JYVÄSKYLÄ UNIVERSITY SCHOOL OF BUSINESS AND ECONOMICS

EFFECTS OF ECONOMIC POLICY UNCERTAINTY ON STOCK AND BOND MARKET INTEGRATION

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Author:
Akseli Savolainen
Supervisor:
Juha Junttila

JYVÄSKYLÄN YLIOPISTON KAUPPAKORKEAKOULU

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Tässä pro gradu – tutkielmassa tarkastellaan sitä, miten talouspoliittinen epävarmuus vaikuttaa osake- ja korkomarkkinatuottojen väliseen yhteyteen. Tutkimuksessa saadut empiiriset havainnot viittaavat siihen, että kun reaalitalouden kasvu ylittää inflaatiovauhdin, talouspoliittisen epävarmuuden kasvu on tekijä, joka vähentää osake- ja korkomarkkinatuottojen korrelaatiota. Sen sijaan kun inflaatiovauhti ylittää reaalitalouden kasvun, jota tässä tutkielmassa on mitattu S&P 500 indeksin osinkojen jaolla, kasvava talouspoliittinen epävarmuus vahvistaa osake- ja korkomarkkinatuottojen korrelaatiota. Tutkimus on toteutettu Yhdysvaltojen rahoitusmarkkinoiden aineistolle, mutta sen tulokset voitaneen yleistää koskemaan myös muiden kehittyneiden avotalouksien markkinoita. Tutkimus antaa myös viitteitä epäillä, että osake- ja korkomarkkinatuottojen yhteys on ollut herkempi talouspoliittisen epävarmuuden ja reaalitalouden kasvua kuvaavan parametrin muutoksille vuonna 2007 alkaneen finanssikriisin jälkeen. Tämän tutkimuksen aikana esiin nousseen, tutkimuskysymyksen kannalta toissijaisen havainnon vahvistaminen vaatisi kuitenkin lisätutkimuksia.</td></tr>
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Abstract:

In this master's thesis, I have investigated how economic policy uncertainty is related to the co-movement between stock- and bond market returns. The empirical results from the U.S markets imply that when the growth of economy is positive, that is, the dividend growth rate exceeds inflation rate, rising economic policy uncertainty will decrease the level of stock and bond market integration. Instead, when the growth of economy is negative, rising economic policy uncertainty will increase the level of the stock and bond market integration. The results of this study may be generalized to other developed open economies as well. The results also indicate that the integration between the stock and bond markets in the U.S has been more sensitive to changes in economic policy uncertainty and the real growth parameter after the global financial crisis that erupted in 2007 than before the crisis. However, drawing robust conclusions about this secondary observation would require more empirical analysis on this set of data.

Key Words
economic policy uncertainty, stock market returns, bond market returns, market integration

Location:
Jyväskylä University School of Business and Economics

Author	Akseli Savolainen Jyväskylä University School of Business and Economics (JSBE) akseli.mikael.savolainen@gmail.com
Supervisor	Professor Juha Junttila Jyväskylä University School of Business and Economics (JSBE)
Reviewers	Professor Juha Junttila (JSBE) Professor Ari Hyytinen (JSBE)

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1 INTRODUCTION

Economic policy uncertainty is always present and has many kinds of effects on behavior of consumers and firms. In order to measure economic policy uncertainty, researchers Scott Baker, Nicholas Bloom and Steven Davis started to maintain the index for economic policy uncertainty and published the index in the internet for broad use. Surely, many institutional investors have found their motive to investigate what kind of effects may economic policy uncertainty have on stock and bond market return integration.

Investors are usually interested in the risk-return tradeoff associated with different combinations of stocks and bonds in their portfolios. On the other hand an investor may buy bonds and take a short position at the same time for stocks. When taking a long position for the both assets, the particular interest is the combination that gives the smallest possible risk. Then, investor needs to take account expected returns, variances and the correlation between the stocks and bonds included in the portfolio. In most cases, correlation is time-varying and driven by macro-economic risks. However, there does not exist any research of the effects of economic policy uncertainty measured by the EPU index (Bloom et al, 2013) on stock and bond return correlation. Diversification is the method of managing risk of portfolio and the concept of time-varying correlation is central in order to manage risks by diversification.

Stock returns have dominated bond returns in the long run. For example the excess return of stocks over the U.S. short debt instruments has been 7.9% during the last century (Elton et al, 2010). However, it is natural to think that for short periods bonds can be considered as substitutes for stocks. This is mainly because the correlation between geographically diversified stocks tends to increase during stock market crashes and bonds have been considered as a "safe heaven" in those circumstances when the stock market uncertainty has been the highest. Since stock market crashes are per se unpredictable, bonds should be held in a portfolio for diversifying purposes even though they offer lower profits than stocks. This idea is in line with modern portfolio theory (Markowitz, 1952). For example in 1998 when the Russian debt crisis erupted, the S&P 500 index decreased almost 7% but at the same time the U.S. bonds appreciated

(Gulko, 2002). The situation, where capital moves from risky assets to less risky is generally called "flight to quality". Although the results of this study may have some monetary policy implications, it can be seen that my motives are related to understanding the effects of economic policy uncertainty in the context of investing into stock and bond markets. Before continuing, it is proper to clarify the definition of the stock and bond market integration that appears in the topic of this thesis.

Bekaert et al (2002) define markets to be integrated if the assets of identical risk command the same expected return, regardless of domicile. This definition is commonly used in the research of international finance and economics but some other definition for market integration has to be defined since this study concerns market integration between the U.S. local stock and bond markets. Bekaert & Harvey (1995) use a less restricting definition for market integration stating that markets are completely integrated if assets with the same risk have identical expected returns irrespective of the market risk. The definition suits for the purposes of this study if we relax the assumption that the assets are identical by their risks. We consider stocks to be a riskier asset type than bonds, so *we define the stock and bond markets to be integrated if those returns are driven by common market risks and an exposure to these risks causes parallel changes in the returns of these assets*. As a measure for market integration we use naturally the correlation estimate of the market returns. I only loosely define the stock and bond markets to be integrated if the correlation of the returns exceeds zero. This presumption does not restrict the level of which the markets have to be correlated in order that we interpret the markets to be integrated. Of course, if the correlation is almost one, we conclude the markets to be almost fully integrated. If the correlation is slightly positive, the market returns follow a parallel trend and are since partially integrated. However, then the effects of risks are not symmetric for the assets.

The structure of this study is following. In chapter two, I set up some theory basis for my assumptions of the dynamics between the stock and bond market returns. In chapter three, I focus on the data and methodological issues and derive the models that I use in my analysis. In chapter four, I introduce the empirical results that have been obtained based on the models. In the last chapter I will discuss how the results have answered to the main question: what effects economic policy uncertainty may have on stock and bond market integration?

2 DYNAMICS BETWEEN STOCK AND BOND MARKET RETURNS

In this chapter, I first introduce the basic discounting model that determines how investors value the fundamental market value of stocks and bonds. Second, I will investigate what are the key factors that govern the dynamics between stock and bond markets. Based on literature from 1980's to the beginning of 2000's, I find three essential macroeconomic factors; dividend growth, inflation and stock market volatility. The more recent literature suggests that economic policy uncertainty plays a major role in stock market fluctuations. I will also cover issues related to stock and bond market *decoupling* which means the situation when the correlation between the markets is highly negative for a short period, usually during stock market crashes.

2.1 Valuation models

In this subchapter, my attempt is to introduce the idea of how investors determine the fundamental prices of stocks and bonds. The notation I have used borrows much from Ilmanen (2003). Generally, the value of any asset can be determined by calculating the present value of all future cash flows of the asset. In the present value calculation, the discount factor incorporates the opportunity cost of investing in risk-free instrument (e.g. U.S 3-month Treasury bill) and the asset specific risk premium. The discount factor is time-varying which means that stocks and bonds are both subject to discount rate uncertainty. Volatility in asset prices is mainly a result of the volatility in the discount factor or in the case of stocks, in dividends. Later, based on the findings of some empirical studies, we learn that returns of the stock and bond markets may react differently to the changes in macroeconomic fundamentals since discount rates for stocks and bonds have both common and separate elements. These assets differ also by their cash flows, because coupons (*C*) and the face value (*FC*) on government bonds are usually considered to be fixed, but stocks have uncertain cash flows. Usually stocks pay growing dividends *(D)* with the expected growth rate *(G)* which is directly linked to the present value of a particular stock via the equation (2.2) for stock price. For simplicity, I denote the discount rate for a bond as Y which incorporates expectations of future risk-free rates and the bond risk premium. It shall be noticed that the nominal discount rate Y may be composed of the real rate (Y^r), expected inflation (i^e) and the term premium (θ), because the remaining maturity of the bond affects its riskiness. The discount rate for a particular stock consists of the bond discount rate and the required equity risk premium (*ERP*) as a compensation for bearing additional risks when compared to bonds. The formulas for stock *(S)* and bond (B) prices and the nominal discount rate can be expressed as follows:

$$Y_t = Y_t^r + i_t^e + \theta \tag{2.1}$$

$$S_t = \sum_{t=1}^{n} \left(\frac{1+G_t}{1+Y_t+ERP_t}\right)^t D \tag{2.2}$$

$$B_t = \sum_{t=1}^{n} \frac{C_t}{(1+Y_t)^t} + \frac{FC}{(1+Y_n)^n} \tag{2.3}$$

Equations (2.2) and (2.3) show that both stocks and bonds have to react on innovations of expected inflation. If the rate of dividend growth is higher than expected inflation rate, it is theoretically possible that inflation has less impact on stock prices.

We have learned actually from the previous equations that the stock and bond markets should be always partially integrated since the prices reflect always changes in the cost of investing in the risk-free instrument. We also accept that the integration is time varying and the relationship may exhibit occasionally a strong negative correlation since there exist several macroeconomic factors that may have different effects on the prices of stocks and bonds.

We also find that the assumption of asset price volatility is in line with Fama (1990) who states that standard valuation models posit actually three sources of variation in stock returns; shocks to expected cash flows, predictable return variation due to variation over time in the discount rates that price the expected cash flows and shocks to discount rates.

Chen & Zhao (2009) suggest that cash flow news is more related to firm fundamentals because of its link to production and discount rate news can reflect time-varying risk aversion and since their relative level provides the empirical basis for theoretical modeling. This study concerns the both issues by linking the productivity growth with dividends share and using several macroeconomic risk factors as the reflector for discount rate news.

In this chapter, my aim is to investigate what are the key macroeconomic factors that are linked to the asset prices via the discount factor and are influential to the correlation between the stock and bond markets. This study investigates the U.S. markets but similar patterns of asset valuation may cause the results of this study to be applied into other developed and open economies. However, the results of this study may not be applied to emerging markets because Bekaert & Harvey (1995) argue that the standard global asset pricing model[1] assumes complete global market integration and has only weak explanatory power when applied to emerging markets. Later, we learn also that due to the method of how the index measuring the economic policy uncertainty is calculated, the results of this study may not be either applied straightforward to economies that can be categorized by limited liberty of the national press.

2.2 Essential macroeconomic factors

Beltratti & Shiller (1992) have investigated dynamics between stocks and interest rates in a *VAR* (Vector Autoregressive Model) - framework. Their large sample covers the U.S. stock and bond markets from 1871 to 1989 and the UK-market from 1918 to 1989. According to the results of Beltratti & Shiller (1992), real stock prices do not show the relation to long-term interest rates that their valuation model predicts. Instead, they find that the negative correlation between the long-term interest rates and stock prices is higher than would be expected by their model. Obviously, an increase in expected future discount rate should lower the price of any asset, so Beltratti & Shiller (1992) argue that: "By present value models an increase in expected future discount rates should, *other things being equal,* cause both stock prices to fall and long-term interest rates to rise; a fall in expected discount rates should have the opposite effect on both". This phrase actually incorporates a couple of assumptions that need to be stated more clearly at this point in order to avoid some misunderstandings; there is a part of discount factor which is a) driven by macroeconomic factors (e.g. inflation) and b) has per se a similar effect on any asset's price. To understand why this part of discount factor does implicitly raise long-term interest rates and lower stock (or any other asset) prices, we can imagine a following scenario. If a rise in people's rational expectations of future inflation would occur, then based on the Fisher hypothesis[2] (see e.g. Barro, 1998) the nominal rate would rise and the real interest rate would remain steady. Hence, the nominal rate is the part of discount rate that will be the same for both assets since it fulfills the presumptions a) and b) I stated above. Due to the rise of the discount rate caused by new expectations of future inflation the values of stocks and bonds that are already in the market will be lower to attract investors to hold these assets in their portfolios.

We learned from this that the possible negative correlation between stock prices and long-term interest rates is actually caused by a rise in discount rate.

[1] The statement concerned primarily the capital asset pricing model (see also Black et al, 1972), but the CAPM is implicitly linked to the discounted cash flow models because many investors calculate the opportunity cost of capital by using the CAPM.

[2] . Simple assumptions of the Fisher hypothesis are valid to explain the direction of price changes, but the nominal rate and inflation does not usually change point-for-point in real world and central banks may favor some contrary monetary policy rules that take into account some other targets than the level of inflation.

It is also meaningful to argue that a rise in long-term interest rate is negatively related to prices of stocks and bonds already existing in the market. However, the mechanism that causes negative correlation between stock prices and long-term interest rates differs essentially from the mechanism that causes stock and bond markets decoupling since the former is a result from discount rate effect that is similar for both asset types and the latter appears when the discount rate effect is asymmetric. Beltratti & Shiller (1992) disregard the asymmetric effects in a sense that they do not consider changes in the risk premium. Barsky (1989) instead has postulated an idea that because of risk-averse investors, the dynamics between stocks and bonds should be expressed in terms of changing risk premium. However, Barsky (1989) didn't support his thoughts by econometric models. In particular, Barsky (1989) points out that low productivity growth assigned with times of high market risk together lowers corporate profits and real interest rates that leads to negative correlation between stock and bond returns. Beltratti & Shiller (1992) suppose that dividends on stocks and coupons on bonds are discounted by the future short rates plus a constant risk premium. I am aware that changing risk premium is very essential factor of varying stock-bond correlation. However, Beltratti & Shiller (1992) mention that cash flows from stocks and bonds can be considered differently and inflation may have different effects on the prices of these assets. This is because usually stocks pay growing dividends and coupons on bonds are considered to remain constant. If the level of growth is near or even greater than inflation rate, stocks can be considered as kind of inflation protected instruments. However, inflation has an effect on firm's assets and higher inflation will decrease the values of firms. Beltratti & Shiller (1992) use inflation as an explanatory variable in their analysis but they can't find evidence of negative correlation between stock prices and inflation.

Campbell and Ammer (1991) have investigated the stock-bond correlation in a VAR framework by including several macroeconomic factors that may have an effect in the correlation; dividend growth, inflation and real interest rate. They found that dividend growth is an indicator for future excess returns in stock market whereas inflation has an effect on bond market fluctuation. They also found that real interest rates have had no effect to asset price levels.

Li (2002) focuses on how the correlation of stock and bond returns can be explained by their common exposure to macroeconomic factors. Li (2002) shows empirically that the uncertainty about expected inflation has a major effect on stock-bond correlation and the uncertainty about expected inflation and the real interest rate is likely to increase the co-movement between stock and bond returns. Since uncertainty about expected inflation is positively related to its level, Li (2002) uses the level of expected inflation as the proxy for its uncertainty. Li (2002) uses the data of 7G countries from the 1960's and finds that there has been a varying trend in stock-bond correlations when correlation has been first raising from zero to 0.5 and then decreasing back near to zero. According to Li (2002) in circumstances of high inflation there has been high co-movement between stock and bond returns and this phenomenon was observed during the

1970's oil crisis when major industrial countries suffered from stagflation which raised people's inflation expectations.

Stivers & Sun (2002) model the co-movement between daily stock and bond returns related to market uncertainty by using lagged implied volatility from equity index options (VIX) to provide an observable and dynamic measure of stock market uncertainty. Stivers & Sun (2002) find evidence that the stock-bond correlation is low or even negative when the implied volatility is high and returns move substantially together during periods of low implied volatility. Stivers & Sun (2002) use daily data which is proper because largest changes in volatility may occur within a day. It can be also supposed that market will behave mostly efficient when news and information will be incorporated into prices relatively fast.

