MASTER THESIS

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Regime Switching bond-stock correlation and asset allocation implications in a Norwegian context

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Introduction

1 Theoretical framework

In the following chapter, I will lay the theoretical basis for the thesis.

1.1 Background

For a long period, the correlation between the assets has been assumed constant; Shiller and Beltratti (1992), Campbell and Ammer (1993) and others considered that the association between stock and bond prices rests constantly over time. But recently, many studies have indicated that the correlation between stock and bond returns demonstrates significant time variation (Gulko (2002); Cappiello et al. (2006); Ilmanen (2003); Bansal et al. (2010)). Though generally, stock and bond prices assumed to change in the same direction, current studies have also recognized periods of negative correlation. There are several driving causes at the back of the time-varying correlation, such as macroeconomic variable inflation. An upsurge in expected inflation ascents discount rates and hence is unavoidably bad news for the bond markets. However, the effect of growing inflation on stock prices is unclear, as the expected future cash flows as well as discount rates are expected to be moved. Other than basic changes in the macroeconomic atmosphere, financial market features, and variations in market participants' valuation about risk may also have an imperative influence on the association between stock and bond returns. For example, during periods of crisis in the financial market, the equity risk premium required by the investors to hold stock may rise in comparison to the premium for bonds. This may cause the so-called process of 'flight-to- quality'[1], portfolio moves from the stock markets to the bond markets, imposing some deviation in the returns between these two asset classes. (Andersson et al., 2008)

The correlation between the assets has been a crucial component of portfolio risk from the time when Markowitz (1956) devised the portfolio diversification. Estimated correlations between asset classes or securities are vital elements of which assets are included in a portfolio and in what amounts. The lower the correlation between portfolio assets, the greater the diversification-benefits and more attractive the combination of two assets. Therefore, the correlation between different assets of a portfolio is very critical to risk measurement and management.

Markowitz (1956) one of the pioneers of the modern portfolio theory, stated that diversification can reduce the risk without changing its expected return, but it cannot eliminate it. The investor should maximize the return of the portfolio and minimize the variance of the portfolio (Rubinstein, 2002).

[1]As bonds are considered less risky than stocks

Financial markets often show variation in their behavior. Sometimes the changes may be temporary like "jumps", but most variations in the behavior of financial markets stay for a longer period. For example, during the financial crisis of 2008-2009; the mean, volatility, and correlation of stock returns changed abruptly at the start but then persisted for a longer time. This type of regime changes can occur again and again such as recessions and expansions but sometimes it can be long-lasting such as breaks in some behavior. These regime changes are often dominant in interest rates, equity returns, and the behavior of many macro variables. Regime switching models can capture the sudden variations of the behaviors and the phenomenon that the new dynamics of prices and fundamentals endure for many periods after a change. (Ang and Timmermann, 2012)

There are many motivations why regime-switching models had become influential in financial modeling. First of all, regime-switching is natural and intuitive, closely connected to the well-known idea of good and bad states or states with low versus high risk, but unexpected and somewhat counterintuitive outcomes can be obtained from regime-switching. The original application of regime switching in Hamilton (1989) was to business cycle recessions and expansions. The regimes logically apprehended cycles of economic activity around a long-term tendency. By using econometric methods of financial series, regimes are classified and often have different characteristics of periods in regulation, policy, and some other secular variations. The interest rate performance changed from 1979 to 1982 as Federal Reserve altered its operating method to targeting monetary aggregates. Other regimes in interest rates show the period of different Federal Reserve Chairpersons such as Sims and Zha, 2006. In terms of equity, different regimes have a different level of high and low volatility, long bull and bear market eras. Therefore, regime-switching models can explain changing fundamentals that sometimes can only be understood ex-post, though it can be used for ex-ante real-time predictions, optimal portfolio selection, and other economic purposes. (Ang and Timmermann, 2012)

Secondly, regime-switching models capture stylized performance of many financial return series such as fat tails, continuously occurring periods of trouble in economy shown by periods of low volatility (ARCH effects), skewness, and time-varying correlations. Even in the case when the true model is unidentified, regime-switching models give a good estimate for more complex processes driving security returns. Finally, another striking feature of regime-switching models is, it captures non-linear dynamics of asset returns based on linear specification framework, or conditionally normal or log-normal distributions, within a regime.(Ang and Timmermann, 2012)

1.2 Correlation

Andersson et al. (2008) examined the effect of macroeconomic expectations and perceived stock market uncertainty on the bond-stock returns correlation. The empirical findings of their work demonstrated that the correlation between stock and bond returns varies significantly over time. They used data from the US, UK and Germany to find that mostly, the stock–bond correlations in all three countries were positive, although some sustained periods of negative correlation were also found. Moreover, they stated that the bond-stock correlations in the three countries exhibit similar patterns over time, for example the periods of negative correlation seem to coincide. Furthermore, their findings showed that the bond-stock correlation changed considerably and turned from positive to negative, in very short periods of time. Further they stated that these rapid changes in the relationship between stock and bond markets may pose challenges for asset allocation and risk management measures. Particularly, their results strongly indicated that high stock market uncertainty led to a decoupling between stock and bond price.

Park, Fang, and Ha (2019) explored the stock and bond returns correlation in Korea as an emerging market case study. They covered the Asian financial crisis of 1997–1999 and the global financial crisis and European fiscal crisis of 2007–2012, in addition with non-crisis years that further increased the sample period to 2005–2017. The showed that sign of stock and bond returns correlation was depenedent upon the origin of risk triggering the crisis. They stated that in the local-risk driven crisis of 1997–1999, a 'flight to quality' arose across countries, driving stock and bond returns in Korea to deline together. Though, in the global-risk driven crises of 2007–2012, the 'flight to quality' arose across asset classes domestically, driving stock returns to fall but bond returns to rise. Furthermore, bond-stock returns correlation was discovered to relate systematically to changes in vital macroeconomic variables, particularly, stock market volatility and a business leading indicator.

Longin and Solnik (2001) investigated the correlation of monthly excess stock returns internationally for seven main countries over the period 1960-90. They modeled the conditional multivariate distribution of international asset returns and test for the presence of expected time-variation in conditional correlation for this period. The correlations are calculated over a rolling window of five years and it showed fluctuating behavior over time. They stated that the addition of October 1987 in the data to estimate the correlation, showed a rise in the correlation for 5 years. Then they did a test for a constant unconditional correlation matrix for the seven countries over six sub-periods of five years and checked for the equality of the correlation matrix over adjacent sub-periods along with non-adjacent sub-periods. The null hypothesis of a constant correlation matrix was rejected. Then they used the GARCH constant-conditional-correlation model to test the null hypothesis of constant conditional correlation and they also did separate tests of specific deviations of this constant correlation as their used econometric method was not able to include all the deviations in one model. And it suggested rejecting the hypothesis of a constant conditional correlation. According to their work, a rise in the international correlation between markets over the past 30 years is clearly shown by their model of the conditional correlation. They also explored that the correlation grows in periods when the markets were having huge conditional volatility. They stated that economic variables like the dividend yield and interest rates possess information about future correlation, that is not enclosed in past returns alone.

Driessen et al. (2009) empirically illustrated that correlation risk is priced; assets that pay off healthy when market-wide correlations are superior to expected, earn negative excess returns. This outcome is coherent with growth in market-wide correlations heading toward a decline of investment opportunities in the form of lesser diversification advantages. Thus, the negative excess return on correlation-based assets can be understood as an insurance premium. They specified a large correlation risk premium in different ways. They showed an option-based trading strategy to exploit correlation risk by selling index options (straddles) and buying individual options, it makes excess returns of 10% per month and has a large Sharpe ratio (77%); the indication of a large correlation risk premium. This strategy has more appealing risk-return properties (particularly higher moments) than other option-based strategies. The return on this correlation trading strategy pronounces 70% of the cross-sectional variation in the index and individual option returns that are not accounted for by market risk.

Their second contribution was; they explained that the priced correlation risk represents the missing connection between unpriced individual variance risk and priced market variance risk. And this allowed them for a risk-based explanation of the discrepancy between the index and individual option returns. Index options are costly; dissimilar to individual options because they let the investors hedge against positive market-wide correlation surprises and the resulting loss in diversification benefits. While presenting realistic market resistances in the form of transaction costs and margin requirements, they explored that investors with such resistances cannot get the maximum benefit of the correlation trading strategy. This specified a potential limits-to-arbitrage analysis for their finding of a large correlation risk premium. They also stated that the market makers who are functioning actively in markets for the index, as well as individual options, are likely to receive the correlation risk premium, as end-users of options are with net long index options and net short individual options and since market-makers are margined on their net positions.

Mueller et al. (2017) explored the empirical properties of conditional foreign exchange correlations. They studied exchange rates against the USD and discovered the considerable cross-sectional variety in the average conditional correlation of FX pairs. They also discovered that the cross-sectional dispersion of FX correlations is countercyclical, as FX pairs with high (low) average correlation developed as more (less) correlated in unfavorable economic periods, by using different business cycle proxies. They also exploited the cyclical properties of conditional FX correlation by defining an FX correlation dispersion measure, foreign exchange-correlation, and sort currencies into portfolios based on the beta of their returns in terms of innovations in foreign exchange-correlation. They found that currencies with low FXC betas have high average excess returns and vice versa.

They also justified their empirical results with a no-arbitrage model of exchange rates. Mainly they addressed the tension between the physical and the risk-neutral measure foreign exchange-correlation dynamics. They stated that in the physical measure, the negative association between foreign exchange-correlation betas and currency returns recommended that US investors want a positive risk premium for being open to states in which the cross-section of foreign exchange correlations broadens. Though, foreign exchange options are priced in such a way that proposed that US investors' concern about states in which the cross-section of foreign exchange-correlations squeezes, as the risk-neutral measure foreign exchange correlation dispersion is averagely lower than its physical measure counterpart. To handle this apparent contradiction, they proposed a model in which foreign exchange-correlation risk is not covered by exchange rates, as some shocks that disturb the pricing root of US investors also disturb conditional foreign exchange correlations, but do not influence exchange rate levels.

