\in [0,1]$							Weights $\in [-1,2]$						
Model	**Mean**	**STD**	Δ_{RF}	Δ_S	Δ_B	Δ_C	Δ_{25}	**Mean**	**STD**	Δ_{RF}	Δ_S	Δ_B	Δ_C	Δ_{25}
REAL	0,70	6,40	-87	-64	-52	15	-84	0,94	9,84	-261	-234	-221	-145	-257
RW	0,65	6,45	-94	-71	-59	8	-91	0,94	10,41	-305	-277	-264	-185	-301
Fisher Transformation														
AR	0,72	6,40	-85	-62	-50	17	-82	1,09	9,26	-204	-178	-166	-91	-201
ForeComb	0,71	6,75	-101	-78	-66	2	-98	1,04	10,16	-275	-248	-234	-157	-271
ARX	0,86	6,64	-81	-58	-47	21	-78	1,46	10,36	-248	-221	-207	-129	-245
PCA	0,74	6,39	-83	-60	-48	19	-80	1,08	9,31	-208	-182	-169	-95	-204
PLS	0,74	6,47	-85	-62	-51	17	-82	1,14	9,47	-213	-187	-174	-99	-209
AR	0,74	6,48	-86	-63	-52	16	-83	1,01	9,37	-219	-193	-180	-105	-215
ForeComb	0,75	6,56	-89	-66	-55	13	-86	1,04	10,09	-269	-242	-229	-151	-266
ARX	0,55	6,73	-116	-92	-81	-13	-113	0,79	11,37	-405	-375	-361	-277	-401
PCA	0,77	6,51	-84	-61	-49	18	-81	1,02	9,38	-219	-193	-180	-106	-216
PLS	0,82	6,50	-79	-56	-44	23	-76	1,14	9,55	-219	-193	-180	-105	-216
AR	0,71	6,43	-87	-64	-53	15	-84	1,14	9,40	-209	-183	-170	-95	-205
ForeComb	0,86	6,32	-68	-44	-33	34	-65	1,43	10,60	-271	-243	-229	-149	-267
ARX	1,30	6,07	-13	10	21	88	-10	2,60	10,61	-155	-127	-113	-34	-151
PCA	0,66	6,54	-97	-73	-62	6	-94	1,10	9,53	-222	-195	-183	-107	-218
PLS	0,68	6,65	-100	-77	-65	2	-97	1,09	9,78	-240	-214	-201	-125	-237
AR	0,68	6,55	-95	-72	-61	7	-92	1,01	9,60	-236	-209	-196	-121	-232
ForeComb	0,87	6,18	-61	-38	-26	41	-58	1,37	10,14	-240	-213	-200	-122	-237
ARX	1,00	6,04	-43	-20	-8	58	-40	1,60	10,58	-253	-225	-212	-132	-249
PCA	0,68	6,57	-96	-73	-62	6	-93	1,04	9,67	-237	-211	-198	-122	-234
PLS	0,67	6,80	-107	-84	-72	-4	-104	0,96	10,38	-301	-273	-260	-181	-297
Custom Transformation														
AR	0,70	6,43	-88	-65	-53	14	-85	1,10	9,40	-212	-186	-173	-99	-209
ForeComb	0,67	6,98	-116	-92	-81	-12	-113	0,96	10,28	-292	-265	-251	-173	-288
ARX	0,85	6,92	-95	-71	-60	8	-92	1,37	10,54	-273	-245	-231	-152	-269
PCA	0,70	6,42	-88	-65	-53	14	-85	1,10	9,47	-218	-191	-179	-104	-214
PLS	0,70	6,51	-92	-69	-57	10	-89	1,13	9,54	-220	-193	-180	-105	-216
AR	0,70	6,52	-92	-69	-57	10	-89	0,93	9,51	-237	-211	-198	-123	-233
ForeComb	0,65	6,98	-117	-94	-82	-14	-114	0,90	10,31	-300	-272	-259	-181	-296
ARX	0,71	6,33	-83	-59	-48	19	-80	1,20	10,27	-268	-240	-227	-149	-264
PCA	0,70	6,55	-93	-70	-58	9	-90	1,03	9,49	-226	-200	-187	-112	-223
PLS	0,79	6,50	-83	-59	-48	20	-80	1,12	9,60	-224	-198	-185	-109	-221
AR	0,66	6,52	-97	-73	-62	6	-93	1,13	9,59	-223	-196	-184	-108	-219
ForeComb	0,80	6,39	-77	-53	-42	25	-73	1,45	10,43	-255	-227	-214	-135	-251
ARX	1,08	5,93	-30	-7	4	71	-27	2,01	10,41	-198	-170	-157	-78	-194
PCA	0,63	6,63	-104	-81	-69	-2	-101	1,11	9,70	-233	-206	-193	-118	-229
PLS	0,79	6,50	-83	-59	-48	20	-80	1,12	9,60	-224	-198	-185	-109	-221
AR	0,66	6,59	-99	-75	-64	4	-96	1,06	9,73	-240	-213	-200	-124	-236
ForeComb	0,88	6,22	-62	-39	-27	40	-59	1,40	10,16	-238	-211	-198	-120	-234
ARX	0,96	6,08	-48	-25	-14	53	-45	1,58	10,43	-242	-214	-201	-122	-238
PCA	0,66	6,65	-102	-78	-67	1	-99	1,08	9,89	-250	-223	-210	-133	-246
PLS	0,63	6,72	-108	-85	-73	-5	-105	1,02	10,19	-280	-252	-239	-161	-276