Ilmanen (2003) examines the stock and bond return sensitivity to the business cycle, inflation, volatility and monetary policy conditions. He found that economic growth and volatility shocks push stock and bond prices in opposite directions. Andersson et al (2004) in turn were not able find economic growth as a factor to stock-bond correlation. Ilmanen (2003) states that inflation is an important determinant of stock-bond correlation and at high levels of inflation, the correlation is also high. Ilmanen (2003) distributes the data in to four key dimensions due to conditions mentioned before and calculates sub sample correlations in different states of the world.

Andersson et al (2004) have also investigated the time varying correlation between stocks and bonds in the U.S and Germany. Their study is in line with earlier assumptions that high expected inflation leads to a higher co-movement between stock and bond returns. Andersson et al (2004) find also that stock market uncertainty is negatively related to the stock-bond correlation which is again in line with Ilmanen (2003), Gulko (2002) and Stivers & Sun (2002). The results of earlier literature have been summarized in Table 1.

Table 1: Summarized findings related to stock and bond market dynamics and macroeconomic factors.

Author(s)	Finding(s)
Barsky (1989)	Dynamics between stocks and bonds should be expressed in terms of changing risk premiums. Low productivity growth assigned with high market risk lowers corporate profits and real interest rates leading to stock and bond market decoupling.
Beltratti & Shiller (1992)	Long term interest rate is negatively related to asset prices, but the effect is larger than expected by valuation models.
Campbell & Ammer (1991)	Dividend growth indicates excess returns of stocks over bonds. Real interest rates have no effect on price levels.
Li (2002)	Uncertainty about expected inflation has a major effect on stock-bond correlation since higher uncertainty is likely to increase the co-movement between stock and bond returns
Stivers & Sun (2002)	Lagged implied stock market volatility is negatively related to stock-bond return correlation. In this sense, volatility is a proxy for stock market uncertainty.
Gulko (2002)	Based on decoupling hypothesis, during stock market crashes the correlation between the returns of stocks and bonds switches sign from positive to negative.
Ilmanen (2003)	Economic growth and volatility pushes stock and bond prices in opposite directions. Inflation is positively related to the correlation.
Andersson et al (2004)	High inflation indicates positive correlation. High stock market uncertainty indicates negative correlation. DCC – model implies volatility spillovers.
Saleem (2008)	DCC – model implies volatility spillovers that indicate changing risk premiums. The effect is universal.

Studies where dynamic conditional correlation models proposed by Engle (2002) have been adopted like Andersson et al (2004) and Saleem (2008) state that volatilities of stocks and bonds are correlated positively. Saleem's (2008) work shows that also in frontier markets stock-bond correlation tend to be similar than in the U.S. or Europe when he investigates Russian markets. The result supports the theory of volatility spillovers between the assets which leads to relative price changes by mechanism of changing risk premiums.

2.3 Decoupling

Gulko (2002) has investigated the stock-bond return correlation during stock market crashes and when the U.S. government obligations have been profitable. In these circumstances the correlation is negative and market volatility is high. Gulko's (2002) empirical analysis covers the U.S. stock market crashes from 1946 to 2000. So, including bonds in a portfolio will make the portfolio more hedged against risk during stock market crashes. This phenomenon is usually explained as a reason for the negative stock-bond correlation in short periods and is essentially related to changing risk premiums when risk-averse investors are changing their position from risky stocks to safer bonds. The negative relationship of stock and bond prices seems to be present in several stock market crashes since 1945. According to Gulko (2002), Table 2 sums up the times when "flight to quality" has been at its strongest.

Table 2: Stock and bond market decoupling during stock market crashes between 1946-2000 (Gulko, 2002).

Crash Date	S&P 500 Decline	T-bond Reaction	Cause/Trigger of Crash
Sept 3, 1946	-9.9%	-0.21%	Internal tensions, fear of inflation and recession, labor strikes
June 26, 1950	-5.4%	0.00%	Korean War declared on June 25
Sept 26, 1955	-6.6%	0.33%	President Eisenhower's heart attack
May 28, 1962	-6.7%	0.28%	Government intention to control wages and prices, particularly steel prices
October 16, 1987 **October 19, 1987** **October 26, 1987**	-5.2% -20.5% -8.3%	0.39% 3.70% 2.10%	Soaring interest rates and inflation fears exacerbated by portfolio insurance
January 8, 1988	-6.8%	1.5%	Possibly an aftershock of October 1987
October 13, 1989	-6.1%	2.00%	Banks abort United Airlines buyout, rising producer prices, falling Tokyo stocks
October 27, 1997	-6.9%	1.90%	East Asian currency crisis
August 31, 1998	-6.8%	0.96%	Russian debt crisis
April 14, 2000	-5.8%	0.22%	Internet bubble

As can be seen, fear of rising inflation has been considered as one reason for the stock and bond market decoupling. Based on my assumptions, inflation should per se have a similar effect on stocks and bonds so it is not obvious why stock and bond markets have decoupled in 1946 and 1987. Similarly, several econometric analyses like Li (2002), Ilmanen (2003) and Andersson et al (2004) have shown that the level of inflation is positively related to the co-movement of these assets. One explanation why inflation seems to have had a substantially strong negative effect on stock prices during 1946 and 1987 may be due to the relative level of dividend growth rate versus inflation rate. My calculations based on data used in "Irrational Exuberance" (Shiller, 2000) show that the average growth in the S&P 500 dividends per share since 1940s has been 5.4% per year when over the same period, *CPI* (Consumer Price Index) has indicated 3.6% inflation growth per year on average. During times when circumstances were not typical for stock markets regarding *the relative level of dividend growth and inflation* investors may have preferred bonds over stocks. The relative level of inflation measured by the U.S CPI and dividend growth can be seen from Figures 1 and 2.

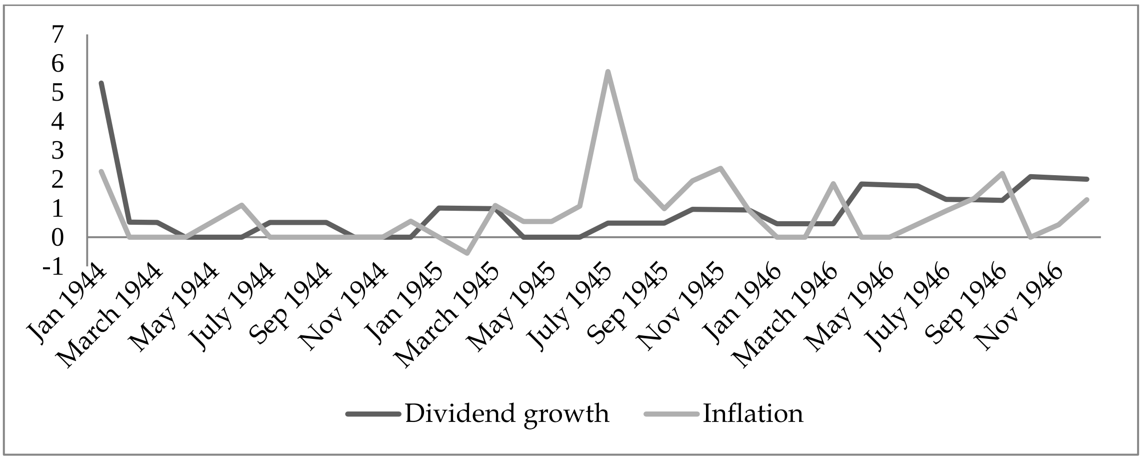

Figure 1: Monthly S&P 500 dividend growth and the U.S inflation (%) 1945-1947.

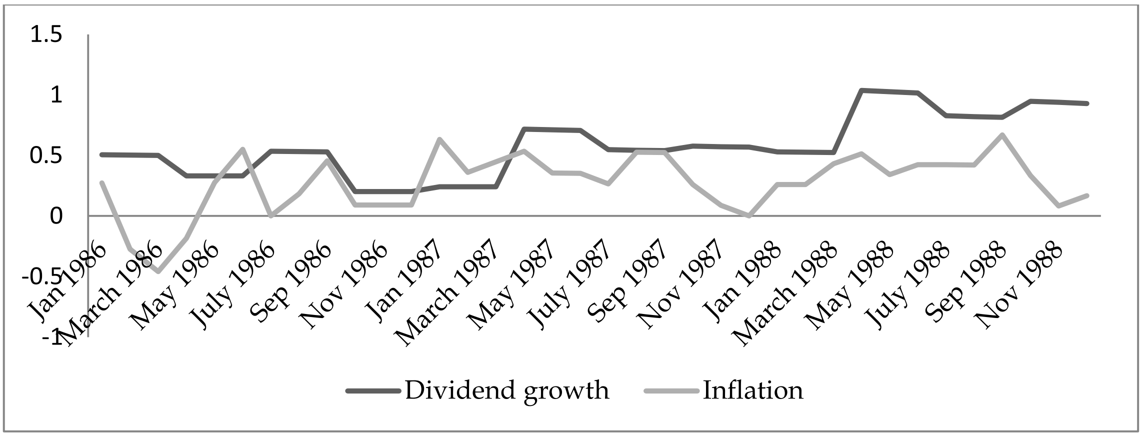

Figure 2: Monthly S&P 500 dividend growth and the U.S inflation (%) 1986-1988.

Figure 1 shows that just after the 2nd World War, inflation measured by monthly change (%) of consumer price index has exceeded the growth rate of dividends almost during the whole year in 1946 when the stock and bond markets decoupled. The situation is to some extent in contradiction with the fundamental idea that stock and bond markets should indicate strong co-movement when inflation expectations are high. It is appropriate to ask why this presumption was not sufficient during the 1946's crash. It is possible that some macroeconomic factor was able to override the effect of inflation in the relationship between the stock and bond markets or due to the atypical conditions for stock market, risk-averse investors have favored bonds strongly over stocks.

Figure 2 shows that unlike in 1946, inflation was not ultimately higher than dividend growth in 1987. However, the period from August to October shows that CPI growth has been de facto at the same level with dividend growth. After the three subsequent stock market crashes in October, the relation has shown more typical behavior according to the long run average levels of inflation and dividend growth. These plots offer some evidence in favor of the view that when inflation exceeds or is about to exceed the dividend growth rate, stocks are exposed to price decline.

Looking at Table 2, it is also remarkable that usually the stock market crashes are related to conditions when some political uncertainty is present. We saw that even a heart attack of the U.S President can be a trigger for market decoupling. It is obvious that in 1946, just after the 2nd World War, political climate was not clear. Also in 1987 the *EPU* (Economic Policy Uncertainty) index was peaking and declined sharply after the "Black Monday" of October 27. Since the index already started to rise sharply in the beginning of August, high political uncertainty measured by the EPU index cannot be a result of the stock market crash itself. This observation actually favors the view that the stock market volatility can be sometimes a result of economic policy uncertainty. *So, it seems that when some political uncertainty is about to progress, the situation is fruitful for stock and bond market decoupling.* This motivates me to investigate what role the policy uncertainty plays in the dynamics between the stock and bond markets.

2.4 Economic policy uncertainty

We learned from Gulko (2002) that usually during stock market crashes, political uncertainty is high. It is possible that stock market volatility can be partly a result from policy uncertainty. Another view is that economic policy uncertainty is not related to the market volatility itself, but instead plays a major role in how the market prices the assets. For these reasons, the next step is to investigate what kind of linkages these two issues have. More precisely, I will closely explore based on the latest literature, the relationship between the two indexes measuring uncertainty; VIX and EPU and how these indexes are related to the movements of stock prices.

2.4.1 The EPU index

Bloom et al (2013) have managed to construct a quantitative measure for, to some extent vague term of economic policy uncertainty. Their research group has put a remarkable effort to quantifying the EPU index from the three underlying components. The first component of the EPU index has been quantified based on the frequency of references to a combination of terms that reflect economic policy uncertainty in newspapers. They cover the most popular newspapers and do an automated text-search for the articles of each newspaper. In order to meet their criteria, the article must include terms in all the following categories: ‘uncertainty’, ‘economy’ and ‘policy’. The second component of the EPU index refers to the federal tax provisions facing expiration. Scheduled tax code expirations are a source of uncertainty since before the date of expiration there is uncertainty among citizens about what the Congress will decide regarding future taxation. The third component of their composite index is the extent of disagreement between economists about inflation and government purchases. The policy uncertainty index is a weighted average of the three mentioned series. The index is available on internet (Bloom et al, 2015) [b] and the monthly series has been constructed for the U.S, Canada, China, India, Japanese, Europe and Russia. Daily index is available for the U.S. Figure 3 shows the U.S monthly index from the beginning of 1985.

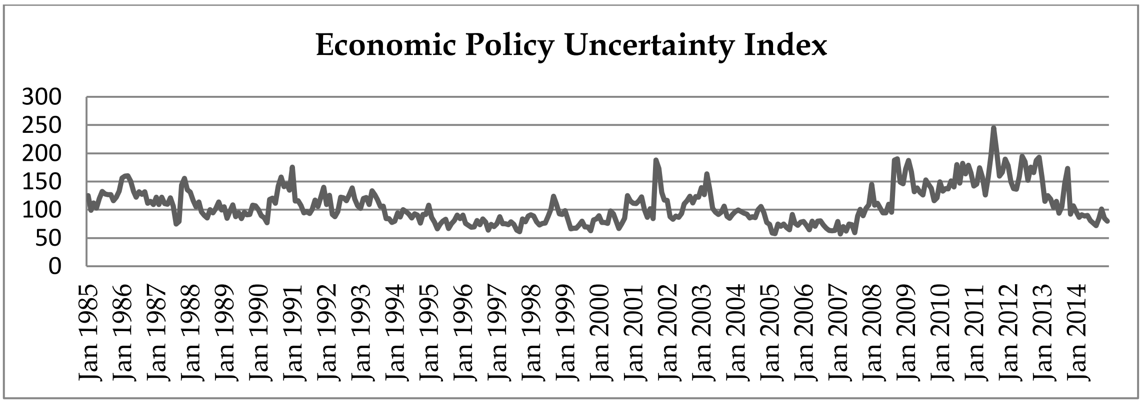

Figure 3: Economic policy uncertainty index for the U.S from 1985 to 2014.

As can be seen, the index spikes during several crises like during the Gulf Wars and 9/11 terrorist attacks. The index reflects also financial crises like the bankruptcy of Lehman Brothers and the subprime mortgage crisis. The European debt crisis also caused the index to spike and stay at a high level for some years. According to Figure 3, the Black Monday of 1987 and the Russian Debt crises can be detected from the index as well as the Internet bubble. Seemingly, the EPU index is able to explain volatility in the stock markets. By the year 2014, the index has been declined to its average level and the mean for the period from its beginning to the end of the 2014 is 107.6 points.

2.4.2 Recent studies related to the EPU index

The EPU index is a somewhat new measure for uncertainty, but there are few papers related to the effects of economic policy uncertainty on stock market fluctuation. The stock market volatility index (VIX) has been usually considered as an indicator for market uncertainty, but Mezrich & Ishikawa (2013) state that uncertainty over economic policy is sometimes more relevant than market volatility. Mezrich & Ishikawa (2013) point out that the role of economic policy uncertainty is directly related to how the market prices itself. The correlation of economic policy uncertainty index and S&P 500 index has been between 0.62 and 0.86 during the period from November 2002 to October 2012 (Gregory & Rangel, 2012) but after 2009, economic policy uncertainty is not reflected in market volatility measured by the VIX. Since the relationship between the EPU index and market's implied earnings growth has been striking after that, Mezrich & Ishikawa (2013) conclude that market is pricing economic policy uncertainty over market volatility. It is evident that the trend of implied earnings growth proposed by the model of Mezrich & Ishikawa (2013) closely follows the behavior of the EPU index and is negatively correlated to the level of EPU index.

Regression analysis of Gregory & Rangel (2012) shows that the forecasted values based on the level of one-month variance of S&P500 index underestimate the implied volatility, but adding economic policy uncertainty as an additional explanatory variable increases the accuracy of the model. Based on these results we have learned that economic policy uncertainty plays a significant role in stock market dynamics and the EPU index offers a good benchmark for e.g. portfolio risk analysts. Still, deeper analysis of the impact of the EPU index on the correlation between stocks and bonds is needed.

Bloom et al (2013) provide also evidence that economic policy uncertainty drives lead businesses and households to cut back on spending, investment and hiring and state that the effect is larger for firms with greater exposure to government policy.