Through this model, they found that conditional foreign exchange-correlation indirectly traded using currency options is open to two global shocks. US investors price the second global shock more brutally than the first one, thus, foreign exchange-correlation risk premiums mirror the want of currency option holders to mainly avoid states with negative achievements of the second shock. Such states are categorized by a shrinking of the cross-sectional dispersion of foreign exchange-correlation, and currency option prices disclose that property. Investing in foreign currency is dissimilar, as investors face only the first global shock. Consequently, currency risk premiums reveal only foreign exchange investors' wish to avoid the corresponding bad states, categorized by a widening of the cross-sectional dispersion of foreign exchange-correlation, and reward investors for experiencing those states. So, the lack of coverage of foreign exchange correlation risk by exchange rates and currency returns and, especially, the lack of experience of exchange rates to the second global shock lets this model to jointly address the empirical properties of foreign exchange-correlations, currency risk premiums, and foreign exchange-correlation risk premiums.

Buraschi et al. (2010) developed a new framework for multivariate intertemporal portfolio choice that permits to develop optimal portfolio effects for economies in which the degree of correlation through industries, countries, or asset classes is stochastic. They stated that optimal portfolios involve separate hedging constituents against both stochastic volatilities as well as correlation risk. They found that the variance-covariance hedging demand [2] is normally larger than in univariate models, and it includes an economically significant covariance hedging component, which tends to increase with the persistence of variance-covariance shocks, the strength of leverage effects, the dimension of the investment opportunity set, and the presence of portfolio constraints.

They also found that the absolute correlation hedging demand rises with the investment horizon. When the correlation hedging demand is positive (negative), this property suggests an optimal investment in risky assets that rises (falls) in the investment horizon. They showed the connection between the persistence of correlation shocks and the demand for correlation hedging. The persistence of correlation shocks is changed across markets. In very liquid markets such as Treasury and foreign exchange markets, which are less disturbed by private information problems, correlation shocks are less persistent. In other markets, resistances like asymmetric information and dissimilarities in beliefs about future cash flows create price divergences from the equilibrium hard to be arbitraged away. Developed and developing equity markets are examples of such markets. They also discovered that the optimal hedging demand against covariance risk rises as the degree of persistence of correlation shocks.

Krishnan et al. (2009) discovered that after controlling the volatility of asset and market, correlation brings a considerably negative price of risk and neither market return can explain it, nor dynamics like

[2] Hedging demand is the demand of the securities to diversify an additional risk

size and book-to-market factors, default spread, inflation, liquidity, and other risk factors. The market price of correlation risk is substantial after considering macroeconomic variables that are known to affect the dynamics of asset correlations. They stated that correlation is a complex function of higher-order moments, and act as a superior proxy for downside risk under tangled utility functions or under the constraints of short-sales or wealth. Yet, the market price of correlation risk is substantial even after controlling for standard higher moments. After purging the correlation factor of the effects of macroeconomic variables, popular risk factors, and higher-order moments, they estimated that the correlation factor is getting varying diversification benefits. The market price of correlation risk is dynamic whether to be used in individual stocks or portfolios as test assets. The market price of correlation risk endures being appreciably negative when allowed for changing with time in the factor loadings of the assets. They also found that the market price of correlation risk is dynamic to different conditions for the correlation factor. Further, they stated that the correlation between assets that span the risk-return range rises, at least part of the diversification benefit is lost by the investors. Stocks that do well in conditions where asset correlations are high are more appealing and the expected returns on these securities are lesser. Thus, the market price of correlation risk is substantially negative.

Knif et al. (2005) investigated the dependence of contemporaneous return correlation between stock market returns in different countries on volatilities of both internal national markets and external world markets. Their key contribution was to propose a model to examine the contribution of volatility level and other variables to correlations between stock market returns. They modeled time-varying conditional correlation as a function of internal national market and external world market volatilities along with other predicting variables by using logit regression. Their Preliminary empirical examination of stock market returns using daily data (1990-2005) established that correlation is more obvious when the world market index is leaning down. However, further planned examination based on the logit-type regression model took them to the conclusion of the national market and world market volatilities as the main causes of time-varying correlations between stock market returns. The world volatility was particularly prominent in the small Nordic market equations, after controlling the usual increasing tendency in the correlations.

Furthermore, concerning economic implication, they realized that large increases in volatility can significantly move correlations. They specified that the results of their study match the prior studies; mutual correlations tend to increase when volatility is high. They were also able to discover that correlations between stock market returns in different countries rise when the global market is bearish. Details of their empirical work showed that the maximum of the stock market correlations between different countries was rising during the period 1990 to 2005. Therefore, the rising trend of market correlations described by Longin and Solnik (1995) from 1960 to 1990 has sustained in the years 1990-2005. They linked this rising stock market correlation to rising capital flows worldwide as well as this trend likely is due to financial market assimilation. The final finding of their work was; contemporaneous correlation for the market's European countries with overlapping trading hours was more trustworthy than the correlation of chief world markets with nonoverlapping trading hours.

1.3 Correlation regime-switching

Chen (2009) stated that the correlation between stocks and bonds switches from high to low when the stock volatility changes from low to high. But it changes from low to high when the volatility of bonds switches from high to low. He proclaimed that the expected correlation of stocks and bonds which is dependent upon stock's high volatility regime is very lower than that of dependent on stock's low volatility regime. And exactly the opposite is true for the bond volatility state-dependent correlation. He also stated that when the bond market is facing high volatility and the stock market is in a low volatility regime, the estimated values of bond-stock correlation in both high and low regimes are non-negative. And when both stock and bond markets are in high volatility regime the estimated value of correlation is highest in high correlation regime and lowest in lower correlation regime of stock and bond. He also found that after 2003 there are huge fluctuations in correlation values (between positive and negative) of stocks and bonds.

Miao et al. (2013) performed an empirical analysis to find the regime-switching in the correlation between the Nasdaq index, the S&P 500 index, and the T-bond interest rate from the U.S with a sample from January 3, 2002, to December 31, 2011. This empirical research showed that the correlation between stock indices and T-bonds has a significant regime-switching process. But the correlation between the two indices possessed an ambiguous structure. The correlation between stock indices and T-bonds had been positive except 2003-2007 and the third quarter of 2010, where correlations for Nasdaq and T-bonds, S&P 500, and T-bonds became negative. This research inferred that this regime changing in correlation was because of the changes in inflation and output growth. The main finding of the research was, the mortgage housing crisis of 2007 was the main reason behind this regime-switching correlation between bonds and stock. This crisis led the correlation to move from high to low correlation regime.

1.4 Regime-switching

Ang and Timmermann (2012) discussed how regime changes are modeled and the influence of regime changes on equilibrium asset prices. They estimated the regime-switching model on equity excess returns on the S&P 500; dividend plus capital gain more than T-bills interest rates (three- month T-bill rates) and foreign exchange excess returns, returns from converting one USD into Deutschmarks or Euros, investing in German T-bill with a return, and then converting back to USD, more than US T-bill return (foreign exchange return; uncovered interest rate parity return). Mean μ, volatility σ, and mean reversion coefficient φ parameters were used to differentiate between two regimes. They stated that most of the time the regimes are recognized by volatility for equity returns, for instance, the period between 1997-2003 is categorized as a high volatility state. This period includes both the bull market of the late 1990s and the succeeding crash of internet stocks and the market decay in the early 2000s.

Secondly, they mentioned that for interest rates, mean reversion coefficients φ mostly differ across the states. Their results were showing that T-bill interest rates were behaving like a random walk when volatility was low. They described that high volatility state contains both the volatile interest rates in the early 1970s due to the OPEC oil shocks, the high and very unstable interest rates during the monetary targeting trial over 1979-1983, and more recently the prominent decline in interest rates during the early 2000s and the financial disaster post-2007. Finally, they described their results about the persistence of the regimes with P_{00} [3] and P_{11} [4] both being adjacent to one. They argued that the persistence of different states plays a vital role in producing volatility assembling, thus periods of high volatility are followed by high volatility, and periods of low volatility are followed by low volatility. Panel C shows that for foreign exchange returns the high volatility state is minimum persistent. This high volatility state communicates that USD undergone abrupt depreciation (μ_0 = 0.46% per month compared to μ_1 = 0.01% per month).

Based on their empirical estimation they stated that the reason that makes the regimes to be different. In some cases; this regime shifts because of the economic policy like a change in monetary policy or change in the state of the exchange rate. On the other hand, in some cases, a key event, for example, the bankruptcy of Lehman in September 2008, or the downfall of the Shah in Iran and the accompanying increase in oil prices, maybe the cause. Another likelihood is that states are motivated by investor expectations. They showed that in equilibrium, agents' beliefs and asset prices are together found in a way that can give birth to multiple misspecified equilibria each with separate means and variances of returns. Therefore, learning dynamics and constrained rationality could thus be some motives behind why there are regimes.

Pelletier (2006) developed multivariate volatility, a regime-switching model called Regime Switching Dynamic Correlation (RSDC) model. The covariances were broken down into standard deviations and correlations, but these correlations are dynamic. The correlation matrix follows a regime-switching model in which correlation is constant within a regime but different across regimes. The switching between the two regimes is directed by the Markov chain. This model possessed a special property of creating smooth patterns for the correlations. It was also mentioned that a constant conditional correlation (CCC) model is a special case of a new proposed model where the number of regimes to be one. Furthermore, they also presented a controlled version of this model in which the changes within the correlation are proportional in a given regime. This regime-switching model for correlation is in between the CCC model of Bollerslev (1990) in which the correlations are persistent and the model like DCC (dynamic conditional correlation) of Engle (2002) in which the correlation matrix changes at each point of time. Pelletier applied this model to four main exchange rate series and observed good behavior of this model. A comparison of this correlation regime-switching model with the DCC model of Engle (2002) suggested that this model showed healthier performance in and out of sample. This model showed strong tenacity in the Markov chain, which creates a smoother time-varying correlation in comparison to the DDC model.

[3]Probability that process stayed in regime 0 at time t when it was in Regime 0 at time $t-1$.

[4]Probability that process stayed in regime 1 at time t given that it was in the same Regime at time $t-1$.

Lee (2010) Introduced a model of independent switching dynamic conditional correlation GARCH (IS-DCC) which is independent of path dependency and recombining issues which are usually characteristics of MS-DCC. It was mentioned that time-varying correlation risk justifies the independent switching model for correlation. This model was used to see the success of hedging in commodity futures when there was a multi-state regime switching in the correlation of spot and futures returns. The outcomes of hedging application for commodity futures, exposed that regime- dependent IS-DCC beats regime-independent DCC GARCH. Furthermore, IS-DCC with three- regimes of high frequency, median frequency, and low frequency unveils high-class hedging effectiveness; indicating the significance of developing higher-state swapping correlations for dynamic futures hedging. The suggested IS-DCC model gives a broad basis for the standards of multi-state regime-switching time-varying correlation for financial assets and allows the IS-DCC hedgers to enhance their hedge functioning.

Henry (2009) determined the influence of London short term interest rates volatility on equity returns by using the weekly data from January 1980-August 2007. The research suggested that equity returns show a substantial indication of regime-switching. The data was showing two regimes, one regime is coherent with a high-mean, low variance state and within this regime, the volatility reacts to news persistently but symmetrically. This regime estimated to continue for nearly 75 weeks. The other regime tends to have low mean and high variance, in which the conditional variance of the returns reacts to news in an asymmetric manner, but without any persistence. And this state estimated to stay for approximately 6 weeks. A two regime Markov-switching Exponential GARCH model was used for equity returns. Furthermore, by extending the Markov-switching Exponential GARCH model, it was also found that interest rate spread volatility at shorter maturities plays a noteworthy role in finding both volatility of return and a transition probability across regimes.

Bansal et al. (2010) investigated regime-switching in daily S&P 500 index and ten-year T-note futures returns in which they found a bivariate, two-state, regime-switching model that predicted the regime-specific means, variances, and correlations concurrently. They used a sample period that possessed various experiences of high equity risk but with steady inflation. A prevalent low-stress regime with an expected duration of 80 days and a high stressed regime which was less common and have an expected duration of 44 days. High-stress regime episodes occurred due to well-known incidents of global economic and political crisis like the Asian financial crisis in 1997, the Russian currency depreciation and debt default in the fall of 1998, the Brazilian currency crunch in early 1999, the terrorism disaster in September 2001, and the Iraq war in 2003. They found that the stock-bond correlation is substantially lower in the high-stress state and the T-bond risk rises only modestly in this regime, as compared to the considerable rise in the stock risk. The stock-bond correlation in high-stress states is always obviously lower than that in the low-stress state.

1.5 Regime-switching and asset allocation

Ang and Bekaert (2015) argued about a high-volatility bear market regime that it did not deny the advantages of international diversification. They evaluated a regime-switching model on American, British, and German equities and came up with a regime of high correlation and high volatility, which corresponded to a bear market. With this situation, they found that typically, a higher volatility regime encouraged a shift towards the lower volatility assets, e.g. cash, U.S equity, and Germen equity (if available). Thus, there are several cases in which higher volatility regimes made the international portfolio more diversified, in comparison to normal regimes. Optimal Asset allocation diversifies risk well in both regimes with an i.i.d data-generating method.

They stated that overlooking regime-switching, cost very high when conditionally risk-free assets are included in the portfolio. The magnitude of the cost was similar to overlooking some foreign equity investment chances. Furthermore, they also stated that when a short rate shifted the regimes and forecasted the equity returns, it made the cash more precious in the bear market regime because the bear market regime had higher average interest rates and a higher negative correlation between equity returns and short rates. The three country-equity system costs about 2.70 cents/dollar for overlooking the regime-switching, for an investor with a risk aversion coefficient of 5 for one year. They also revealed nonparametric results for domestic dynamic asset allocation studies that intertemporal hedging demands with regime switches are economically minimal and statistically unimportant. This conclusion stands even in the presence of conditionally risk-free assets and short rate forecasting of equity returns.

Guidolin and Timmermann (2007) investigated asset allocation decisions with regime-switching in asset returns. They defined four regimes, crash state, slow-growth state, bull and recovery states to catch the joint distribution of bond and stock returns. 'Crash' state was having large, negative mean excess returns and high volatility. It includes the two oil price shocks in the 1970s, the October 1987 crash, the early 1990s, and the 'Asian flu'. 'Low growth' regime characterized by having low volatility and minor positive mean excess returns on all assets. 'Bull' state in which stock prices-particularly those of small firms-develop quickly on average, long-term bonds have negative mean excess returns in this state. 'Recovery' state with tough market demonstrations and great volatility for small stocks and bonds. Crash and recovery regimes were short-lived, but the slow growth and bull regimes were long-lived (persistent) which implied regime-switching models capture both temporary and long-term variations in investment opportunities. They made the states to be unobservable for the investors who screen state probabilities from return observations and therefore never see current or future states with assurance. They found that the asset allocation changes significantly across these regimes as the weights of the different asset classes depend upon which regime the economy is noticed to be in. They also found that stock allocations increased monotonically as the investment horizon increased only in one of the four regimes. In remaining regimes, there was a decreasing allocation to stocks.

Carroll et al. (2017) investigated the power of asset allocation strategies with dynamic correlation to deal minimum-variance portfolios which beat a simple equally weighted benchmark. Their main finding was that estimation error in correlation may be appropriately overcome to beat the equally weighted benchmark. Allocation strategies based on dynamic correlation (CCC, DCC, DECO) frequently provide performance (measured in variance and Sharpe ratio) advantages in comparison to the equally weighted benchmark former to transaction costs.

They mentioned that relative to previous papers; backing the equally weighted strategy, applying short-run correlation forecasts may aid to clarify the performance advantages; from the optimal strategies directed. A more breakdown of the empirical findings indicates the relative significance of the conditional correlation, rather than conditional variance, in finding the performance specified. They also stated that swapping between DECO (Dynamic Equi-Correlation) minimum-variance optimized strategy and an equally weighted portfolio during different regimes might be assumed to give performance advantages, but they found that this not to be the case. Instead, this recommended the extreme transaction costs related to regular switching from the equally-weighted portfolio (low asset weighting), to a strategy in which more wealth is invested in a small number of assets. Their findings also suggested the potential advantages of using a Markov switching DCC or DECO model to the portfolio allocation problem.

Jang and Kim (2015) explored the optimal reinsurance and asset allocation strategies for an insurer who is afraid of economic regime-switching. They assumed two regimes in economic conditions: Regime 1 with low stock volatility and Regime 2 with high stock volatility. They established different parameters, for example, risk-free interest rate, stock returns, stock volatility, insurance claims volatility, and drift, the correlation between stock prices and insurance claims which change according to the regime shifts. They showed numerically with estimated factors the following economic implications:

• Optimal insurance companies that are afraid of fluctuations in economic market conditions, in most situations, they choose strategies with a higher reinsurance rate and a lower risk investment (or stock-holdings) within a highly volatile regime.

• However, insurance companies with low financial caution most likely to act shortsightedly in decision making, thus the optimal strategies are close to the strategies of a single regime model.

• Drastic changes in correlation between stock prices and insurance claims, investment opportunity, and loading factors considerably affect optimal reinsurance or asset allocation strategy, or both of an insurance company.

Bae et al. (2014) identified different regimes for the stock, bond, and commodity markets, they applied this information to portfolio optimization in handling the restrictions of the Markowitz model. They developed a four-state Hidden Markov Model with three-dimensional input data and taught the model with yearly developments using historical market returns. The factors of this model rationally describe the characteristics of the financial market; the states are visibly well separated, and each state possesses its discrete features. They found in equity market state 1 and state 3 has exceptionally positive market conditions, with positive mean returns, perfect for investing in the equity index because there is almost no probability of going into the crash state (state 4). State 4 was characterized as market crashes with the lowest mean returns. On the other side, state 2 was recognized as a transition state between state 1 and state 4, with mean return lower than the return of state 3 and it has non-zero switching probability only to state 1.

They showed that the commodity market index behaves differently than the equity market. The commodity index showed profound growth in state 2 instead of states 1 and 3 which exhibited nearly zero returns. Though the state 4 shows parallel features of mean return and volatility to the equity index and this justified the equity and commodity markets were rushed together. State 4 showed large volatilities for the equity and the commodity indices, but the bond market showed relatively high returns in the initial periods however it dropped significantly year by year. It was also found that the correlation between the equity and bond indices in states 2 and 4 have been declining more and more over time, it indicated that the diversification advantage of bonds in the volatile stock market periods is quite applicable. They stated that this information of multiple markets in each regime was employed to a stochastic program to optimize the portfolio. And these four recognized regimes offered multiple distributions for assets therefore, the belief of a single static return distribution of the mean-variance model is relieved.