Bloom et al (2015) [a] have recently obtained new evidence about the forces that trigger large stock and bond market jumps in the U.S. They found that policy news trigger 20-25% of jumps in most advanced economies and a larger share in other countries like China and India. Besides, macroeconomic performance accounts for 23-38 % of jumps in advanced economies and less in other countries. Macro news are the main trigger for bond market jumps in the U.S but macro and monetary policy news together trigger a vast majority of bond market fluctuations. They also found that shocks to risk premium and expected returns dominated market fluctuations in 2008-2012.

2.4.3 Other measures for political risk factors

Usually in the international finance literature, a measure for political risk is composed from the *ICRG* (International Country Risk Guide). For example Lehkonen (2014) measures the level of institutions in developed and emerging economies based on the ICRG and divides political risk into 12 subcomponents; (1) government stability, (2) socioeconomic conditions, (3) investment profile, (4) internal conflict, (5) external conflict, (6) corruption, (7) military in politics, (8) religious tensions, (9) law and order, (10) ethnic tension, (11) democratic accountability and (12) bureaucracy quality. Since, the EPU index for the U.S is a daily basis updated quantification of the newspaper articles that indicates precise 'economic policy uncertainty' it can be considered more accurate measure for policy related risks in the context of financial markets in such developed local markets like the U.S market. However, it is clear that in countries with a high degree of corruption and a low degree of democracy, the press may not have all the authority to write about political risks without any censorship. This actually restricts the EPU index to be a good measure for countries that can be classified by those features. However, the measure composed from the ICRG comprises many essential factors that affect financial markets and therefore the measure may be more relevant for the purposes of the global market literature, especially in the case of emerging economies.

2.5 Lessons learned

Based on valuation models, there are several factors that affect asset price levels by the mechanism of changing risk premium. We learned that some factors have an asymmetric effect on stock and bond prices depending on their levels. We found also that especially three macroeconomic factors are essentially related to the stock and bond return correlation; the dividend growth, inflation and stock market uncertainty. Since economic policy uncertainty also seems to drive stock market fluctuations, it is evident that it should be considered as the fourth one.

2.5.1 Dividend growth

Because productivity growth is closely connected to dividend growth, Barsky's (1989) statement is in fact consistent with the predictions of Campbell and Ammer (1991) who state that the dividend growth indicates excess returns of stock markets. Also Ilmanen (2003) considers economic growth as a factor that pushes stock and bond prices in opposite directions. Based on these findings, the *rate of dividend growth* is certainly a factor that has an effect on stock and bond return correlation.

2.5.2 Inflation

Another factor that has a significant effect on the dynamics between stocks and bonds is the *level of inflation*. Andersson et al (2004), Ilmanen (2003) and Li (2002) find unanimously that high inflation leads to high correlation of stock and bond returns. In this context actual inflation can be considered as a proxy for uncertainty about expected inflation. There is a strong consensus among the researchers about the effect of inflation in the long run. However, during some stock market crashes like in September 1946 and October 1987 the level of inflation has been high according to the relative level of dividend growth, but still the correlation between the assets has been strongly negative in the short run. For this reason the effect of inflation may be ambiguous.

2.5.3 Stock market volatility

Stock market volatility measured e.g. by VIX (Chicago Board Options Exchange Market Volatility Index) is the third factor that plays a major role in the relationships between stock and bond markets. It is evident that volatility in the stock markets implies uncertainty and decreases the degree of stock and bond market co-movement. This finding is consistent with Stivers & Sun (2002), Ilmanen (2003) and Andersson et al (2004), but also with Barsky (1989) and Gulko (2002) who theoretically predict that the correlation between the assets depends on changing risk premiums. Dynamic correlation models (e.g. Saleem, 2008) strengthen the view of changing risk premiums in the sense of volatility spillovers.

2.5.4 Economic policy uncertainty

From Mezrich & Ishikawa (2013) and Gregory & Rangel (2012) we learned that economic policy uncertainty is a significant benchmark for the S&P500 fluctuation and earnings growth. Economic policy uncertainty is a driver for the stock market uncertainty and sometimes it can be considered as better indicator for the implied market volatility than the VIX. Coincidence or not, policy uncertainty was present also during 1946's and 1987's stock market crashes when dividend growth was modest. News on economic policy uncertainty may be considered as news on discount rate and because of that it affects to stock and bond prices via discount rate.

In this chapter, we described macroeconomic factors regarding the dynamics between stock and bond market returns. We also found that economic policy uncertainty is sometimes the most influencing factor in market fluctuations. Based on these findings, my aim is to develop a regression model that predicts the time varying correlation between stock and bond returns. The following questions are essentially related to the main research question: i) How economic policy uncertainty is related to the co-movement of stock and bond returns and

ii) Does any additional factor (e.g. the relative dividend growth vs. inflation) help to predict the effects of economic policy uncertainty on the correlation between stock and bond markets? I assume that the anticipated effect of economic policy uncertainty on the stock and bond market integration may be similar than the effects of news on VIX because *the indexes are alternative indicators for market uncertainty*. I also assume that the effects may differ depending on the state of real economy.

3 DATA AND METHODS

In this chapter, I consider the issues related to the data and the methods used in the empirical analysis. Firstly, I familiarize the reader with the data set and the transformations that have been made for the original time series in order to capture the relevant information from the data. Then we learn that the EPU index and the dynamic conditional correlation estimates are stationary that limits us to use the so called co-integration technique in order to find if economic policy uncertainty and the market integration exhibits any long run equilibrium. Then, I introduce the dynamic conditional correlation estimation procedure I have used in order to obtain the measure for the integration level of the stock and bond markets. After that, I approach the relationship between the market integration and economic policy uncertainty by conditioning the probability for the market integration to the level of the EPU index. I also control the macroeconomic state with dummy variables and find contrary behavior for the conditional probability depending on the state of economic growth. Then, I analyze straightforward the relationship by basic linear regression model. The results of the linear regression model motivates the investigation of the dynamics also in the VAR- framework in order to track how the level of stock and bond market integration develops if some economic policy uncertainty shocks and economic growth impulses are imposed into the system The focus is in periods of *pre* and *post-crisis* in order to find if the progress of the shocks exhibits similar or different pattern before and after the latest global financial crisis. I also discuss some statistical validity issues of the proposed models in this chapter. The regression results are discussed later in chapter four.

3.1 Data

Considering that the correlation between stock and bond market returns has been varying from negative to positive and vice versa almost 30 times during the last century (Johnson et al, 2013), it is evident that at least monthly data set needs to be gathered in order to capture the dynamics between the stock and bond markets. According to the Efficient market hypothesis (Fama, 1970), market news are supposed to be incorporated in price levels faster than is possible to be captured in annual return data. Andersson et al (2004), Ilmanen (2003), Gulko (2002) and Stivers & Sun (2002) also demonstrated that the sign of correlation can change from positive to negative and turn during very short periods of time. This supports the efficient market hypothesis and favors using higher frequencies of data for the analysis.

Global stock markets in developed countries tend to follow more or less the U.S stock markets, so I will consider the S&P500 index as the aggregate measure for the stock price levels. Consistently, earlier studies have chosen some specific debt instrument to reflect the bond price levels. However, each bond is different in its coupon rate and maturity so the nature of the U.S. bond market is not homogenous. A very comprehensive survey of the bond market structure in G10 countries has been made by Inoue (1999) who found that short term debt instruments with original maturity under one year represent 21% of total U.S bond markets. Most bonds (62%) have original maturity of 1-5 years while the rest of bonds have original maturity of ten years or more. In this study, I consider the Barclays Capital Aggregate Bond Index (former Lehman Aggregate Bond Index) as the aggregate measure for bond market prices since it imitates the structure of the total bond markets in the U.S. The end of month prices of the both asset types have been transformed into monthly log returns:

$$r_{asset}\% = ln\left(\frac{P_t}{P_{t-1}}\right) * 100 \tag{3.1}$$

I have also gathered monthly measures for the U.S dividends and consumer price index and transformed the series to represent monthly dividend growth rate and inflation in the U.S.

$$g = ln\left(\frac{DIV}{DIV_{t-1}}\right) * 100 \tag{3.2}$$

$$inflation = ln\left(\frac{CPI_t}{CPI_{t-1}}\right) * 100 \tag{3.3}$$

Totally, we have a time series with 360 monthly data points representing the period from the beginning of the EPU index (Jan 1985) to the end of 2014. Table 3 summarizes the original variables used in this study and the sources for them.

Table 3: Data & sources

Variable	Description	Period	Source
S&P500	Month end	1984- 2014	Yahoo Finance
Barclays Agg	Month end	1984- 2014	Datastream
EPU index	Month mean	1984- 2014	Bloom et al (2015) [b]
U.S dividends	Month mean	1984- 2014	Shiller (2000)
U.S CPI	Month mean	1984- 2014	Shiller (2000)

Sometimes, a time series has to be transformed or differentiated if it contains unit roots. Logarithmic transformation handles this well for the asset returns, dividend growth and inflation, that is, the transformed series are stationary. The monthly EPU index is stationary in its levels as well as the time series for dynamic conditional correlations that have been calculated based on the market returns. The results of the Augmented Dickey Fuller test (Dickey & Fuller, 1979) are shown in Table 4.

Table 4: Unit root tests

	SP500	**Bond**	**EPU**	**Dividends**	**CPI**
DF-stat.[3]	-1.397	-3.8073**	-5.5698***	4.8225	-2.4182
p-value	0.8314	0.01892	< 0.01	> 0.99	0.4004
	R(SP500)	**R(Bond)**	**Inflation**	**G**	**DCC**
DF-stat.	-17.73***	-17.74***	-11.464***	-3.5891**	-3.2334*
p-value	< 0.01	< 0.01	< 0.01	0.03429	0.08251

Stationarity is an essential concept in time series analysis since if a stochastic process is non-stationary, its mean and variance changes over time which makes most analysis methods invalid. Next, I will introduce the estimation procedure for the DCC estimates that represent the correlation between the stock and bond market returns.

3.2 Dynamic conditional correlation

I will first introduce the basic *GARCH* (Generalized Autoregressive Conditional Heteroskedasticity) – model by Bollerslev (1986) and Taylor (1986) since it is essential to know how univariate GARCH works when applying it to the multivariate DCC-GARCH by Engle (2002). The literature (see e.g. Andersson et al, 2004) suggests that the correlation measured by DCC-estimates adjusts faster to new information than simple rolling window correlation estimates and capture adequately the dynamics of cross-return linkages.

[3] In this study, following notation has been used to indicate statistical significance for different statistics; '*' = 10% significance, '**' = 5 % signicicance and '***' = 1 % significance.

3.2.1 The GARCH(1,1)

Due to the heteroskedasticity in variances and other violations in assumptions of linearity, the parameters of GARCH have to be estimated by maximum likelihood estimation procedure. For further discussion of maximum likelihood estimation, see e.g. Brooks (2008). The GARCH(1,1) – model allows the conditional variance to depend upon its own first lag, so that the conditional variance equation can be expressed as follows:

$$\sigma_t^2 = \varphi_0 + \varphi_k u_{t-1}^2 + \beta_k \sigma_{t-1}^2 \tag{3.4}$$

where φ_0 denotes the long term mean variance, φ_k is the parameter for lagged volatility and the parameter β_k is for previous fitted variance. Next step is to extend univariate model to multivariate because in financial markets, volatilities tend to influence more or less to other volatilities. This phenomenon appears essentially between the stock and bond markets. The results of univariate GARCH(1,1) – estimation procedure are shown in Table 5.

Table 5: GARCH(1,1) estimates

	$\boldsymbol{\varphi_0^{stock}}$	$\boldsymbol{\varphi_0^{bond}}$	$\boldsymbol{\varphi_{stock}}$	$\boldsymbol{\varphi_{bond}}$	$\boldsymbol{\beta_{stock}}$	$\boldsymbol{\beta_{bond}}$
Estimate	0.377	0.022	0.152***	0.024	0.846***	0.958***
Std.Err	0.323	0.0453	0.049	0.028	0.019	0.031
t-stat	1.167	0.486	3.102	0.857	44.526	30.903

I also provide the R codes for the estimation procedure in Appendix 1. The R program for the GARCH-procedure does not provide t-statistics automatically for the coefficients, so I have calculated the statistics based on the critical values of the normal distribution. The null hypothesis for the one sided t-test is that a particular coefficient does not differ from zero. Table 5 shows that the estimate of long term mean variance is not statistically significant for the either assets nor the ARCH-term for bond returns. The other parameters are statistically highly significant in 1% level.

3.2.2 The bivariate DCC-GARCH

First, we suppose returns α_t from the stock and bond markets with expected value 0, and a covariance matrix H_t , that is, the market returns are multivariate normally distributed with $E[\alpha_t] = 0$ and $Cov[\alpha_t] = H_t$. The idea of the model is that the covariance matrix H_t can be decomposed into conditional standard deviations D_t and a correlation matrix R_t where D_t and R_t both are time-varying. Then the dynamic conditional correlation model is defined as follows:

$$r_t = \mu_t + \alpha_t \tag{3.5}$$

$$\alpha_t = H_t^{1/2} z_t \tag{3.6}$$

$$H_t = D_t R_t D_t \tag{3.7}$$

Notation:

r_t: 2×1 vector of log returns of the stock and bond markets at time *t*.

α_t: 2×1 vector of mean-corrected returns of the stock and bond markets at time *t*.

μ_t: 2×1 vector of the expected value of the conditional r_t.

H_t: 2×2 matrix of conditional variances of α_t at time *t (*estimates of the GARCH(1,1) procedure from equation 3.4).

$H_t^{1/2}$: Any 2×2 matrix at time t such that H_t is the conditional variance matrix of α_t. $H_t^{1/2}$may be obtained by a Cholesky factorization of H_t (see e.g. Hazewinkel, 2001).

D_t: 2×2 diagonal matrix of conditional standard deviations of α_t at time *t.*

R_t: 2×2 conditional correlation matrix of α_t at time *t.*

z_t: 2×1 vector of independent and identically distributed errors such that $E[z_t] = 0$ and $E[z_t z_t^T] = I$ where I is the identity matrix of order 2.

The elements in the diagonal matrix D_t are standard deviations from the univariate GARCH(1,1) - equation (3.4):

$$D_t = \begin{pmatrix} \sqrt{\sigma^2_{stock,t}} & 0 \\ 0 & \sqrt{\sigma^2_{bond,t}} \end{pmatrix} \tag{3.8}$$

R_t is the 2×2 conditional correlation matrix of the standardized disturbances ε_t.

$$\varepsilon_t = D_t^{-1} r_t \sim N(0, R_t) \tag{3.9}$$

$$R_t = \begin{pmatrix} 1 & \rho_{12,t} \\ \rho_{21,t} & 1 \end{pmatrix} \tag{3.10}$$

Since H_t is quadratic and has to be positive definite matrix, it follows from the basics of linear algebra that R_t has to be positive definite to ensure that H_t is positive definite. Also by definition of the conditional correlation matrix, all the elements have to equal or be less than one. D_t is positive definite since all the diagonal elements are positive. To guarantee that these requirements are met, R_t is decomposed into:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{3.11}$$

where $Q_t$is a positive definite matrix defining the structure of the dynamics and Q_t^{*-1} rescales the elements in Q to ensure that $|\rho_{12,t}| \leq 1$ and $|\rho_{21,t}| \leq 1$. Then we suppose that the Q_t has the following dynamics:

$$Q_t = (1 - \alpha - \beta)Q^u + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^T + \beta Q_{t-1} \tag{3.12}$$

where Q^u is the unconditional covariance of these standardized disturbances

$$Q^u = Cov(\varepsilon_t\varepsilon_t^T) = E[\varepsilon_t\varepsilon_t^T] \tag{3.13}$$

Some conditions to the parameters α and β has to bet imposed to guarantee H_t to be positive definite. The parameters must satisfy $\alpha \geq 0, \beta \geq 0$ and $\alpha + \beta < 1$. I have used $\alpha = 0.2$ and $\beta = 0.6$ as the starting values for Q_0 (Appendix 1). Now we see that the structure in equation (3.12) is similar to the GARCH(1,1) - process and we obtain following parameters summarized in Table 6.