Konermann et al. (2013) has investigated the optimal dynamic asset allocation strategy for a CRRA (constant relative risk aversion) investor, who confronts contagion risk in an imperfect market with only two risky assets. This market follows a basic Markov chain with two economic regimes, a calm and a contagion regime. One of the unique characteristics of the model, the regime shift to the contagion condition is initiated internally by a big loss in one of the risky assets. They also investigated how the relationship between volatilities, correlations, jump risk, and contagion properties influences the investor's optimal portfolio choice. They also found that the correlation leverage aspect has a huge influence on the optimal portfolio especially a portfolio with heterogeneous risky assets. If the contagion regime has a nonzero correlation, then the investor will use an asset that can fine-tune his exposure against the diffusion risk of an asset sensitive to the contagion regime. This leads to a flight to quality upon shift to the contagion regime. Though these interdependencies are very much relying upon how much risk premia are paid in a particular economy. Higher risk premia in the contagion regime change the interaction between correlations, jump intensities, and volatilities dramatically.

Collin-Dufresne et al. (2020) attained a closed-form solution for portfolio problem with regime switching in expected returns, covariances, and price impact parameters (trading costs) when the investor had an objective function of mean-variance. They developed an optimal trading rule which was categorized by a set of aim portfolios and trading speed vectors. Particularly, the aim portfolio was a weighted average of the conditional Markowitz portfolios in all possible future states. The weight of each conditional Markowitz portfolio was dependent upon the following things: the likelihood of transitioning to that state, the state's persistence, and the risk, and transaction costs confronted in that state compared to the present one. Likewise, the optimal trading speed was a function of the relative magnitude of the transaction costs in several states and their transition probabilities. One of the noteworthy inferences of their model was that the optimal portfolio can depart considerably from the conditional Markowitz portfolio in anticipation of likely future shifts in relative risk and/or transaction costs.

They demonstrated that the model was equally manageable when either price changes or returns obey a regime-switching model. The returns aligned better with the empirical dynamics of asset returns. They applied this framework to optimally time the broad value-weighted market portfolio, accounting for time-varying expected returns, volatility, and transaction costs. They applied a large proprietary data set on institutional trading costs to evaluate the impact of price parameters. They also explored that trading costs changed considerably across regimes and inclined to be higher when market return volatility was higher. They examined their trading strategy both in-sample and out-of-sample and found that there were plentiful advantages of using this method.

Ang and Bekaert (2004) recognized that International equity returns were categorized by episodes of high volatility and unusually high correlations coinciding with bear markets. They provided models of asset returns that match these patterns and demonstrates their use in asset allocation. They stated that the existence of regimes with different correlations and expected returns was hard to exploit within a framework dedicated to global equities. Yet, for global all-equity portfolios, the regime-switching strategy ruled static strategies in an out-of-sample test. Furthermore, the significant value was additional when an investor switched between domestic cash, bonds, and equity investments. In a persistent high-volatility market, the model conveyed the investor to switch mainly to cash. Large market-timing benefits were achievable because high-volatility regimes inclined to coincide with periods of relatively high interest rates. They further stated that their results pointed towards two robust conclusions. First, a global manager can add value in all- equity portfolios; the existence of a bear market (a high-correlation regime) did not negate the benefits of international diversification. Although indorsed portfolios in that regime are more home biased, they still include substantial international exposure. Secondly, RS models are very appreciated in tactical asset allocation programs that allow switching to a risk-free asset

2 Data

This section presents the sources of data used for the computation of Norwegian bond-stock correlation and performing related analysis. The data is obtained from the TITLON database, which contains the Norwegian market (Oslo Børs) data from 1983. The database contains Norwegian data of equities, mutual funds, indices, bonds, and derivatives. The database contains a variety of variables such as unadjusted, fully adjusted prices, logarithmic risk-free rate, logarithmic returns, and many more. As this research is done on the Norwegian market, the Oslo Stock Exchange Benchmark Index (OSEBX) is used as the stock market proxy. OSEBX contains a representative selection of all listed shares on the Oslo Stock Exchange and is rebalanced semi-annually. It has 65 stocks from 8 different sectors.

DNB Obligasjon 20 (IV) bond mutual fund was used as a proxy of the bond market. As S&P Norway Sovereign Bond index is the oldest bond index in Norway, and it has data history from 2014 which was not enough to check the structural changes in Correlation between stock and bond. The mutual fund is an actively managed bond fund, invests in interest-bearing 88 bonds dominated in Norwegian Kroner. Most of the bonds are Norwegian but some Danish Bonds are also included. I used daily logarithmic returns from September 2004 till June 2019 for calculating correlation.

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Table 1.1: DNB Obligasjon 20 (IV) bond mutual fund

Panel (A): Credit Rating		Panel (B): Maturity	
Credit quality breakdown	Percentage %	Distribution maturity	Percentage %
AAA	4.33	1 to3	28.38
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BBB	28.26	7 to 10	1.73
BB	0	10 to 15	0
B	0	15 to 20	0
Under B	0	20 to 30	0
No Rating	20.32	Over 30	0

Note: Panel (A)shows the Credit rating break down of the bonds in bond fund and Panel (B) shows the maturity of bonds

Table 1.2 shows the statistics of the bond and stock returns. The bond index has an annualized mean return of 4.081 % with a standard deviation of 1.5 % but the stock index has a large annualized mean return of 23.47 % with a standard deviation of 9.53 %.

Table 1.2: Return statistics

	Annualized.mean	Annualized.standard.deviation
Bond	0.0408143	0.0150064
Stock	0.2347222	0.0953339

Bond and stock returns were used to find the one-year rolling correlation. Figure 1.1 shows the plot of the correlation time series. Mostly the correlation is below the zero showing a negative relationship between the two indices. One year rolling correlation is positive only from the 20th September 2004 to the 1st of December 2005 and from the 17th of September 2012 until the 27th of June 2014.

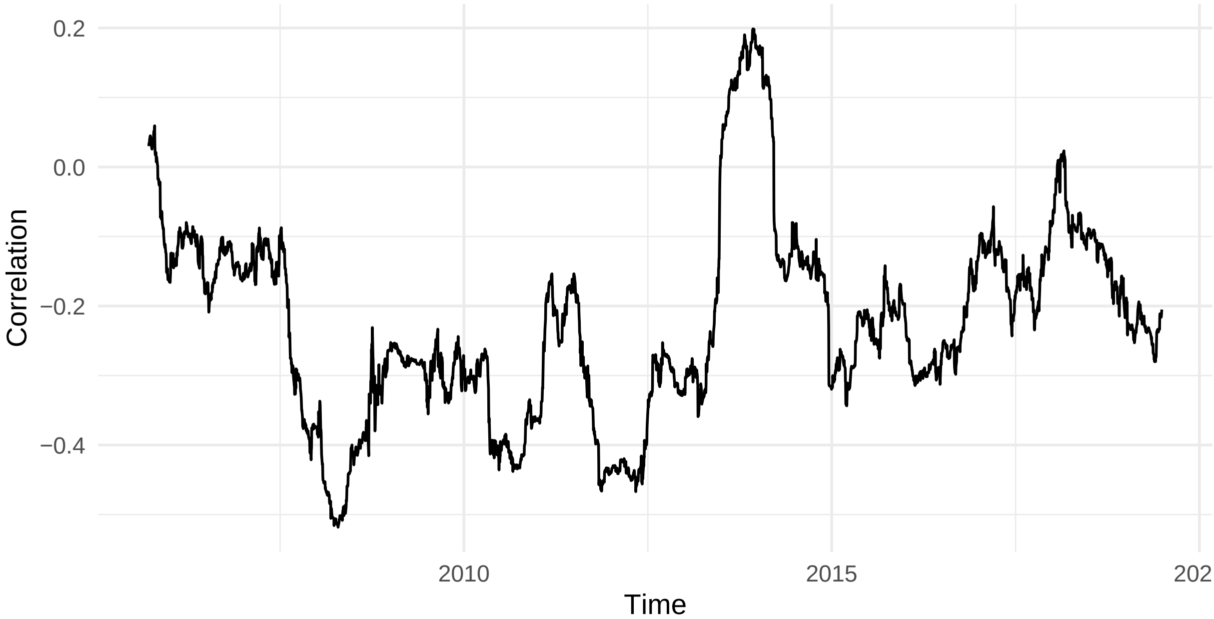

Figure 1.1: One year rolling bond-stock Correlation

3 Methodology

This part of the paper critically investigates the process of the Markov regime-switching model and Markov Switching Dynamic Regression in the time-varying correlation between Norwegian stock and bond indices.

3.1 Regime-switching model

"Regime Switching and Threshold Models" are important non-linear regression models commonly used to model the dynamics in macroeconomic and financial time-series. Commonly cited cases comprise the very different behavior of second moments for several macroeconomic time series before and after the Great Moderation in the early eighties, the different behavior of U.S. interest rates during the Federal Reserve's Monetarist Experiment from 1979 to 1982, and the behavior of a range of risk pointers during the current global financial crisis. These are incidents that can be tough to model in the context of standard linear regression models. The main difference between Markov switching models and threshold models is that the earlier belief that the underlying state process that gives rise to the nonlinear dynamics (regime-switching) is hidden, whereas threshold models commonly accept the nonlinear effect to be determined by observable variables but believe the number of thresholds and the threshold values to be unknown. Empirically, both kinds of models can, by design, allow for discrete, nonlinear effects. (Chan et al., 2017)

The Markov-switching regression model was initially developed by Quandt (1972) and Goldfeld and Quandt (1973), but it was introduced in time series by Hamilton 1989 in a ground-breaking paper and provided a nonlinear filter for estimation. Different extensions of regime-switching models have been introduced such as regime-switching ARCH models introduced by Hamilton and Susmel (1994) and Lin (1996). A version of regime-switching GARCH was suggested by Gray (1996). Miao, Wu, Su (2013) applied two-state Markov-switching to range based dynamic conditional correlation process. However, these models involve the estimation of several parameters and are complex to apply. To estimate the regime-switching in bond-stock returns correlation in the Norwegian economy, I used Markov switching dynamic regression (MSDR) developed by Hamilton (1988, 1989). This method is very simple, intuitive, and easy to apply.

Markov-switching models are non-linear models used for series that are supposed to transition over a finite number of unobserved regimes, letting the process to develop differently in each state. The state variable S_t is unobserved and follows a discrete[5] Markov chain. The Markov chain followed by S_t is governed by a first-order process; the probability that S_t is equal to $j = (1, 2, .., k)$ depends only on the most recent realization S_{t-1} (Hamilton, 1994) and is given by:

$$Pr\ (S_t = j|S_{t-1} = i) = P_{ij} \tag{1.1}$$

In this model S_t follows a Markov chain in transitions between the unobserved states. The time of transition from one state to another and the duration between changes in the state is random. It is not possible to know with the certainty that in which state the process is, but probabilities of being in each state called transition probabilities are calculated by Markov chain. These transition probabilities are time-homogeneous or constant over time[6]. The Markov chain is ergodic[7] and irreducible[8] (Hamilton, 1994). For a two-state process, equation (2.2) shows $P_{11}$is the probability of staying in state 1 in the next period given that the process is in state 1 in the current period. Similarly, P_{22} denotes the probability of staying in state 2. Transition Matrix for a two-state Markov switching can be expressed as:

$$Pr = \begin{bmatrix} P_{11} & P_{21} \\ P_{12} & P_{22} \end{bmatrix} \tag{1.2}$$

[5]It can take only a finite number of k regimes.

[6]More complex time-varying transition probability models with a dynamic transition matrix P have been studied by econometricians, called time-heterogeneous transition probabilities. (Guidolin, 2016)

[7]It is possible to go from every state to every state. see Hamilton,1994

[8]All unobservable states are possible over time and no absorbing states exist, in reducible Markov chain, absorbing states can exist. When the probability of any state is $P = 1$ in transition matrics, that state is called absorbing state.

$$P_{11} + P_{12} = 1 \tag{1.3}$$

Equation (2.3) shows that every column of P sum to unity. Different econometric methods can be used to estimate regime-switching models. Maximum likelihood and EM algorithms are outlined by Hamilton (1988, 1989) and Gray (1996). Markov Switching dynamic regression used in this work also uses EM (Estimation maximization) algorithm.

3.2 Markov Switching Dynamic Regression

Markov Switching Dynamic Regression (MSDR) is the simplest form of the Markov Regime Switching Regression. It is suitable for the high-frequency data like daily observations in this case and allows a quick adjustment after the process (Hamilton, 1994). The process is in state S at time t, a general specification of the MSDR model is written as:

$$y_t = \mu_{s_t} + \sigma^2_{s_t}\epsilon_t \tag{1.4}$$

Where μ_{S_t} is the state dependent intercept when the state variable S_t is absent it will be μ_0 as shown in equation (2.5) but when the state variable is present the intercept is μ_1 as shown in equation (2.6). The two states model shifts in the intercept term. The error term ϵ is identically, independently distributed (i.i.d) normal error which is state independent but its variance σ^2 is regime-dependent.

MSDR for two state process can be express as:

$$State1\ S_t = 1, y_t = \mu_1 + \epsilon_t \tag{1.5}$$

$$State2\ S_t = 0, y_t = \mu_0 + \epsilon_t \tag{1.6}$$

3.3 Method criticism and study limitations

3.3.1 Bond fund

One of the aspects that can affect the results of this work is the use of DNB Obligasjon 20 (IV) bond mutual fund instead of the bond index. As the data for the Norwegian bond index was not available and bond mutual fund used as proxy. A bond mutual fund is managed by the fund manager, who manages the fund to optimize the returns while managing risks of the bond portfolio. Whereas bond index has a different objective than the bond fund. Bond index is created to measure the value of a certain section of a bond market, it represents the market risk and returns. It gives the investors in the bond market with portfolio benchmarks where returns can be replicated. Bond fund possess a different level of risk than bond index because usually the fund manager aims to outperform the bond index. The information that which bonds are included in the fund is not available and has not been available from TITLON database. Therefore, it is unknown that how much this mutual fund is representative of the Norewgian bond market.

3.3.2 Markov-Switching Dynamic Regression

Miao et al. (2013) used two-state Markov-switching range-based DCC model and Chen (2009) used regime-switching bivariate GARCH model to estimate regime-switching in correlation but these models estimate several other parameters and are more complex to apply. The regime-switching model used in this paper is a simplest form of Markov-switching models, suitable for daily data but using a simple regime-switching model may also effect the results of the research.

3.3.3 Number of regimes

An important matter in estimating regime-switching models is specifying the number of regimes. This is often challenging to decide from data and as far as possible the selection should be based on economic opinions. Such a decision can be difficult since the regimes themselves are often thought of as approximations to underlying states that are unobserved. The two numbers of states in this work were selected by following the tradition of most of the regime-switching models such as Miao et al. (2013); Chen (2009) to avoid complexities, rather than basing the decision on econometric tests. The reason is that tests for the number of states are usually hard to implement because they do not track standard distributions. Therefore, number of regimes may also potentially effect the results.

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Scientific article

REGIME SWITCHING BOND-STOCK CORRELATION AND ASSET ALLOCATION IMPLICATIONS IN A NORWEGIAN CONTEXT

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Abstract

This paper investigates the time-varying properties of the correlation between stocks and bonds. Specifically, I estimate a two-state regime-switching model in the Norwegian context and find that there is significant variation in correlation. Two states are detected by applying a two-state univariate Markov switching model to one year rolling bond-stock correlation. A high correlation regime (less negative) with higher volatility and a lower correlation (more negative) regime with lower volatility were detected. Both regimes are highly persistent with more than 99% transition probabilities. This has potentially large implications for asset allocation but it does not lead to strong results in a simple asset allocation problem while ignoring transaction costs. Correlation hedging demand is ignored and a simplified model for optimal weights was used.

Keywords: Regime Switching Correlation, Regime Switching and Asset Allocation, Markov Switching Dynamic Regression

1 Introduction

This paper investigates the regime-switching in the time-varying correlation between Norwegian bond and stock. This research also explores the effects of regime-switching correlation on asset allocation. The correlation structure between assets establishes one of the vital notions in financial economics and is crucial for portfolio choice, risk management, and asset pricing as it determines portfolio and market risk. Although this correlation structure between assets was assumed to be constant, there is considerable evidence that correlations are time-varying and subject to risk themselves. Besides, as correlations manage to increase during a market crisis, correlation risk upsets investor's wellbeing by making diversification harder in expensive states of nature. There has been comparatively less attention and research done into the prediction of correlation until 1990. Most research that has been published, had applied a constant correlation between the assets. Early on, this might have been due to a belief that correlation was, to a certain degree, constant. It could also be because of the absence of any clear theoretical model for the estimation process. However, recent studies Buraschi et al. (2010), Mueller et al. (2017), and others have shown that correlation is varying substantially over time. A time-varying correlation now has entered into a new phase of research; regime-switching. Recently Miao et al. (2013), Chen (2009) discovered regime switching in correlation.

Chen (2009) explored that correlation between stocks and bonds switches in the opposite direction of stock volatility. Miao et al. (2013) found a significant regime-switching process in the correlation between the S&P 500 index and U.S T-bonds returns. Correlation between the Nasdaq index and the S&P 500 index was not found to have regime-switching because of the vague structure of correlation. This research inferred that the regime-changing in correlation was because of the changes in inflation and output growth. Pelletier (2006) developed multivariate volatility, a regime-switching model called Regime Switching Dynamic Correlation (RSDC) model. The covariances were broken down into standard deviations and correlations, but these correlations were dynamic.

Extensive literature has discussed regime-switching like optimal dynamic asset allocation strategy was explored by Konermann et al. (2013) for constant relative risk-averse investor who faces risk in an imperfect market; follows basic Markov chain with two economic regimes, with only two risky assets. Ang and Bekaert (2015) studied the effects of regime switching in asset return on international asset allocation. A regime-switching model was assessed by using equities of the U.S, UK, and Germany. Guidolin and Timmermann (2007) studied asset allocation decisions with regime-switching in asset returns. Jang and Kim (2015) found the optimal reinsurance and asset allocation strategies for the insurers who are afraid of regime-switching in economic conditions. Bae et al. (2014) identified different regimes for the stock-bond and commodity markets for portfolio optimization. Bansal et al. (2010) found a two-state, bivariate regime-switching model in the S&P 500 index and ten-year T-note futures returns. A lower bond-stock correlation was discovered in high stressed regime (international economic and political periods) as compared to the low-stress regime. Henry (2009) found that short-term interbank interest rate effects the equity returns in the UK, which led the equity to switch the regimes. A two regime Markov switching exponential GARCH model was used. This regime-switching model for correlation is in between the CCC (constant conditional correlation) model of Bollerslev (1990) in which the correlations are persistent and the model like DCC (dynamic conditional correlation) of Engle (2002) in which the correlation matrix changes at each point of time. Lee (2010) presented a model of independent switching dynamic conditional correlation to understand the success of hedging in the commodity futures in the presence of a multi-state regime switching between the correlation of the spot and futures returns.

Most of the researchers have been involved in finding the regime-switching of asset returns in asset allocation. A few pieces of research found regime-switching correlation; changes the sign when it moves from normal economic conditions to a crisis. This research particularly focused on regime switching in correlation within the context of Norwegian stocks and bonds. The main questions of this Research are:

- Does the correlation between Norwegian stock and bond returns switch the regimes?
- If there is regime-switching what are the properties of the regime-switching correlation?
- How correlation in different regimes affects the asset allocation decision of an investor.