Table 6: DCC - estimates

	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$
Estimate	0.068*	0.886***
Std.Err	0.035	0.078
t-stat	1.943	11.359

Figure 4 plots the time varying correlation between the stock and bond market returns based on the DCC-parameters.:

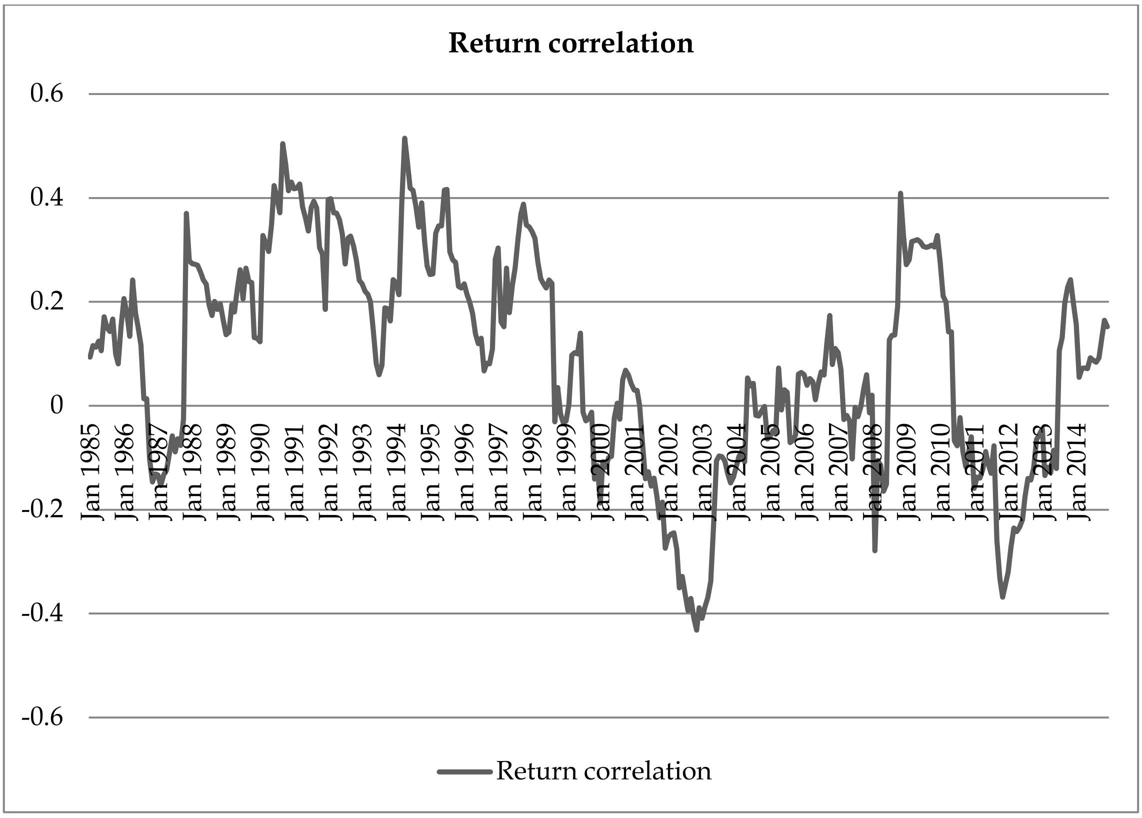

Figure 4: DCC- estimates from 1985 to 2014

The correlation between the stock and bond market returns measured by the DCC-estimates has been varying from negative to positive and vice versa about twenty times in overall during the history of the EPU index. The range is [-0.43, 0.52] and the mean for the period is 0.086.

3.3 Logistic regression

The logistic regression model is appropriate when the dependent variable follows a binomial distribution, that is, the variable takes one of only two possible values. I use logistic regression in my analysis of the effects of economic policy uncertainty on the correlation between the stock and bond market returns. By following Rodríguez (2007), I introduce the concept of logistic regression analysis. For the dependent variable, response is binary which means that the values may be coded e.g. as one or zero. In our case the attribute of interest is whether the stock and bond market returns are correlated positively or negatively. I want to predict the presence or absence of positive correlation between the markets, so I define the dichotomous response variable Y_i as follows:

$$Y_i = \begin{cases} 1\ if\ the\ correlation\ is\ positive\ in\ i^{th}\ observation \\ 0\ otherwise\ (the\ correlation\ is\ negative). \end{cases}$$

In practice, the values of Y_i in this study are the dynamic conditional correlation estimates for the stock and bond market returns that have been transformed into dichotomous form depending on whether a particular DCC-estimate is positive or negative. I have coded the positive correlation estimates in the SPSS with one and the negative correlation estimates with zero. The observation y_i is a realization of a random variable Y_i that takes the values one and zero with probabilities of π_i and $1-\pi_i$ respectively. The distribution of Y_i is called a *Bernoulli* distribution with parameter π_i and can be written in compact form as

$$Pr\{Y_i = y_i\} = \pi_i^{y_i}(1-\pi_i)^{1-y_i}. \tag{3.14}$$

The expected value and variance of Y_i are

$$E(Y_i) = \mu_i = \pi_i \text{ and } var(Y_i) = \sigma_i^2 = \pi_i(1-\pi_i). \tag{3.15}$$

Because the mean and variance depend on the probability, any factor that affects the probability will alter not just the mean but also the variance of the observations. This violates the *OLS* (Ordinary Least Squares) assumptions of homoscedasticity in variance. To avoid this problem maximum likelihood estimation algorithm is used to solve for the parameters that best fit the data.

The predictive variable in the model is the level of the EPU index that has been denoted as $x_i \in X$. However, the logistic regression procedure is most effective when the independent variable is categorical. Since the EPU index represents continuous variable, the linear regression model has been used later in the analysis to take the advantage of the richer information offered by the continuous nature of the EPU index. At this stage, actually we are not interested if the correlation between the markets and the EPU index exhibits a linear relationship. Instead, I intend to build a model to obtain a benchmark for the effects of policy uncertainty on the correlation between the market returns. The purpose of the logit model is to equate the linear component to *the logit transform function* of the probability of a given outcome on the y_i. The linear component of the model is the vector of independent variable $x_i \in X$. My aim is also to control macroeconomic state in the experiment by using the slope and the intercept dummies that take the value of one if the growth of the real economy is positive. I consider the growth of the real economy positive if the monthly dividend growth exceeds the inflation rate measured by the monthly change of the consumer price index. My regression model will be predicting the logit, that is, the natural logarithm of the odds of having a positive or a negative correlation between the stock and bond markets. Before deriving the model for the conditional probability of the correlation between the market returns given the value of the EPU index, I elucidate some notation used in the logit regression model:

i) As the predictive variable in the model I use the level of the EPU index that has been denoted as $x \in X$.

ii) The conditional probabilities have been denoted as follows:
   a. $P^{+} = \pi(x) = P(\text{Y=1} \mid \text{x})$
   b. $P^{-} = 1 - \pi(x) = P(Y = 0|x)$

iii) Depending on the state of the real economy, dummies take the value of 1 or 0.
   a. $D_1 = D_2 = 1, if\ g > inflation$
   b. $D_1 = D_2 = 0$, else

Finally, the model gets the following representation:

$$\frac{P(Y=1|x)}{P(Y=0|x)} = ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \alpha_1 + D_1\alpha_2 + (\beta_1 + D_2\beta_2)X \quad (3.16)$$

$$\Leftrightarrow \frac{\pi(x)}{1-\pi(x)} = e^{\alpha_1+D_1\alpha_2+(\beta_1+D_2\beta_2)X} \quad (3.17)$$

$$\Leftrightarrow \pi(x) = \frac{e^{\alpha_1+D_1\alpha_2+(\beta_1+D_2\beta_2)X}}{1+e^{\alpha_1+D_1\alpha_2+(\beta_1+D_2\beta_2)X}} \quad (3.18)$$

$$\Leftrightarrow \pi(x) = \frac{1}{1+e^{-[\alpha_1+D_1\alpha_2+(\beta_1+D_2\beta_2)X]}} \quad (3.19)$$

where the equation 3.16 represents the logit transformation function and the rest is simple derivation for the probability that y_i equals one, that is, the correlation between the markets is positive. The coefficients α_i and β_i have been derived using the MLE-algorithm implemented in the SPSS software.

3.4 Linear regression

The logit model represents how probably the stock and bond market returns are integrated due to the level of economic policy uncertainty. The second stage is to build a model to predict the correlation straightforward by conditioning it to the given level of economic policy uncertainty. Surely, various autoregressive models are dominant what comes to forecasting accuracy of predicting the correlation. This may be seen from the simplest possible AR(1) – model plotted in Figure 5.

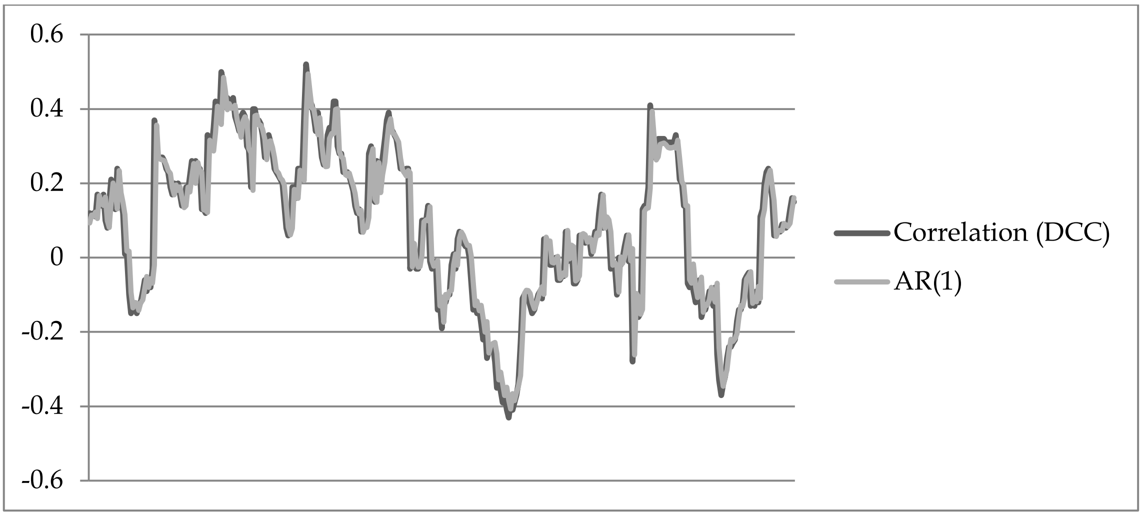

Figure 5: AR(1) – model for the correlation between the markets

However, the aim of this study is to track possible causal effects of economic policy uncertainty on stock and bond return correlation, so my intend is not to consider any AR - terms in the regression analysis, even though it would be possible to do very precise forecasts for a period forward. The first step in the linear regression analysis is to do a simple regression for the transformation of the log returns using the level of the EPU index as the explanatory variable. Naturally, the range of correlation estimates is restricted to $[-1,1]$ but the basic linear regression analysis requires the dependent variable no to be limited. Hence, the correlation estimates obtained from DCC - procedure has to be transformed so that the dependent variable is able to get values from the whole set of real numbers $[-\infty, \infty]$. I use the same transformation than Andersson et al (2004):

$$\rho_t \to ln\left(\frac{1+\rho_t}{1-\rho_t}\right) \tag{3.20}$$

Then, we do two different regressions for the dependent variable (3.20) firstly using only the level of the EPU index, and second, by controlling the macroeconomic state with the state-dummy variables.

3.4.1 The simple linear model

First, we obtain the following model:

$$ln\left(\frac{1+\rho_t}{1-\rho_t}\right) = \alpha + \beta \times EPU_t + \varepsilon_t \tag{3.21}$$

where the residuals ε_t are positively serially correlated because the Durbin-Watson statistics (Durbin & Watson, 1950) is $0.161 < d_{L,\alpha=.05} = 1.664$ $(n > 200)$. This actually violates the assumptions of linearity (see e.g. Högmander et al, 2009) and weakens the statistical plausibility of the model. Another assumption of linearity is that the series are from normal distribution. Unfortunately this does not occur in the case of transformed DCC-estimates nor in the EPU index because the Kolmogorov-Smirnov (see e.g. Hazelwinkel, 2001) and Shapiro-Wilk (Shapiro & Wilk, 1965) tests show that the series are not from the normal distribution (Table 7).

Table 7: Normality tests

	Kolmogorov-Smirnov			**Shapiro-Wilk**		
	Statistic	DF	Sig.	Statistic	DF	Sig.
DCC	0.046	360	0.069	0.986	360	0.001
EPU	0.103	360	0.000	0.933	360	0.000

Because we cannot assume that the relationship between the correlation estimates and the EPU index exhibits linearity, we can use the results of the linear regression for illustrative purposes only. On the other hand, due to the complex relationship between macroeconomic factors and the prices of financial assets, a straightforward linear relationship was not the expectation. I guess it is a “curse” or a “relief”, depending on a view that in economics we are not always restricted by the strict assumptions of linearity or other demanding statistical details when we are trying to track how one factor affects to another.

3.4.2 The linear model with control variables

Next, we analyzed a model that controls the state of macro-economy by using the same dummy variables as in the case of the logit model. We assume the relationship to be different when the growth of real economy is positive than when inflation is relatively high compared to the dividend growth. The model is:

$$ln\left(\frac{1+\rho_t}{1-\rho_t}\right) = \alpha_1 + D_1 \times \alpha_2 + (\beta_1 + D_2\beta_2) \times EPU_t + \varepsilon_t \qquad (3.22)$$

where depending on the state of the real economy, dummies take the value of 1 or 0;

a. $D_1 = D_2 = 1, if\ g > inflation$
b. $D_1 = D_2 = 0$, else.

3.5 Confluences to earlier empirical modelling

The logistic regression model, so as the linear regression model with control variables I have use in my analysis are actually modified versions of the Andersson et al (2004) model specification[4]. There exist several differences and

[4] $\ln\left(\frac{1+\rho_t}{1-\rho_t}\right) = \alpha + \beta_1 CPI_{t-i} + \beta_2 GDP_{t-i} + \beta_3 IV_{t-1} + AR(1) + \varepsilon_t$
where ρ_t denotes the correlation between stock and bond market returns at time *t, CPI* is the expected growth rate of consumer price index, *GDP* is the expected growth rate

similarities between Andersson et al (2004) and our specification. First, like Andersson et al (2004), we capture the dynamic correlation by the DCC - estimates by using them as the dependent variable.

The actual differences between our and Anderrsson et al (2004) derive from i) the method of controlling the productivity growth and the macroeconomic state and ii) using different indicator for market uncertainty. The previous issue is a result from that Andersson et al (2004) link the productivity growth with GDP, but our model uses the dividends because we anticipated the market dynamics to derive from the DCF – models. Andersson et al (2004) also use the levels of the U.S GDP and CPI as explanatory variables. I have instead used relative levels of the variables measuring productivity and inflation by controlling real growth by dummy variables. The latter issue, using different indicators for market uncertainty is a result from using the EPU index as the explanatory variable in the regression rather than the implied volatility.

By implementing the logistic regression model, I have basically approached the same model specification from a different view by dividing the correlation to positive and negative by the dichotomous transformation. It is also evident that the logistic and the linear regression models provide same information of the relation between the dependent and independent variables, but from a different perspective.

It is also evident that there exists autocorrelation in the dependent variable and so Andersson et al (2004) have included the autoregressive term to the model specification which improves the model accuracy but is not relevant what comes to obtaining conclusions about the effects of the macroeconomic factors to the market correlation. We a more interested in capturing the effects of economic policy uncertainty on the stock and bond market correlation rather than the accuracy of the model and chose not to include any AR – terms in the model.

3.6 Vector autoregressive models

Due to the relatively good forecasting accuracy of the EPU index on the stock and bond market correlation after the year 2007 (see Figure 11), my next intent is to investigate the market dynamics before and after the global financial crisis erupted in year 2007. For this purpose I build two VAR-models. VAR-modeling allows us to use *impulse response functions* and *variance decompositions* to track possible differences in the relationship between the stock and bond market integration and the macroeconomic risks during the periods before and after the outbreak of the latest global financial crisis.