The regime-switching modeling of the stock-bond correlation in this study will allow better insight into the dynamic properties of the correlation of the stock and bond. This study will also provide a better understanding of the time-varying correlation between stocks and bonds that can be useful for the institutions which are involved in monetary policy. Furthermore, this study will further enrich the literature on explaining regime-switching in correlation, particularly stock-bond correlation. This study will also open the ways for a new line of research in regime-switching in Norway. The remaining paper proceeds as follows. Section 2 describes the dataset, section 3 outlines the statistical methodology. Section 4 presents the empirical findings of this work. Section 5 presents the implications of regime-switching correlation in a simple asset allocation scenerio. Finally, section 6 offers a conclusion.

2 Data

This section presents the sources of data used for the computation of Norwegian bond-stock correlation and performing related analysis. The data is obtained from the TITLON database, which contains the Norwegian market (Oslo Børs) data from 1983. The database contains Norwegian data of equities, mutual funds, indices, bonds, and derivatives. The database contains a variety of variables such as unadjusted, fully adjusted prices, logarithmic risk-free rate, logarithmic returns, and many more. As this research is done on the Norwegian market, the Oslo Stock Exchange Benchmark Index (OSEBX) is used as the stock market proxy. OSEBX contains a representative selection of all listed shares on the Oslo Stock Exchange and is rebalanced semi-annually. It has 65 stocks from 8 different sectors. DNB Obligasjon 20 (IV) bond mutual fund was used as a proxy of the bond market. As S&P Norway Sovereign Bond index is the oldest bond index in Norway, and it has data history from 2014 which was not enough to check the structural changes in Correlation between stock and bond. The mutual fund is an actively managed bond fund, invests in interest-bearing 88 bonds dominated in Norwegian Kroner. Most of the bonds are Norwegian but some Danish Bonds are also included. I used daily logarithmic returns from September 2004 till June 2019 for calculating correlation.

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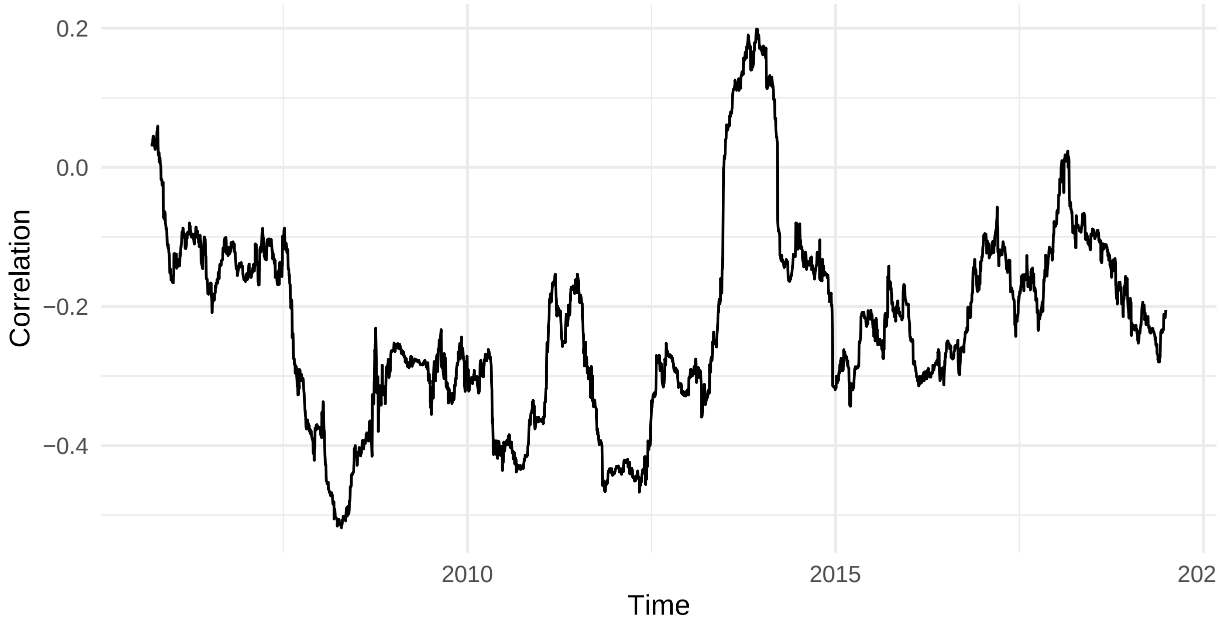

Figure 2.1: One year rolling bond-stock Correlation

3 Methodology

This part of the paper critically investigates the process of Markov switching, Markov Switching Dynamic Regression used to check the regime switching in the time-varying correlation between Norwegian stock and bond indices.

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Markov-switching models are non-linear models used for series that are supposed to transition over a finite number of unobserved regimes, letting the process to develop differently in each state. The state variable S_t is unobserved and follows a discrete[1] Markov chain. The Markov chain followed by S_t is governed by a first order; the probability that S_t is equal to $j = (1, 2, .., k)$ depends only on the most recent realization S_{t-1} (Hamilton, 1994) and is given by:

$$Pr\ (S_t = j | S_{t-1} = i) = P_{ij} \tag{2.1}$$

In this model S_t follows a Markov chain in transitions between the unobserved states. The time of transition from one state to another and the duration between changes in the state is random. It is not possible to know with the certainty that in which state the process is, but probabilities of being in each state called transition probabilities are calculated by Markov chain. These transition probabilities are time-homogeneous or constant over time[2]. The Markov chain is ergodic[3] and irreducible[4] (Hamilton, 1994). For a two-state process, equation (2.2) shows P_{11} is the probability of staying in state 1 in the current period t given that the process was in state 1 in the previous period $t-1$. Similarly, P_{22} denotes the probability of staying in state 2 in the current period t given that the process was in state 2 in the previous period $t - 1$. Transition Matrix for a two-state Markov-switching model can be expressed as:

$$Pr = \begin{bmatrix} P_{11} & P_{21} \\ P_{12} & P_{22} \end{bmatrix} \tag{2.2}$$

$$P_{11} + P_{12} = 1 \tag{2.3}$$

Equation (2.3) shows that every column of P sum to unity. Different econometric methods can be used to estimate regime-switching models. Maximum likelihood and EM algorithms are outlined by

[1]It can take only a finite number of k regimes.

[2]More complex time-varying transition probability models with a dynamic transition matrix have been studied by econometricians, called time-heterogeneous transition probabilities. (Guidolin, 2016)

[3]It is possible to go from every state to every state.

[4]All unobservable states are possible over time and no absorbing states exist, in reducible Markov chain, absorbing states can exist. When the probability of any state is $P = 1$ in transition matrics, that state is called absorbing state.

Hamilton (1988, 1989) and Gray (1996). Markov Switching dynamic regression used in this work also uses EM (Estimation maximization) algorithm.

Markov Switching Dynamic Regression (MSDR) is the simplest form of the Markov regime switching regression. It is suitable for the high frequency data like daily observations in this case and allow a quick adjustment after the process (Hamilton, 1994). The process is in state S at time t, a general specification of the MSDR model is written as:

$$y_t = \mu_{s_t} + \sigma^2_{s_t}\epsilon_t \tag{2.4}$$

Where μ_{S_t} is the state dependent intercept when the state variable S_t is absent it will be μ_0 as shown in equation (2.5) but when the state variable is present the intercept is μ_1 as shown in equation (2.6). The two states model shifts in the intercept term. The error term ϵ is identically, independently distributed (i.i.d) normal error which is state independent but its variance σ^2 is regime dependent.

MSDR for two state process can be expressed as:

$$State1\ S_t = 1, y_t = \mu_1 + \epsilon_t \tag{2.5}$$

$$State2\ S_t = 0, y_t = \mu_0 + \epsilon_t \tag{2.6}$$

4 Empirical Findings

In this section, I will estimate the econometric equations discussed in the Methodology section.

The correlation time series is non-stationary. Augmented Dickey-Fuller (1979) Test [5] was applied to the time series with a null hypothesis of "*time series has a unit root and is not non-stationary*" and an alternative hypothesis of "*time series does not have a unit root and is stationary*" (DeFusco et al., 2015).

[5]Dicky and Fuller (1979) developed a regression-based test on a transformed version of the AR(1) model

$$x_t = \beta_0 + \beta_1 x_{t-1} + \epsilon_t$$

see DeFusco et al., 2015,p490.

Table 2.3: Augmented Dickey-Fuller Test

statistic	p.value	method	alternative
-2.600187	0.3242044	Augmented Dickey-Fuller Test	stationary

Note: ADF with alternative hypothesis of Stationary time series was applied

The standard Dickey-Fuller test was computed with zero number of lags in the regression. Table 2.3 shows the results for ADF test, the value of the t-statistic[6] is -2.6002, a p-value of 0.3242 which was greater than the significance level of 0.05, accepting the null hypothesis of non-stationarity in the time series. The untabulated critical value of the revised t-test at 5% significance level was 6.25. Autocorrelation Function of correlation time series in Figure 2.2 shows a slowly decaying behavior of non-stationary time series. MSDR was applied as it is suitable for non-stationary data.

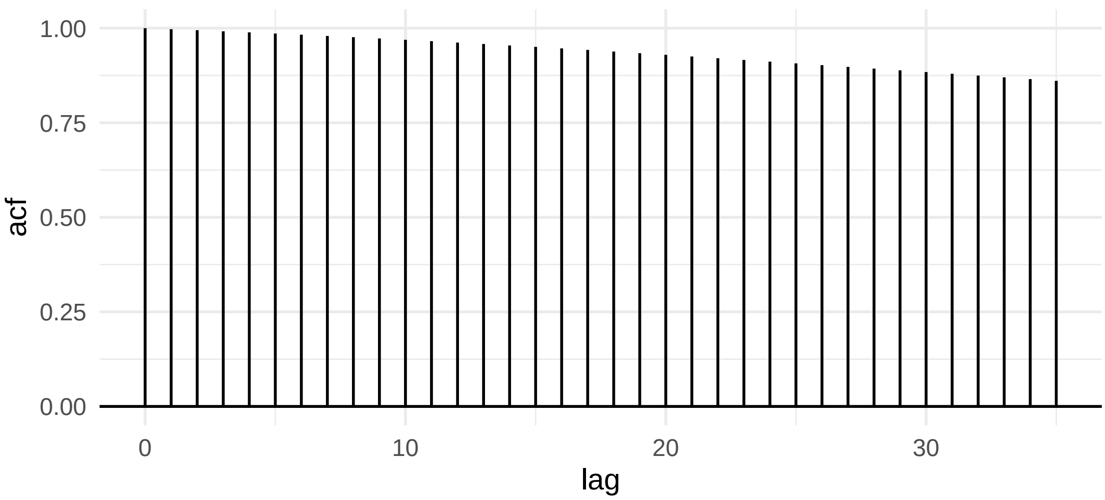

Figure 2.2: AutoCorrelation Function of bond-stock correlation time series

A two-state univariate Markov Switching Model was applied by using R. The model was allowed to switch both the mean and volatility (standard deviation) of the correlation to reveal two states with two different means and volatilities. As the table 2.4 shows regime 1 had a higher mean of -0.1163 with higher volatility of 0.099 than regime 2 with lower mean of -0.3348 and a lower volatility of 0.070. The intercepts of the two regimes were statistically highly significant.

[6] t-statistic for ADF test is computed conventionally way but instead of using conventional critical value, revised set of critical values computed by Dicky and Fuller is used. This critical value is larger in absolute value than the conventional critical value.

Table 2.4: Markov Switching Model:Coefficients

	(Intercept)	Standard Deviation
Regime 1	-0.1163	0.0994
Regime 2	-0.3348	0.0703

Note: Means (intercepts) and standard deviations of the two Regimes were found by applying Markov Switching Model in R. Both Mean and volatility of the Correlation were allowed to switch.

Figure 2.3 and Figure 2.4 show plots for each regime with the response variable correlation at the top showing the periods where the variable is in regime 1 and regime 2. The smoothed probabilities at the bottom, displays the probability that the time-series was in the respective state for any point in time. Figure 2.3 shows seven periods of regime 1 in fifteen years of correlation between Norwegian stock and bond (September 2004 to June 2019) and Figure 2.4 shows six periods of regime 2.

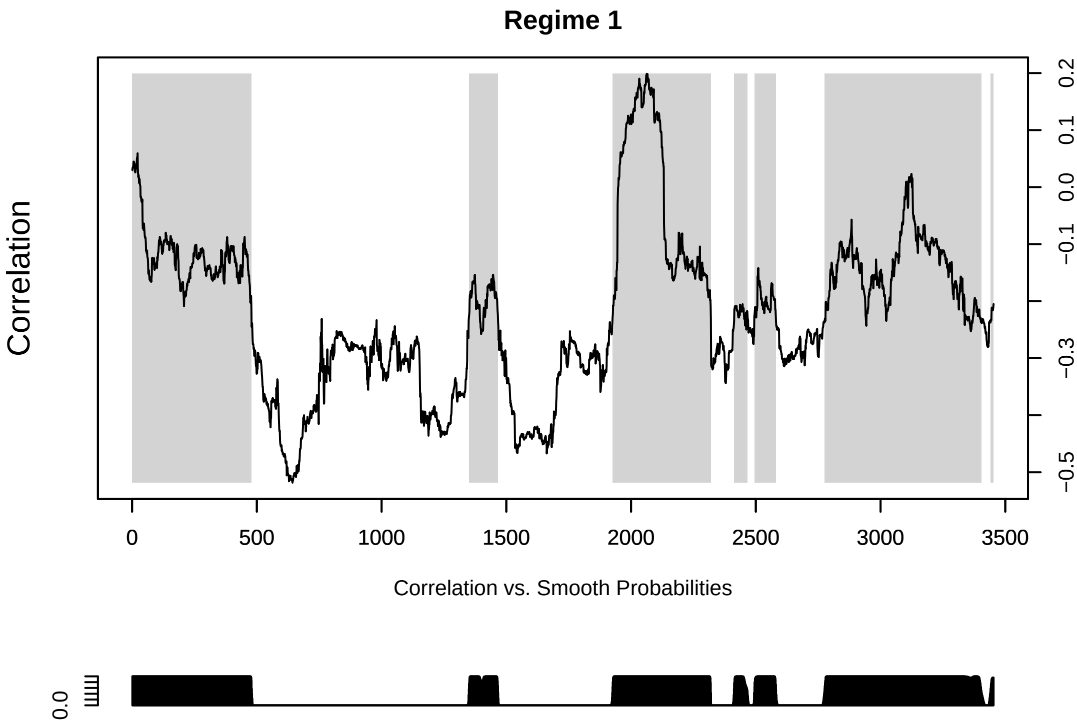

Figure 2.3: Correlation in Regime 1

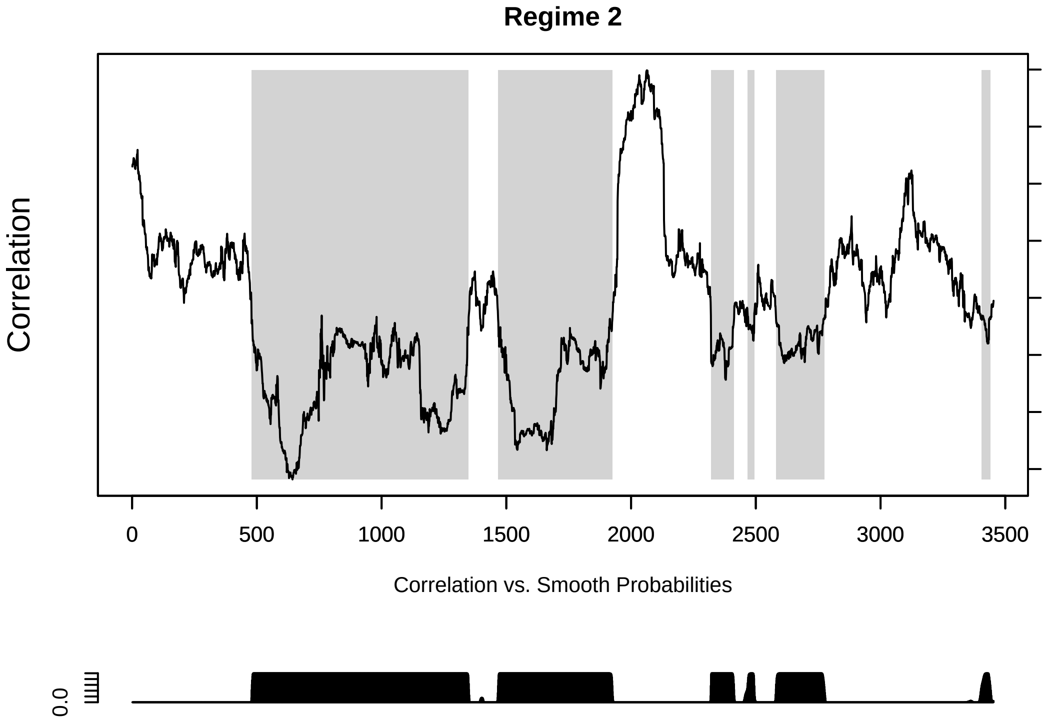

Figure 2.4: Correlation in Regime 2

Both the regimes are incredibly persistent, as the equation (2.7) shows the time-homogeneous probability transition matrix of the two states. P_{11} of 99.65% shows that if the correlation was in regime 1 at time $t-1$; there is 99.65% probability that the correlation of these two indices stayed in the regime 1 in the next time period t. And there is only 0.335% probability of switching to the regime 2 from regime 1 in the next period.P_{22} shows that there is 99.63% probability that the correlation stayed in regime 2 at t given that it remained in the same regime in the previous period $t-1$. And there is just 0.37% probability of switching from the regime 2 to regime 1. So, periods of high correlation were followed by high correlation, and periods of low correlation were followed by low correlation. Equation (2.7) also shows the irreducible behavior of the Markov chain.

$$Pr = \begin{bmatrix} 0.9965 & 0.0037 \\ 0.0033 & 0.9963 \end{bmatrix} \tag{2.7}$$

5 Implications for Asset allocation

The correlation between the assets has been a crucial component of portfolio risk from the time when Markowitz (1956) devised the portfolio diversification. In this section, three bond-stock portfolios were constructed, one with the correlation without considering regime-switching, second with correlation of regime 1 and third with correlation of regime 2 to check the effects of regime-switching correlation on these optimal portfolios. The optimal weights of the three portfolios were found by maximizing the

Sharpe ratio. As the correlation between the assets effect the variance (risk) of the portfolio According to modern portfolio theory:

$$\sigma_p^2 = w_B^2 \cdot \sigma_B^2 + w_S^2 \cdot \sigma_S^2 + 2 \cdot w_B \cdot w_S \cdot \sigma_D \cdot \sigma_S \cdot \rho_{B,S} \tag{2.8}$$

To check the effect of regime-switching correlation the results for the two-state Markov switching correlation model were used to create optimal portfolios consist of bond and stock for the two different regimes and then compared with an optimal portfolio of correlation without regime-switching. The optimal weights of the portfolios were calculated with the objective of maximum sharp ratio (portfolios with highest sharp ratios) which is given as:

$$\underset{w_i}{Max}\ S_P = (E(r_p) - r_f)/\sigma_p \tag{2.9}$$

The above equation subject to $\sum w_i = 1$. Sharpe ratio can be defined as the portfolio's risk premium in excess of the risk-free return(Bodie et al., 2013).