Vector autoregressive model is a system of regression equations for more than one dependent variables. All of the variables are considered as

of real gross domestic product, *IV* is the implied stock market volatility, and *i* is either 0 or 1. AR(1) stands for the lagged correlation.

endogenous so the method allows to regress dynamic systems that otherwise could be exposed to simultanoues equation bias if a wrong regression procedure is used. In VAR – model, value of a variable depends on more than just its own lags and combinations of white noise terms u_t^n. Provided that there are no contemporaneous terms on the RHS of the equations, it is possible to simply use the OLS estimation separately on each equation (Brooks, 2008). The VAR – system can be expressed in its analytical form as follows :

$$\begin{pmatrix} y_t^1 \\ y_t^2 \\ \dots \\ y_t^n \end{pmatrix} = \begin{pmatrix} \beta_0^1 \\ \beta_0^2 \\ \dots \\ \beta_0^n \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} \beta_{1i}^1 & \alpha_{1i}^1 & \cdots & \alpha_{ni}^1 \\ \alpha_{1i}^2 & \beta_{2i}^2 & \cdots & \alpha_{ni}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{1i}^n & \alpha_{2i}^n & \dots & \beta_{ni}^n \end{pmatrix} \begin{pmatrix} y_{t-i}^1 \\ y_{t-i}^2 \\ \dots \\ y_{t-i}^n \end{pmatrix} + \begin{pmatrix} u_t^1 \\ u_t^2 \\ \dots \\ u_t^n \end{pmatrix} \tag{3.23}$$

where $\forall u_t^n : \{E(u_t^n) = 0 \wedge E(u_t^1, u_t^2, \dots, u_t^n)\}$, when n denotes the number of dependent variables included in the system, p denotes lag length and u_t^n is an i.i.d disturbance term. Lag length p for a VAR(p) model can be chosen especially based on economic theory but the decision can be also based on multivariate versions of the different information criteria: The Akaike (1973), Hannan-Quinn (1979) and Schwarz (1978) and The *FPE (*Final Prediction Error*)* (Akaike, 1970).

Sometimes, VAR – models are used in *a-theoretical* context meaning that they are implemented with a little theoretical information about the relationships between the variables. Since our theory is based strongly on the earlier literature, we can conclude that our variables have been chosen properly to guide the specification of the model.

My assumption of market efficiency in the sense that market news will be incorporated fast into the asset price levels indicates that VAR - model with one lag may capture the dynamics correctly. Also different information criteria suggest implementing the VAR(1) – model (Table 8).

Table 8: Optimal lag length for an unrestricted VAR

	AIC	HQ	SC	FPE
Pre-crisis	1	1	1	1
Post-crisis	5	1	1	5

Although the Akaike's information criteria and the FPE suggest lag length of five for the period of 2007-2014 (*post-crisis*), the theory of efficient markets favors minimizing the lag and because of that I use the VAR(1) – model for the periods before and after the financial crisis. The period of *pre-crisis* in the analysis is 1985-2006. Totally three variables are included to the suggested VAR(1) – system based on our theory; *the dynamic conditional correlation estimate* (see transformation 3.20*), the level of the EPU index* and *the difference between the dividend growth rate and inflation* representing economic growth. Estimation of the VAR(1) – model is done by using the R-code I provide in Appendix 2. I discuss the estimation results further in the next chapter.

4 EMPIRICAL RESULTS

In this chapter I will report the results from the empirical analysis. The first model, logistic regression, evaluates the conditional probability for the market integration based on the level of the EPU index. The subsequent model utilizes the continuous nature of the EPU index by joining the relationship between dependent and explanatory variables by linear regression, controlling the state of macro-economy at the same time. I find that the level of market integration depends on both the state of economic growth and the level of the EPU index. Also, before and after the global financial crisis that broke out in 2007, the relationship between the stock and bond market integration and the EPU index has exhibited a different nature in the sense that during the post-crisis period the relationship has been very close whereas before the crisis the forecasting power of the EPU index has been very modest. The results of the linear regression model motivated to do some time series analysis for both the pre- and post-crisis era (the latest global financial crisis) in order to track the dynamics between the variables, practically by implementing the VAR – model. Because in this chapter the focus is in introducing the empirical results and statistics, the results will be discussed only briefly in a wider context. More comprehensive analysis of the main results obtained from the empirical part will be discussed in the next chapter.

4.1 Analysis of the logistic regression model

Table 9 shows the coefficients for the “constant model” that has been automatically generated by the SPSS software.

Table 9: Variables in the equation without explanatory variables (logit model)

	B
Coefficient	0.571***
S.E	0.110
Wald	27.036
P-value	0.000

The constant model without any explanatory variables predicts the presence of positive correlation between the stock and bond market returns without any independent variables in the logit regression. The Wald test statistic with one degree of freedom is 27.036 indicating that the p-value is near zero and the constant coefficient is statistically highly significant.

Overall Chi-square test in SPSS suggests the rejection of $H_0\colon \beta_i = 0$ for all *i:s* in our model since the Chi-square statistic at 3 degrees of freedom is 36.782. Regression results can be seen from Table 10 in which the coefficients for the equation 3.4 are shown.

Table 10: Variables in the equation (logit model)

	$\boldsymbol{\alpha_1}$	$\boldsymbol{\alpha_2}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$
Coefficient	-1.423	4.181***	0.02**	-0.041***
S.E	1.009	1.113	0.009	0.010
Wald	1.988	14.110	4.837	16.884
P-value	0.159	0.000	0.028	0.000

It seems that the coefficients for the EPU index and the dummy variables are statistically highly significant. The constant parameter in the model does not exhibit statistical significance at 10% level. The coefficient β_1 for the level of the EPU index suggests that the probability for positive correlation between the stock and bond market returns rises due to a positive change in the EPU index. Coefficients $\beta_1$and β_2 together suggest an inverse effect when the growth rate of the real economy is positive. The coefficient α_2 for the intercept dummy is also statistically significant.

We can also write the model using the obtained parameter values:

$$ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \begin{cases} -1.423 + 4.181 + (0.02 - 0.041) \cdot X, if\ g > inflation \\ -1.423 + 0.02 \cdot X, else \end{cases} \tag{4.1}$$

$$ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \begin{cases} 2.758 - 0.021 \cdot X, if\ g > inflation \\ -1.423 + 0.02 \cdot X, else \end{cases} \tag{4.2}$$

$$\Leftrightarrow \pi(x) = \begin{cases} \frac{1}{1+e^{-2.758+0.021 \cdot X}}, if\ g > inflation \\ \frac{1}{1+e^{+1.423-0.02 \cdot X}}, else \end{cases} \tag{4.3}$$

Table 11 shows how correctly it is possible to categorize the correlation between the markets based on the constant model and our model.

Table 11: Classification table (logit model)

Constant model					
	Observed		Predicted		
			Correlation is positive		Percentage Correct
			No	Yes	
	Correlation is positive	No	0	130	0%
		Yes	0	230	100%
	Overall Percentage				63.9%
Model (4.1 & 4.2)					
	Observed		Predicted		
			Correlation is positive		Percentage Correct
			No	Yes	
	Correlation is positive	No	38	92	29.2%
		Yes	25	205	89.1%
	Overall Percentage				67.5%

It can be seen that our model predicts negative correlation in 29.2% of the cases when the observed correlation was truly negative. In contrast, by establishing the decision based on the constant model, there would be no option to guess that the correlation is negative. Instead, the best strategy to guess would be that the correlation is positive in 63.9% of the cases that of course leads to 100% right guesses when the observed correlation is truly positive. In our model, the prediction of positive correlation is right in 89.1% of the cases so that the model predicts the correlation correctly in overall 67.5% of the cases which is better than in the case of the constant model. I also provide the SPSS output of the *ROC* (Receiver Operating characteristic) – curve in Appendix 3.

To provide a clear view of how the probability of having a positive or negative correlation between the stock and bond markets changes due to the level of economic policy uncertainty, I have calculated the predicted probabilities for different percentiles of the EPU index. The results have been summarized in Table 12.

Table 12: Conditional probabilities for the market integration with given level of the EPU index (percentiles).

	Percentiles							
	5%	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	
EPU	66.8	73	83.7	100.4	125.5	157.3	175.2	**Real growth**
$\boldsymbol{\pi(x)}$	47.83%	50.92%	56.24%	64.22%	74.78%	84.85%	88.90%	**Negative**
$\boldsymbol{\pi(x)}$	79.50%	77.29%	73.11%	65.69%	53.06%	36.70%	28.47%	**Positive**

The results indicate that when the growth of the real economy is positive, rising economic policy uncertainty lowers the probability that the stock and bond market returns are integrated. When inflation exceeds the growth rate of dividends, the influence of rising economic policy is positive to the probability that the market returns are integrated. At the median level of the EPU index, the probability that the markets are integrated is the same irrespective of growth of the real economy. The same can be seen from Figure 6 that plots the conditional probabilities for y_i using the range [57.2, 245.13] that the level of the EPU index has exhibited during its history (1985 – 2014).

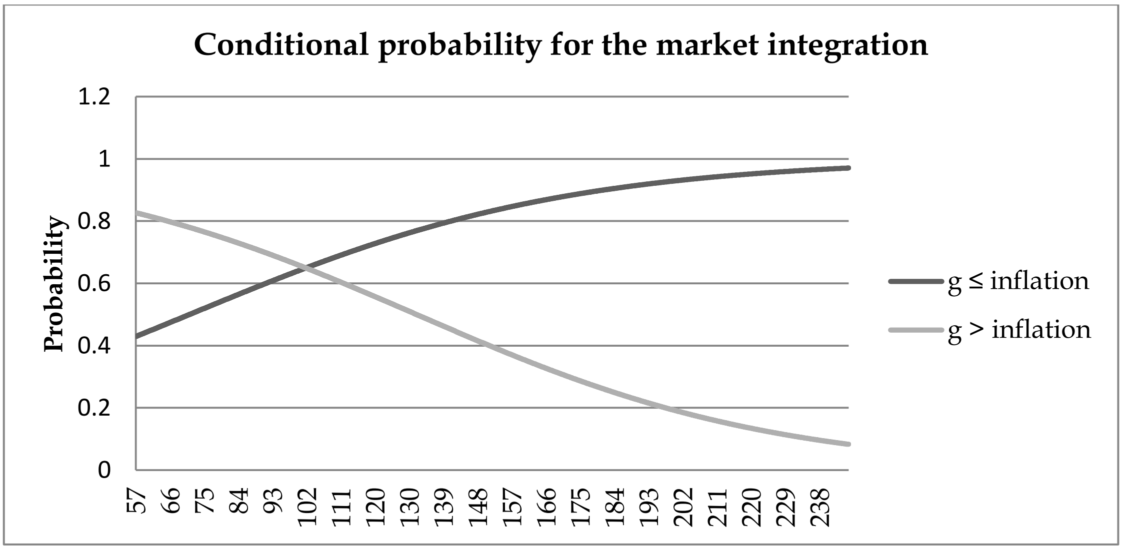

Figure 6: Conditional probability for the market integration with given level of the EPU index.

However, the logistic regression model does not take a stance on the level of the integration between the stock markets since we only loosely defined the markets to be integrated if the correlation is positive. Hence, next step is to analyze directly the effects of the level of the EPU index to the level of integration.

4.2 Analysis of the linear regression model

We learned from the logit model that the probability for the market integration increases for the high levels of the EPU index when the rate of inflation exceeds the dividend growth. When the growth rate of the economy is positive, rising economic policy uncertainty decreases the probability for the stock and bond markets to be integrated. Now, my aim is to investigate the relationship between the correlation and the EPU index straightforward by forming two regression models, using the level of the EPU index as the independent variable.

4.2.1 The simple linear model with one independent variable

First, I form a simple linear regression model with one independent variable in order to find the pure effect of economic policy uncertainty to the stock and bond market return correlation without any presumptions about the macroeconomic state. Results from the regression are shown in Table 13.

Table 13: Coefficients of the linear regression model with one independent variable

	Value	**Std. error**	**t-value**	**p-value**	**R^2 = 0.093**
$\boldsymbol{\alpha}$	0.406***	0.077	5.285	0.000	
$\boldsymbol{\beta}$	-0.002**	0.001	-3.095	0.002	

We see that both the constant and the coefficient for the EPU index are statistically highly significant. The coefficient β is indicating that without any information about the growth rate of the economy, we can conclude a one unit raise in the EPU index leading to 0.002 points decrease in the correlation between the market return and hence lowering the integration between the stock and bond markets. The plot of the fitted regression line is shown in Figure 7.

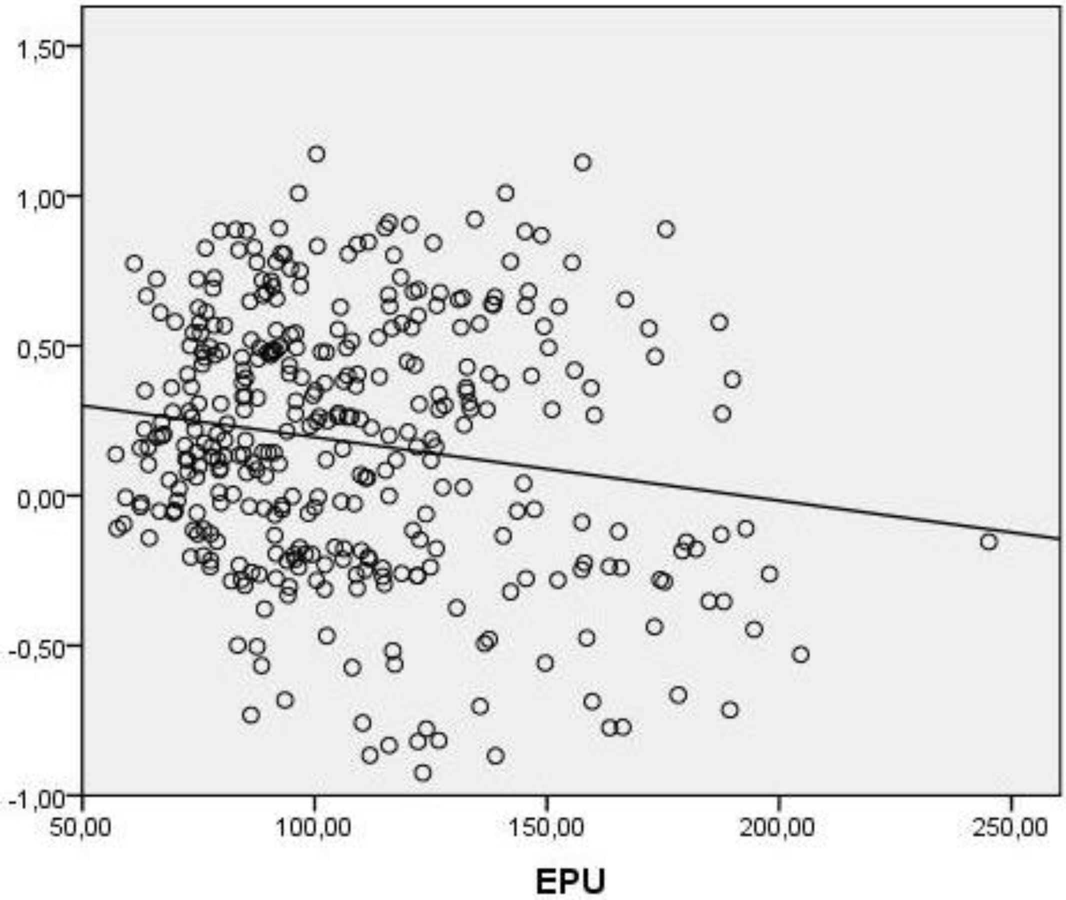

Figure 7: The plot of the linear regression with one independent variable

The dispersion of the DCC-estimates is relatively large and because of that the EPU index is not a very precise predictive variable for the correlation. The R squared is 0.093 indicating that 9.3% of the variation of the transformed correlation estimate between the markets can be explained by variation of the EPU index. It is evident that by formulating such a simple regression model for such complicated relationship, a high R squared is not to be expected. We learned before that if we want to predict the correlation precisely, an AR-term should be included to the regression. However, we have obtained statistically significant evidence that there might be causal relationship between the EPU index and the level of the market integration. For statistical details, see chapter 3.4 for further discussion. However, correlation between two variables is not an indication of causality. The observed and predicted values from the model are shown in Figure 8.

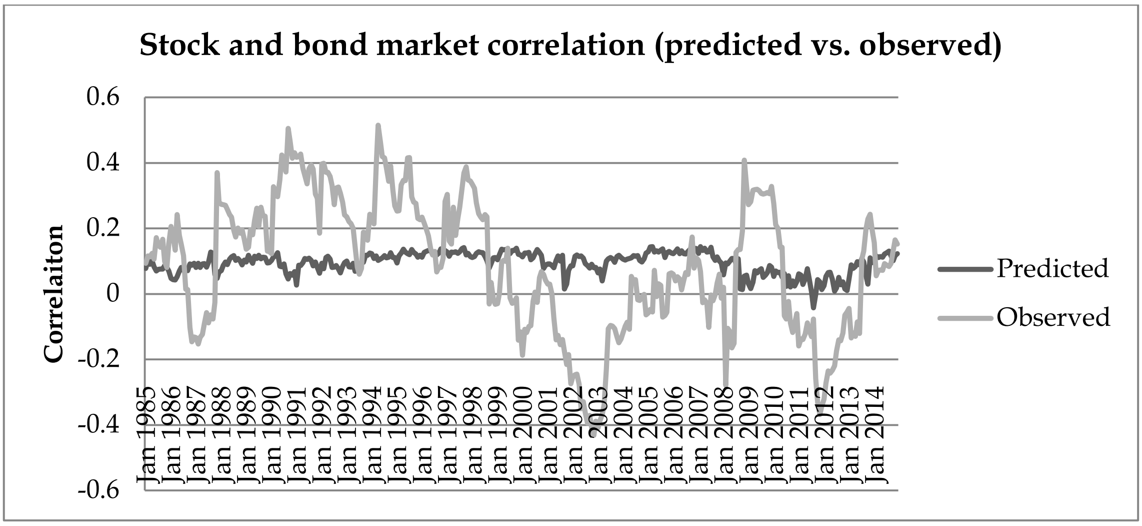

Figure 8: The observed and predicted values for the market integration (linear regression with one independent variable)

The predicted values have been transformed back to the normal representation of correlation and vary between the range [-1, 1]. It is evident that the predicted values underestimate the volatility of the stock and bond market integration level. The long term trend of the stock and bond market return correlation follows approximately the trend of the fitted values. The variation in the fitted values is so small that it is hard to track just by looking the picture if the observed and fitted values exhibit any co-movement.

4.2.2 The linear regression model with control variables

The simple model with single explanatory variable suggested a negative relationship between the market integration and the EPU index. Based on the previous assumptions of the relationship between the macroeconomic factors and the market dynamics we may find more interesting results by controlling the growth rate of the economy. Parameters for the model (3.22) are shown in Table 14.

Table 14: Coefficients of the linear regression model with control variables

	Value	**Std. error**	**t-value**	**p-value**	**R^2 = 0.081**
$\boldsymbol{\alpha_1}$	-0.131	0.178	-0.737	0.462	
$\boldsymbol{\alpha_2}$	0.658***	0.196	3.354	0.001	
$\boldsymbol{\beta_1}$	0.003**	0.002	2.159	0.032	
$\boldsymbol{\beta_2}$	-0.007***	0.002	-4.022	0.000	

We see that the constant coefficient α_1 is not statistically significant but the constant parameter α_2 exhibits high statistical significance. The co-effect of the constant parameters suggests the market correlation to be per se higher during times of positive growth. Coefficients β_1 and β_2 indicate the same phenomenon that we learned from the logit model ,that is, the correlation between the stock and bond markets decreases due to increasing economic policy uncertainty when the economic growth is positive. The effect is inverse during high levels of inflation when the market returns tend to be more integrated. The R squared is 8.1%. We see the both situations in Figures 9 and 10.

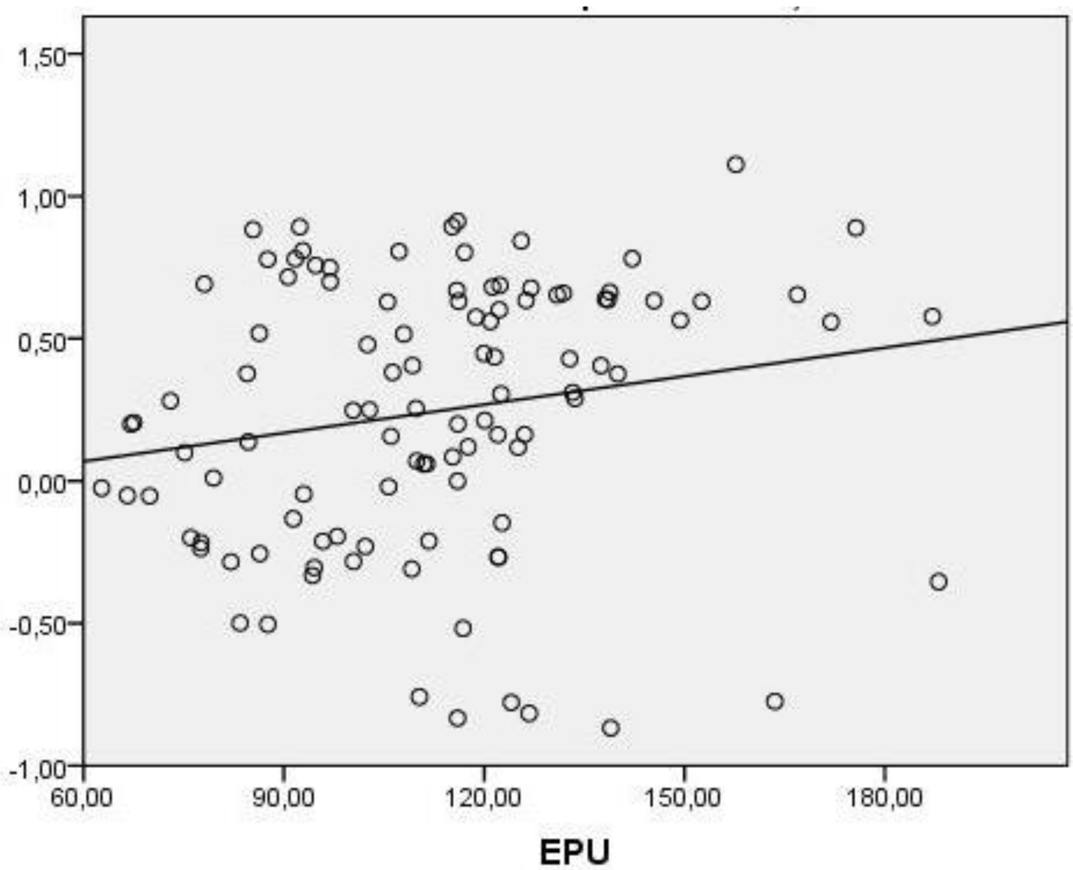

Figure 9: The plot of the linear regression model with control variables (inflation exceeds economic growth)

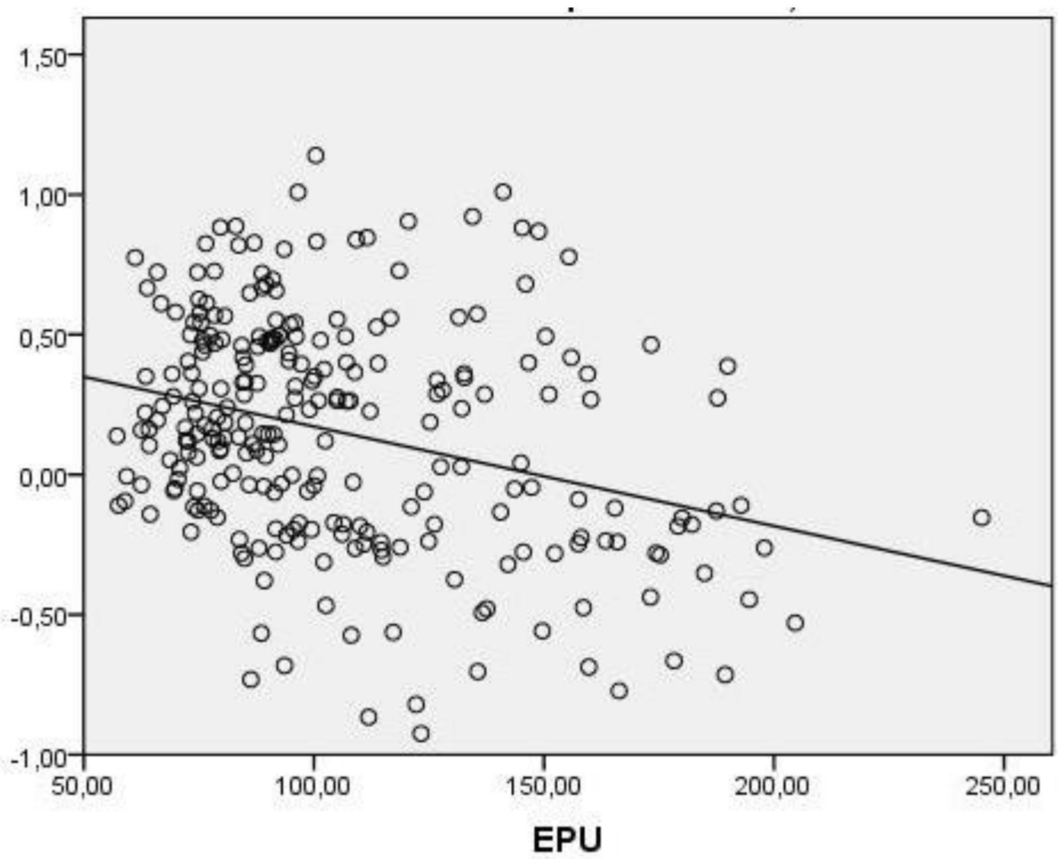

Figure 10: The plot of the linear regression model with control variables (positive economic growth)

During the period 1985-2014 the economic growth has been merely positive and because of that there are fewer observations of the dependent variable during negative growth. It is remarkable that when the EPU index exceeds the percentile of 75% (125.5), observations of the dependent variable are highly positive with a few exceptions (n=4). We see that the regression for the state of positive economic growth indicates lower degree of the stock and bond market integration when economic policy uncertainty increases. The plot of the predicted and observed values is shown in Figure 11.

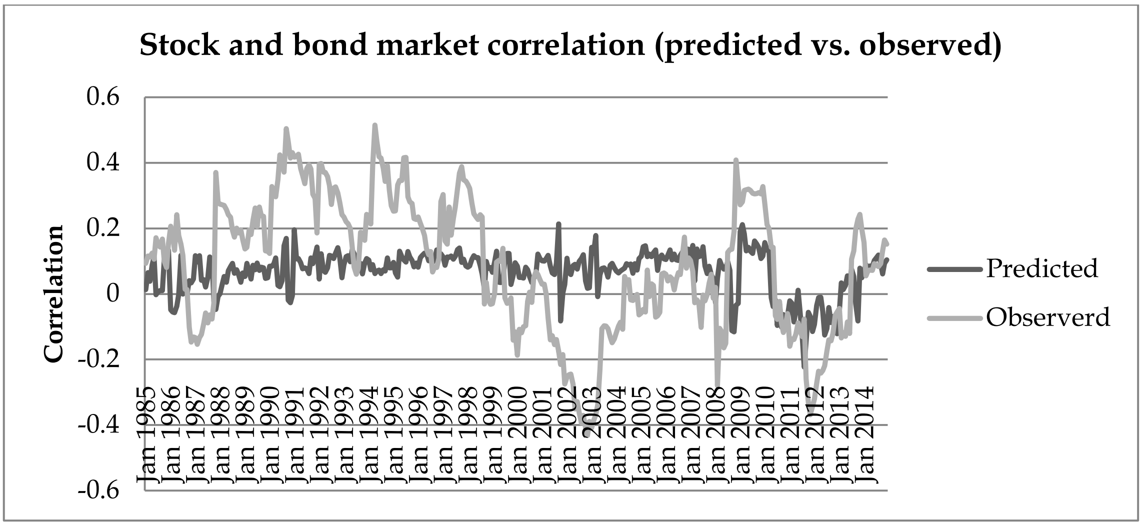

Figure 11: The observed and predicted values for the market integration (linear regression with control variables)

If we compare Figure 11 and Figure 8 it is evident that adding the control variables to the regression has improved accuracy of the model. Although the variation of the fitted variables is relatively small we can track the co-movements of the variation between the predicted and observed values. However, I find most interesting that the fitted values are actually very close to the observed values during the period from 2008 to 2014, practically after the financial crisis that erupted in 2007. Before the year 2008 the predicted values underestimate strongly the movements of the correlation but during the last six years the co-movement between the values has been very strong. For this reason my intent is to form one more model in order to investigate the dynamics before and after the latest global financial crisis.

4.3 Short comparison to the earlier literature

The regression results of Andersson et al (2004) indicated that inflation, measured by the U.S. CPI is positively related to the stock and bond market correlation. The economic growth measured by the U.S GDP is negatively related to the correlation between the market returns. They also found that stock market uncertainty measured by the VIX is a factor that is negatively related to the correlation between the stock and bond market returns (see also Ilmanen, 2003 and Stivers & Sun, 2002).

The results of our linear model with one independent variable (Table 13) favored the assumption of that the level of EPU index should a priori have similar effects to the correlation between the markets than the level of VIX because the coefficient for the EPU index is negative.

According to the regression results presented in Table 14, the findings are in line with Andersson et al (2004), so as with Campbell & Ammer (1991), Ilmanen (2003), Li (2002) and Stivers & Sun (2002) because real growth seems to be negatively related to the level of stock and bond market correlation.

The new finding is that the market uncertainty, measured by the EPU index, has a contrary effect to the stock and bond market integration depending on the state of real growth.

4.4 Analysis of the VAR – models

Previous results from the linear regression model motivated me to investigate the dynamics between the stock and bond market correlation and the macroeconomic factors by the VAR – analysis conducted in next sub-chapters.

4.4.1 Pre-crisis period

The theory behind our assumptions of the market efficiency and the various information criteria suggested using the VAR(1) – model (see chapter 3.5). We are interested especially in the regression in which the correlation between the stock and bond market returns has been treated as the dependent variable. In chapter 3.5, I introduced the general form of the VAR(p) – model. Now, I use a slightly different notation since it is clearer to represent the results by denoting the coefficients with their names than using the betas. The suffix-*(1)* represents the lagged value. The model can be defined as follows:

$$correlation = constant + epu(1) + correlation(1) + realGrowth(1) \tag{4.4}$$

The regression results are shown in Table 15.

Table 15: VAR – estimates (pre-crisis)

	Estimate	Std. Error	t-value	p-value
epu(1)	0.000032	0.000334	0.096	0.924
correlation(1)	0.956***	0.01822	52.466	~0.00
realGrowth(1)	0.00832	0.01582	0.526	0.599
constant	0.00534	0.03512	0.152	0.879

We see that the autoregressive part plays a huge role in the estimation since the lagged value of the market return correlation is near to one and coefficients for the other variables are near to zero. It is also evident that the other coefficients do not differ statistically from zero. However, the results are more or less what we've expected because we believe that the other variables will account more in the relationship during the post crisis era than before the financial crisis. We did this conclusion in chapter 4.2 (see also Figure 11). Just to discuss a little about the possible autocorrelation in the regression residuals I provide the graph of the autocorrelation functions (see Figure 12).