Optimal weight of the bond while maximizing above Sharpe ratio for the two risky assets (bond and stock) (Bodie et al., 2013) can be written as:

$$w*_B = \frac{E(R_B) \cdot \sigma_S^2 - E(R_S) \cdot \sigma_B \cdot \sigma_S \cdot \rho_{B,S}}{E(R_B) \cdot \sigma_S^2 + E(R_S) \cdot \sigma_B^2 - [E(R_B) \cdot E(R_S)] \cdot \sigma_B \cdot \sigma_S \cdot \rho_{B,S}} \tag{2.10}$$

But when the correlation is assumed to be time varying as in this work the optimal weight of the bond is:

$$w*_B = \frac{E(R_B) \cdot \sigma_S^2 - E(R_S) \cdot \sigma_B \cdot \sigma_S \cdot \rho_{B,S}}{E(R_B) \cdot \sigma_S^2 + E(R_S) \cdot \sigma_B^2 - [E(R_B) \cdot E(R_S)] \cdot \sigma_B \cdot \sigma_S \cdot \rho_{B,S}} + hd \tag{2.11}$$

Where:

$E(R_B)$ = Expected return of the bond in excess of risk free return r_f

σ_B = Standard deviation of the bond

$E(R_S)$ = Expected return of the stock in excess of risk free return r_f

σ_S = Standard deviation of the stock

$\rho_{B,S}$ = Correlation between bond and stock

$hd =$ hedging demand of the correlation risk

Hedging demand is the demand of the securities to diversify an additional risk. In this work, the correlation risk needs hedging demand and needs a separate hedging demand component as shown by

(Buraschi et al., 2010). Optimal portfolios are created by maximizing the Sharpe ratio but a distinct hedging component against correlation risk is not included to calculate the optimal weights therefore, the optimal portfolios are not optimal. The primary purpose of this work was to check the regime-switching in bond-stock correlation and secondary purpose was to check the effects of regime-switching correlation in asset allocation. The correlation hedging demand was ignored as it was out of the scope of this work and a simplified model to calculate optimal weights as shown in equation (2.10). Though it can lead to erroneous portfolio choice and risk management decisions in real settings (Buraschi et al., 2010). The calculations behind the values in table 2.5 do not contain a distinct correlation hedging demand component. Buraschi et al. (2010) showed that the optimal portfolio can be very different from the one obtained in the more common setting in which the investment opportunity set is affected only by time-varying expected returns and volatilities.

And the optimal weight of the stock is given as:

$$w_S = 1 - w*_B \tag{2.12}$$

The ten-year Govt bonds rate 2019 in Norway was taken as a risk-free rate r_f to calculate the maximum sharp ratios S_P. These optimal weights and correlations were used to calculate expected returns and volatilities for the three optimal portfolios.

Table 2.5: Optimal Portfolios

	Without Regime	Regime 1	Regime 2
Correlation	-0.2656	-0.1163	-0.3348
Expected Return	0.0761	0.0790	0.0749
Expected Volatility	0.0386	0.0432	0.0363
Sharpe Ratio	1.6095	1.5022	1.6769
Optimal Weights			
Bond	0.3533	0.3005	0.3744
Stock	0.6467	0.6995	0.6256

Note: This Table represents the Correlations, Expected returns, Expected volatilities (standard deviation),maximum Sharpe Ratios and Optimal weights of optimal portfolios for Regime 1, Regime 2 and optimal portfolio without regimes.

The expected return of optimal portfolio without considering correlation regimes was found to be 7.61% with expected volatility of 3.86% leading to a Sharpe ratio of 1.6095. On the other hand, if the correlation assumed to be in regime 1 the expected return was found 7.90% with an expected volatility of 4.32% and a Sharpe ratio of 1.5022. But if the correlation is assumed to be in regime 2, the optimal portfolio expected to have a return of 7.49% with an expected volatility of 3.63% leading to a sharp ratio of 1.6769. If an investor who does not consider the regimes in the correlation between bond and stock and regime 1 is existing the investor will face a loss of (7.90-7.61) 0.29%. And if the regime 2 is existing the investor will gain (7.61%-7.49%) 0.11% additional. But there is a net (0.29%-0.11%) 0.17% loss if the investor will not consider the regimes. Or the other way around an investor will gain 0.17% additional who considers the regimes.

The optimal weights of the bond and stock were 35.33% and 64.67% respectively for an investor's portfolio without considering regimes in correlation. The optimal weights in regime 1 were 30% and 70% for bond and stock respectively and in regime 2, the optimal weights were found 37.45% for bond and 62.6% stock. If the investor did not take into account the regimes and the correlation was in regime 1 the investor should have invested 5.3% more in stock instead of a bond. Whereas, if the correlation was in regime 2 the investor should have invested 1.9% more in bond than stock as compared to an investor, not considering regimes in correlation. As the transaction costs were ignored in the process of finding asset allocation so, the benefits from considering the regimes in correlation were not enough to overcome the transaction costs.

6 Conclusion

The contribution of this article is to provide an insight into different regimes in Norwegian bond-stock correlation and how it affects the decision of asset allocation of an investor who invests in stock and bond for diversification. This research has used daily data of stock and bond proxy indices to find the correlation. A two-state Markov Switching Dynamic Regression was applied to the correlation to find the regimes. Three bond-stock portfolios were constructed, by maximizing their Sharpe ratios to compare the effects of considering and ignoring regimes in bond-stock correlation.

In conclusion, the empirical findings of the research showed two different regimes of correlation with two different means (intercepts) and volatilities. Regime 1 with higher correlation intercept (lower negative mean) and higher volatility. Regime 2 with lower correlation intercept (higher negative mean) and lower volatility. Both the intercepts were highly significant. The higher transition probabilities of the two regimes showed that both the regimes were highly persistent. For both the regimes, there were more than 99% chances that the process stayed in the same regime at the time $t-1$ and t. So, periods of high correlation were followed by high correlation, and periods of low correlation were followed by low correlation. Moreover, the results for asset allocation displayed that, different regimes in correlation did not show any significant differences in optimal weights, expected returns, volatilities, and Sharpe ratios of the three different portfolios. It led to the conclusion that an investor who did not consider the regimes in correlation, will face a net loss of 0.17 %. Correlation hedging demand was ignored in constructing the optimal portfolios as it was out of the scope of this research and a simplified model for optimal weights was used.

6.0.1 *Acknowledgments*

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7 Appendix

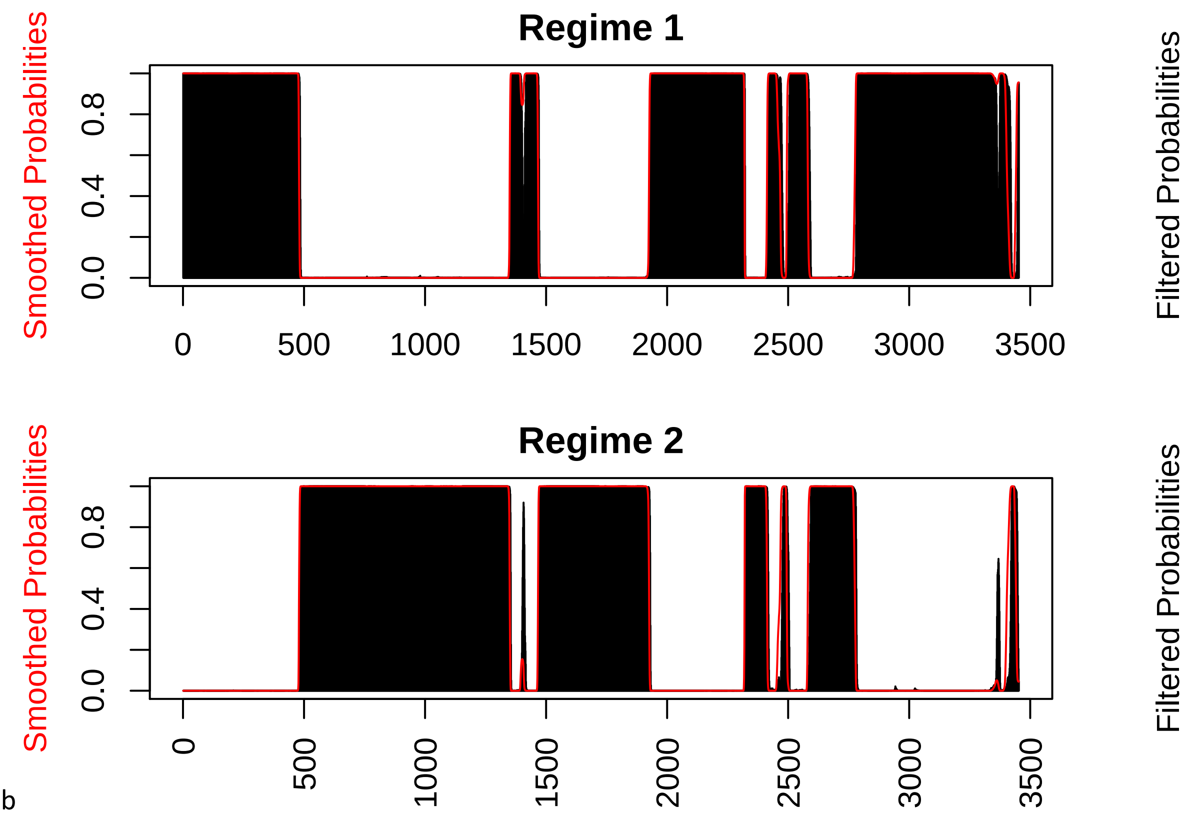

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Figure 2.5: Smoothed and Filtered probabilities of Regimes

Figure 2.5 shows the Filtered and Smoothed probabilities of the two regimes found in the bond-stock correlation. The red lines show the smoothed probabilities of the two regimes.

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