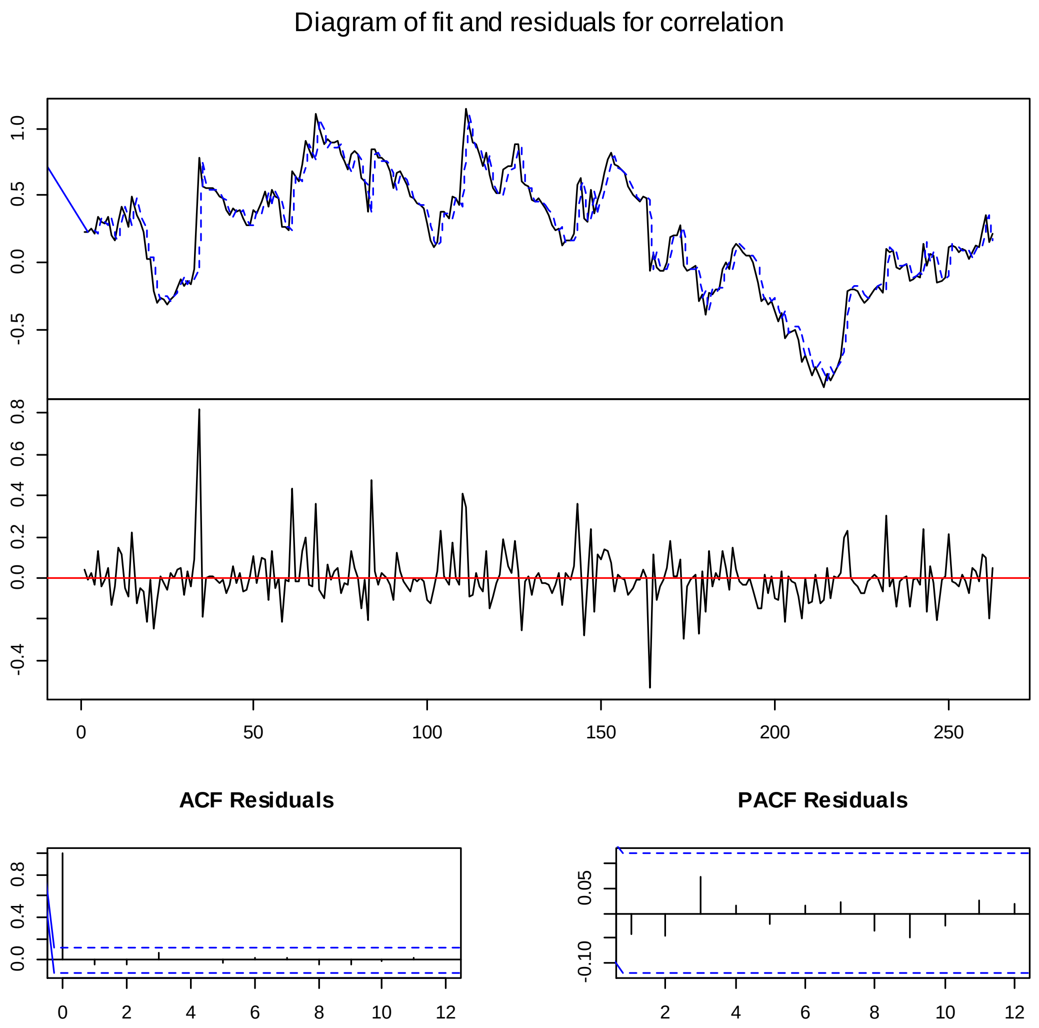

Figure 12: Diagram of fit and residuals for correlation (pre-crisis)

Seemingly, there is an outlier in the residuals which actually is timed synchronically with the stock market crash in October 1987. The second peak can be found approximately during times when the Russian debt crisis erupted in 1998. Dismissing those circumstances, the model has captured the data quite well which is mainly a result from large predictive power of the autoregressive part of the model. The ACF – plot indicates that there is hardly any autocorrelation left in the residuals but the model may be still slightly improved. This does not mean that the forecasts of the current model are unbiased, but will have larger prediction intervals than they need to. In order to pursuing a very accurate model to forecast the correlation, the *ARIMA* (Autoregressive Integrated Moving Average) may be suggested for those purposes.

4.4.2 Impulse responses and variance decompositions (pre-crisis)

By implementing impulse response functions for the obtained VAR – system, it is possible to track theoretically how different shocks will develop in that system when time goes by. We see that economic policy uncertainty shock causes the correlation between the market returns to decrease a small amount and within 48 months the shock has been absorbed in the system (see Figure 13).

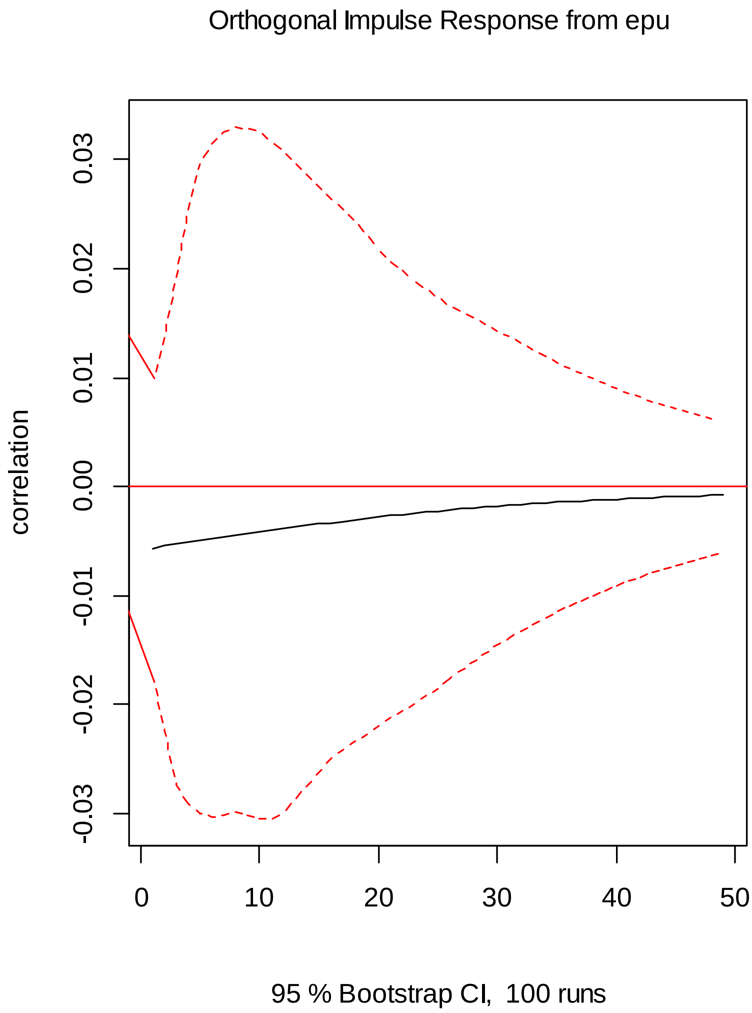

Figure 13: Impulse response from epu to correlation (pre-crisis)

Instead, sudden positive news of the real growth – parameter causes the market correlation to increase and gradually return to the original level (see Figure 14).

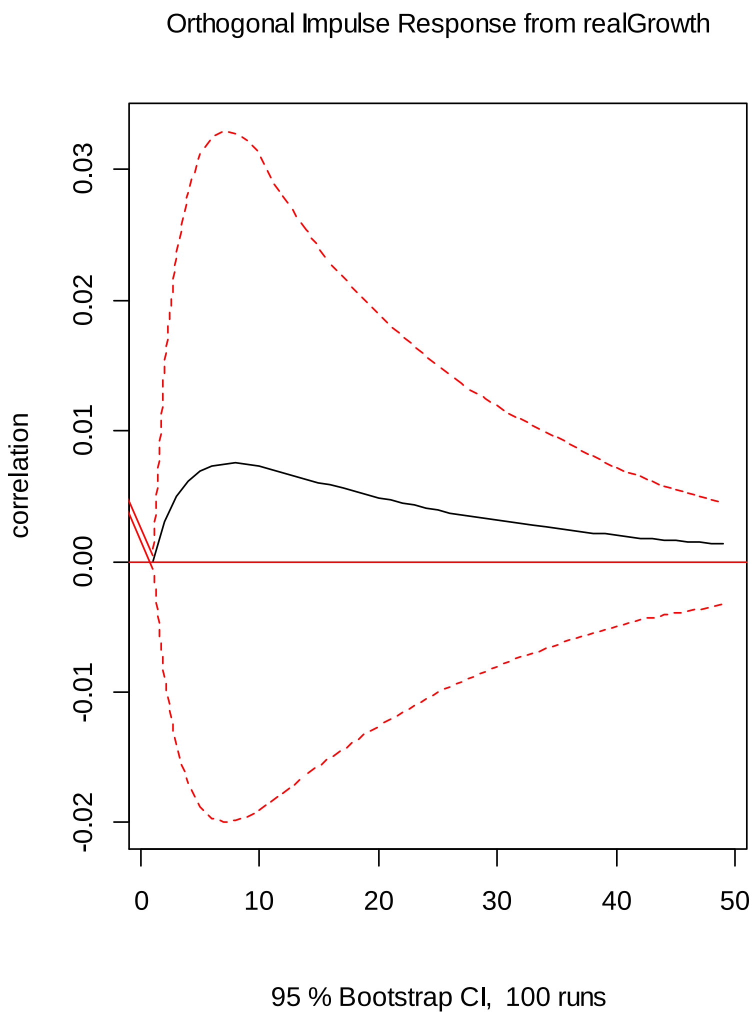

Figure 14: Impulse response from the real growth – parameter to correlation (pre-crisis)

One may be interested in looking the variance decompositions (Appendix 4). The variance decompositions indicate that only 0.2% of the forecast error variance of the correlation can be explained by exogenous shocks to the EPU index. The contribution of the real growth parameter is slightly larger, but never exceeding 0.4%.

We concluded that the effect of economic policy uncertainty has not been remarkable to the stock and bond market integration during the pre-crisis era. The findings of the obtained VAR(1) – model favored this assumption. Instead, by doing the same time series analysis for the post-crisis period we may be able to find different results regarding to the explanatory power of the economic policy uncertainty parameter, but also to track how the shocks generated into the system develop within time and affect to the market integration.

4.4.3 Post-crisis period

At the first glance , the estimation results of the VAR(1) – obtained for the post-crisis era exhibit two differences that favor our assumptions of the importance of economic policy uncertainty to the market integration after the global financial crisis. Firstly, by looking at Table 16 we see that the sign of the coefficient has turned from positive to negative and secondly, the statistical significance of the parameter has been improved according to the p-value.

Table 16: VAR – estimates (post-crisis)

	Estimate	Std. Error	t-value	p-value
epu(1)	-0.0003675	0.0004007	-0.917	0.361
correlation(1)	0.8893157***	0.0520661	17.081	~0.00
realGrowth(1)	0.0153402	0.0174719	-0.878	0.382
constant	0.0588417	0.0566792	1.038	0.302

However, the p-value is still too large to do robust conclusions about the relationship. Residuals from the regression do not exhibit remarkable serial correlation after the first lag likewise during the pre-crisis period, but the ACF indicates that the fifth and sixth lag may be significant (see Figure 15).

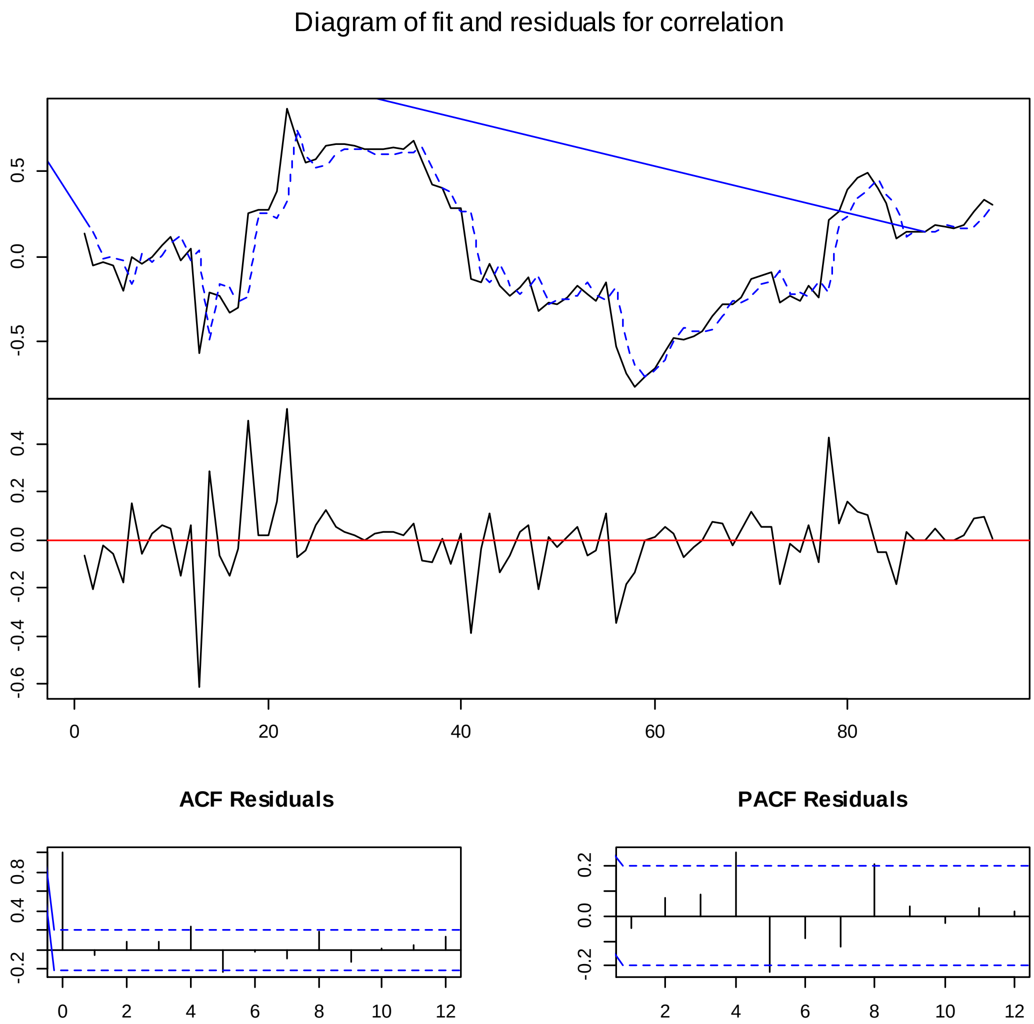

Figure 15: Diagram of fit and residuals for correlation (post-crisis)

Also the PACF shows that additional lags may be considered. Next we look at the impulse response functions and variance decompositions generated into the theoretical VAR – system obtained for the post-crisis period.

4.4.4 Impulse responses and variance decompositions (post-crisis)

There exist differences between the impulse responses during the pre-crisis and post-crisis periods. Figure 16 shows that the impulse response from economic policy uncertainty follows approximately the same pattern after the financial crisis than during the pre-crisis era, but the positive response from the real growth parameter (see Figure 17) causes the stock and bond market integration to decrease which is opposite to the case in the VAR-model obtained for the pre-crisis period. The similar magnitudes of opposite signs from both sources of shocks will cancel the effect of each other in the pre-crisis era. We see that the co-effect of the both shocks is cumulated during the post-crisis era causing the stock and bond market integration to decrease.

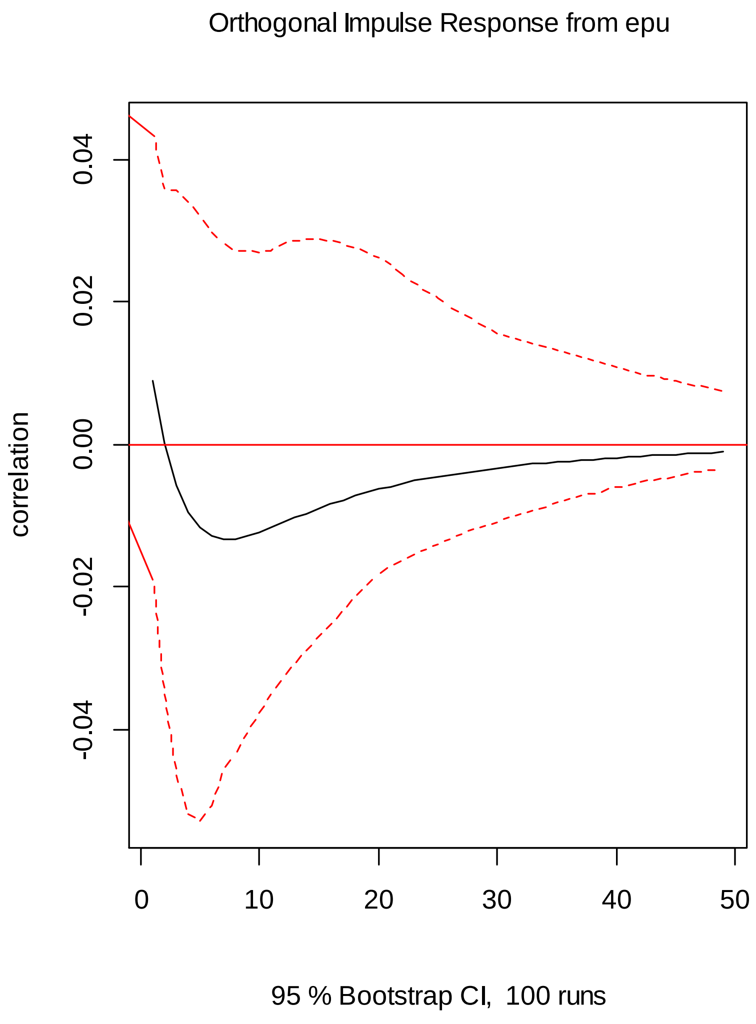

Figure 16: Impulse response from epu to correlation (post-crisis)

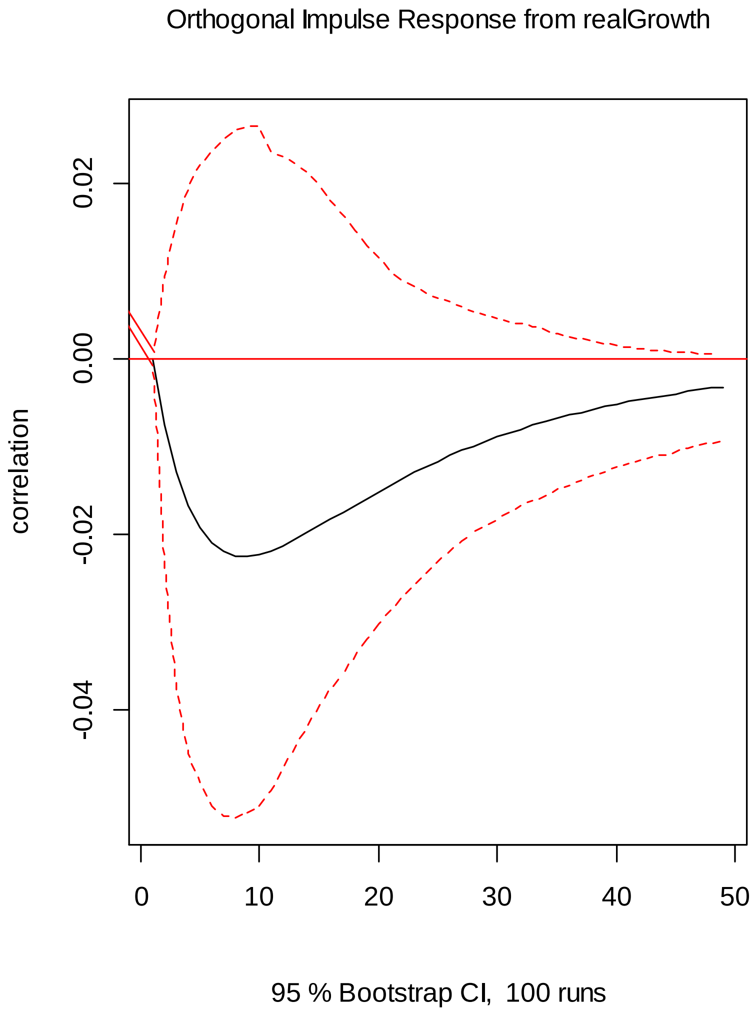

Figure 17: Impulse response from the real growth parameter to correlation (post-crisis)

The VAR – analysis has favored our assumptions that the economic policy uncertainty has accounted for the relationship between stock and bond market integration more during the post-crisis era than before the outbreak of the global financial crisis. Secondly, we have obtained some evidence that the co-effect of policy related risks and the real growth has been negative to the level of the market integration after the crisis. In next chapter, I discuss more extensively about the results obtained from the empirical analysis and how the results are linked to the previous literature and the research question.

5 CONCLUSIONS

The main research question was: what effects economic policy uncertainty may have on stock and bond market return integration? Investigating how the co-movements of the S&P500 and the U.S bond market returns vary depending on the level of the EPU index and the state of the macro-economy answered to the question. The results are essential since due to the short history of the EPU index, there does not exist any research that investigates what effects economic policy uncertainty may have on stock and bond market integration and this thesis contributes to that research gap. In order to provide a measure for the integration, I have obtained the dynamic conditional correlation estimates by Engle (2002) to represent the level of market integration. In the light of the recent literature (Andersson et al 2008 and Saleem 2008) the dynamic conditional correlation estimates capture the volatility spillovers between the assets slightly better than other estimates for the market integration or disintegration.

The previous research literature suggests that economic policy uncertainty is a significant benchmark for the S&P500 fluctuation and earnings growth (Mezrich & Ishikawa 2013 and Gregory & Rangel 2012). It is also obvious that economic policy uncertainty is a driver for the stock market uncertainty which is one of the essential factors that affects the volatility of the stock prices, but is also related to the bond price levels because in financial markets volatilities will affect to other volatilities.

Several research papers consider also productivity and dividend growth (Barsky 1989, Campbell & Ammer 1991 and Ilmanen 2003), inflation (Li 2002, Ilmanen 2002, Andersson et al 2008) and stock market volatility (Stivers & Sun 2002, Ilmanen 2003 and Andersson et al 2008) as the fundamental factors that have an influence on the stock and bond market return correlation. Based on the fundamental valuation models, positive news to the dividend growth parameter linked to the productivity of firms will provide information about possible excess returns of stocks over bonds, and hence push the stock and bond prices to opposite directions. High level of inflation has per se similar effects, via the symmetric discount rate effect to stock and bond values leading to high correlation between stock and bond returns. Stock market uncertainty, usually measured by the VIX in the U.S. market, decreases the stock and bond market return correlation, that is, the effect is asymmetric for the assets. I concluded that the EPU index measuring economic policy uncertainty captures similar effects to the market integration than VIX, and therefore expect the market integration to be negatively related to the level of the EPU index. However, I concluded that the relationship between the market integration and economic policy uncertainty may depend on the state of the real economy and so I conducted the empirical analysis by adopting both the effects of dividend growth and inflation, basically using the difference of their values to represent the real economic growth and using the level of the EPU index as a measure for economic policy uncertainty. I found contrary effects of economic policy uncertainty to the stock and bond market integration by controlling the macro-economic state.

The first part of the empirical analysis was to form the logistic regression model for the conditional probability of the stock and bond market integration. Firstly, I transformed the DCC – estimates into dichotomous form in order to separate positively and negatively correlated market returns, that is, denoting positive values as one, loosely indicating that the stock and bond markets are integrated. Second, I controlled the state of macro-economy by using the slope and intercept dummies in order to split the data into two states representing times of negative and positive economic growth. The logistic regression model built on these assumptions conditioned the probability for positive and negative market integration depending on the level of the EPU index and the macro-economic state and provided a decision rule that classifies the level of market integration based on these fundamentals. I found that the conditional probability for the market integration depends on both the state of economic growth and the level of economic policy uncertainty. This is because when the EPU index is at its mean level, the probability for positive market correlation (integration) is approximately the same for the states of positive and negative economic growth. The model indicates that when dividend growth rate is higher than inflation rate, rising economic policy uncertainty lowers the probability that the markets are integrated. The effect is opposite during the times when inflation exceeds the dividend growth.

The second model utilized the continuous nature of the time series and conditioned the level of EPU index to the DCC – estimates straightforward. I conducted first the simple regression using the EPU index as the independent variable and found a negative relationship between the market integration and economic policy uncertainty. However, the logistic regression model had provided the evidence that the relationship may differ when controlling the macro-economic state and the findings were in line with those assumptions. The results indicated that during the times of positive economic growth, rising economic policy uncertainty decreases the market integration. In contrast, during relatively high levels of inflation, the results indicate that rising economic policy uncertainty will raise the level of market integration. The predicted values from the linear regression model underestimated the level of the market integration before the year 2007, but after that the predicted and observed values have indicated a strong co-movement. At this point I had actually answered to the main research question by providing evidence of the effects of economic policy uncertainty on the stock and bond market return integration. However, I wanted to explore the relationship between economic policy uncertainty and the market integration before and after the year 2007 since the prediction accuracy of the linear model had exhibited remarkable improving after that.

Basically, I included the same variables to the vector autoregressive system that I used in the logistic and linear regression models. However, I divided the data into two parts to investigate the relationship before and after the global financial crisis that started in 2007. I did the same analysis for the both series, first implementing the regression with the one period lagged variables and the correlation estimates and then produced shocks to the economic growth variable and the economic policy uncertainty. The findings only slightly favored the assumptions that the effects of macroeconomic factors including economic policy uncertainty and the level of economic growth have had different effects to the stock and bond market integration during the pre-crisis and post-crises era. The problems regarding the statistical significance of the explanatory variables may be due to the major effect of the autoregressive part of the market correlation. However, there is some improvement in the p-values in the regression for the post-crisis time series compared to the pre-crisis era, but still there is not enough evidence to do robust conclusions about the dynamics. The impulse response functions indicate that shocks to the system from economic policy uncertainty and real growth parameter cancel the effects of each other during the pre-crisis period, but during the post-crisis period, shocks to economic policy uncertainty and economic growth have both a negative effect to the stock and bond market integration. The latter is in line with Ilmanen (2003) who states that economic growth and volatility shocks push stock and bond prices in opposite directions since volatility may be at least partially result from uncertain policy conditions. The results of the VAR –model may be a fruitful benchmark for further analysis but the model does not offer very thorough answers to the question of why the stock and bond market integration has been more sensitive to the policy related risks and shocks to economic growth after the latest global financial crisis than before the crisis.

These models have provided evidence for possible causal relationship of economic policy uncertainty on the stock and bond market integration. Especially the logistic regression and the linear model provided statistically highly significant parameters in order to strengthen the postulated assumptions of the dynamics. However, the methods are not fully solid in the sense of statistical validity due to the restrictions of linearity. Problems with the VAR – model arose mainly because of the large autoregressive part of the correlation and because the method did not work very well for capturing the anticipated effects regarding the dynamics between the stock and bond market return correlation and economic policy uncertainty. The results are in line with the previous literature, and I think that especially the logistic and linear regression models can be considered as benchmarks for the further analysis in the future.

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APPENDIX 1: R-CODE FOR THE DCC ESTIMATES

```
library("tseries")
df = read.table("sbc_data.csv",sep=";", header = TRUE)
stock = df[,8]
bond = df[,9]
stock = stock-mean(stock)
bond = bond-mean(bond)
returns = cbind(stock,bond)
T = length(stock)

library(ccgarch)
library(fGarch)
f1 = garchFit(~ garch(1,1), data = returns[,1], include.mean=FALSE)
f1 = f1@fit$coef
f2 = garchFit(~ garch(1,1), data = returns[,2], include.mean=FALSE)
f2 = f2@fit$coef

a = c(f1[1], f2[1])
A = diag(c(f1[2], f2[2]))
B = diag(c(f1[3], f2[3]))

dccpara = c(0.2, 0.6)
dccresults = dcc.estimation(inia = a, iniA = A, iniB = B, ini.dcc = dccpara, dvar =
returns, model = "diagonal")

DCCrho = dccresults$DCC[,2]
corrs = cbind(df[,0],DCCrho)
write.table(corrs, "c:/r/DCCcorrs.txt", sep="\t")
```

APPENDIX 2: R-CODE FOR THE VAR ANALYSIS

```
library("vars")
library("plyr")
library("tseries")
df = read.table("sbc_data.csv", sep=";", header = TRUE)
data = data.frame(df[,"EPU"], df[,"dccCorr"], df[,"difference"])
data = rename(data, c("df....EPU.." = "epu","df....dccCorr.." = "correlation","df....difference.." = "realGrowth"))
data$correlation = log((1+data$correlation)/(1-data$correlation))
summary(data)

# Determining an optimal lag length for an unrestricted VAR for a maximal lag length of twelve
VARselect(data, lag.max=12, type="const")

#Estimation of the VAR(1), the summary ouput and the diagram of fit for equation is shown
e1 = VAR(data, p=1, type="const")
summary(e1, equation="correlation")
plot(e1, names  = "correlation")

#Impulse response
e1.irf=irf(e1, response = "correlation", n.ahead = 48, boot = TRUE)
plot(e1.irf)

# Variance decompositions
fevd.correlation = fevd(e1, n.ahead = 12)$correlation
fevd.correlation
```

APPENDIX 3: ROC CURVE OF THE LOGIT MODEL

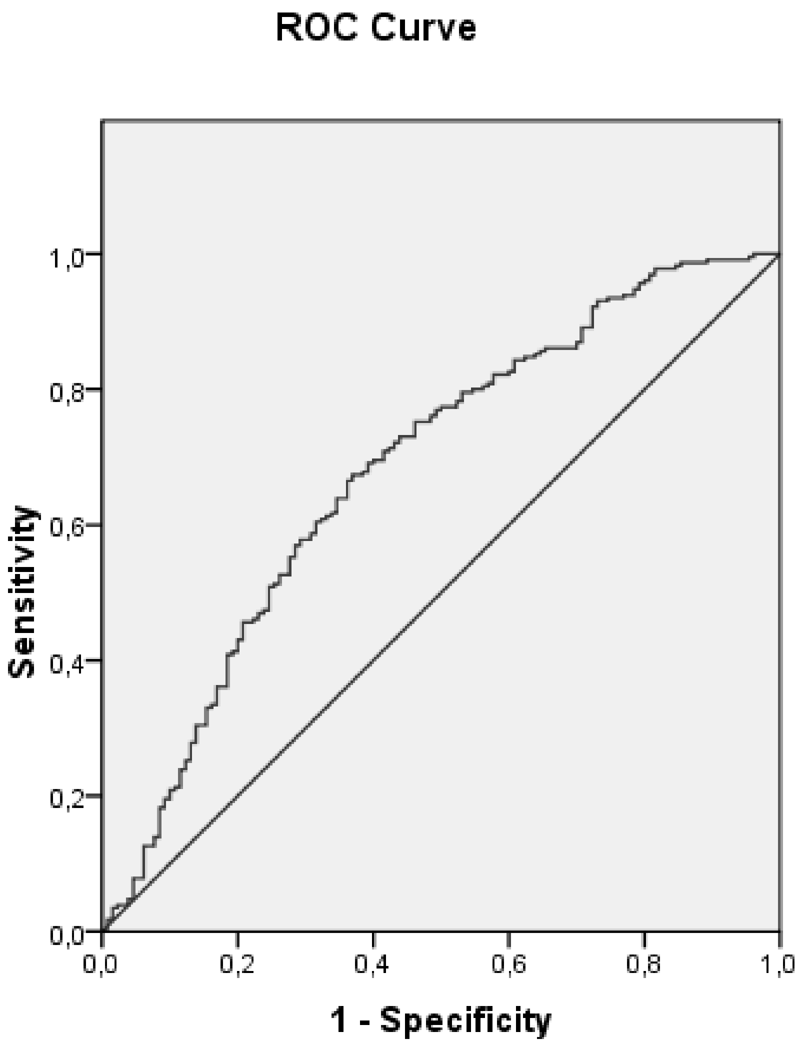
Area Under the Curve

Test Result Variable(s):Predicted probability

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
,681	,030	,000	,623	,740

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5



APPENDIX 4: VARIANCE DECOMPOSITIONS FOR THE RETURN CORRELATION

Pre-crisis

	epu	correlation	realGrowth
[1,]	0.001971948	0.9980281	0.0000000000
[2,]	0.001973305	0.9977366	0.0002900890
[3,]	0.001983540	0.9972640	0.0007524433
[4,]	0.001999391	0.9967401	0.0012605467
[5,]	0.002018545	0.9962283	0.0017531125
[6,]	0.002039372	0.9957572	0.0022034253
[7,]	0.002060738	0.9953367	0.0026026086
[8,]	0.002081873	0.9949675	0.0029505848
[9,]	0.002102269	0.9946465	0.0032512620
[10,]	0.002121611	0.9943684	0.0035100292
[11,]	0.002139719	0.9941278	0.0037325033
[12,]	0.002156512	0.9939195	0.0039239459

Post-crisis

	epu	correlation	realGrowth
[1,]	0.003563940	0.9964361	0.000000000
[2,]	0.001989154	0.9966539	0.001356903
[3,]	0.002066541	0.9939673	0.003966112
[4,]	0.003029764	0.9896277	0.007342575
[5,]	0.004385755	0.9844994	0.011114823
[6,]	0.005839628	0.9791444	0.015015992
[7,]	0.007229638	0.9739052	0.018865113
[8,]	0.008478076	0.9689750	0.022546942
[9,]	0.009557201	0.9644487	0.025994097
[10,]	0.010466990	0.9603603	0.029172697
[11,]	0.011221323	0.9567072	0.032071454
[12,]	0.011839813	0.9534665	0.034693721