The Relationship between consumer confidence and the stock market in the European Union

Master Thesis, Quantitative Finance

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Abstract

This thesis uses the consumer confidence index (CCI) and the headline stock indices of 11 European countries to study the relationship between the CCI and the stock market. The co-movement between the CCI and the stock market are examined by using a VAR model, testing for Granger causality and estimating the dependence structure by using copula models. I find that, the stock market has a significant influence on the consumer confidence. Although there is a slight change in correlation through time and in different stages of the economy, this influence does not significantly change.

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1 Introduction

Consumer confidence and stock prices are both considered leading indicators of general economic conditions (Kim and Oh, 2009). Stock prices reflect the future cash flows of companies, which explains the leading effect. The consumer confidence index (CCI) contains consumer views on the future general economic situation, which also show the leading effect. As stock prices and the consumer confidence are leading indicators, it is important to know if and how these variables are related. This Master thesis looks into the relationship between consumer confidence and stock market developments in the European Union (EU). This relationship is examined by looking at the full sample contemporaneous and dynamic dependence structures. And in which direction the relationship is running. Does the stock market influences the CCI or does the CCI influences the stock market? Next to looking at the full sample relationship I am exploring the development of this relationship over the past years. Is the relationship stable and linear through time? And is this relationship similar in different stages of the economy?

There is a variety of reasons why the relationship between consumer confidence and stock market developments could change over time. For example, nowadays consumers are far more involved in the stock market than they used to be. This development can be explained by a number of reasons. First, if we take a look at the number of households holding stocks we see for most of the countries in the EU a doubling in the period of 1990 to 2000. Guiso, Haliassos and Jappelli (2003) report that currently between 15 and 25 percent of all households in the Netherlands, Italy, France and Germany have their savings put in stocks. In the UK this is even over one-third of the households. As a result nowadays far more people have a direct stake in the stock market. Second, because pension funds investments in the stock market increased heavily over the past years more people have an indirect stake in the stock market. For example, between 2001 and 2010 the value of the stock portfolio of pension funds in the Netherlands has more than doubled (CBS, 2011). The third factor that could be influencing the involvement of people in the stock market is the changing media landscape. With the up rise of the internet, social media, apps, and blogs in the late 20th century and beginning 21th century news about the stock market has been reaching people at much greater speed. Information regarding the financial markets is more easily accessible exposing people more to developments in the stock market. Especially since the recent crisis, the attention is more focused on the stock market than before.

As mentioned earlier, it is also interesting to zoom in on the relationship between consumer confidence and stock market developments in different economic stages, especially periods of crisis. Doms and Morin (2004) and Alsem et al. (2008) find that the tone and volume of economic reporting in the media affect consumer confidence. In periods of crisis a greater volume of economic news is expected, which could result in a change in the relationship between consumer confidence and the stock market.

The CCI provides accurate information about consumer views with regard to the general economic situation and the financial situation of the consumers' own household. In the past years we observed a severe decline in consumer confidence in most of the EU countries (EC, 2012). Consumer confidence has reached its lowest level of all times. The CCI is a crucial factor for the economic developments in a country. For example if consumers have a low confidence in the economy they will put a hold on their purchases in luxury goods. Research has shown that consumers in our society can postpone 75% of their purchases without any difficulty for a year or longer (NU.nl, 2011). This can result in disastrous economic consequences. Therefore, to avoid economic crunches it is important for governments to manage consumer confidence.

Many institutions monitor consumer confidence and use it in their decision making process. A decreasing trend in the CCI suggests that consumers have a negative view on the general economic situation as well as on their own financial situation. For example, manufacturers than may expect consumers to avoid big ticket purchases and they might bring down their inventories and postpone investments in new projects. Likewise, governments anticipate on decreases in the CCI by taking fiscal or monetary actions to stimulate the economy. On the contrary, an increasing trend in the CCI indicates an improvement in the buying patterns of consumers. In this case, manufacturers can increase production and raise their hiring pattern. Banks may expect an increasing demand for credit and construction companies might anticipate on increasing investments in real estate.

There are many authors who investigate the relationship of CCI with different economic variables. Carroll, Fuhrer and Wilcox (1994) and Ludvigson (2004) find a link between consumer confidence and real consumer spending. Matsusaka and Sbordone (1995) find a relationship between consumer confidence and GNP (Gross National Product) growth. As well as Howrey (2001), who reports that consumer confidence is a statistically significant predictor of the future rate of real GDP. Otoo (1999) and Jansen and Nahuis (2003), study the relationship between CCI and the stock market. They find that stock returns Granger-cause consumer confidence at short horizons, and that the reverse does not hold. This means that the lagged stock returns provide statistically significant information about future consumer confidence. Fisher and Statman (2003) find that consumer confidence rises with high stock returns, but high consumer confidence is followed by low stock returns. In general, it appears that the empirical literature is investigating the relationship between consumer sentiment and the stock market quite superficially. This thesis tries to address this gap in the literature by analyzing this relationship more thorough by including an analyses which involves looking at periods of crisis and working with copulas to get a better understanding about the relationship between the CCI and the stock market.

In this research I begin the analysis between the CCI and the stock market by looking at the contemporaneous and dynamic correlations over the full sample period, January 1985 until June 2012. VAR models are constructed to analyze the Granger causality between the CCI and the stock market, and to see in which direction the relationship is running. The lag structure that is used in these VAR models is extracted from the Schwarz information criteria in combination with the Portmanteau autocorrelation residual test. To explore the development of the relationship through time, the sample period is divided in two parts. I split the data at January 1999, because of the introduction of the euro as an accounting currency in the financial markets. The contemporaneous and dynamic correlations, and the VAR models are calculated for the period 1985-1998 and 1999-2012. To examine if the relationship changes in different stages of the economy I split the CCI and stock market data in bull and bear market data. The Lunde and Timmerman (2004) algorithm is used to identify bullish and bearish periods in the stock market data. A bull market is characterized by rising stock prices, while a bear market is distinguished as a market with falling prices and higher volatility. Again the contemporaneous and dynamic correlations, and the VAR models are calculated for the bullish and bearish data. To model the dependence between the CCI and the stock market using copula models, I first look at the quantile, tail and symmetric dependences to find out what copula model is most suitable.

My results show that there is indeed a relationship between the CCI and the stock market. The dynamic correlations and Granger causality tests show that this relationship is running from the stock market to the CCI, and not the other way around. Although the contemporaneous correlations for the two periods, 1985-1998 and 1999-2012, show that there is an increased correlation in the second period. The dynamic correlations and Granger causality results do not show this difference. Indicating that the relationship is stable through time. Between bull and bear markets these same results are found. Although some small changes in the contemporaneous results between bull and bear periods, there is no apparent difference when looking at the dynamic results. This indicates that also through different stages of the economy the relationship is not changing. Looking at the dependence measures, I conclude that zero tail dependence and asymmetry in the tails cannot be rejected. Although statistically speaking there is no tail dependence and no asymmetry between the tails, economically speaking there is some non zero tail dependence and slight difference between the tails detected for some countries. Therefore copula models with these properties are also considered besides the copula models that have zero tail dependence, and thus symmetry, as a property. Again there is slightly higher dependence measured in the lower tail when looking at the symmetrized Joe-Clayton copula estimates, although not significant.

This thesis is structured as follows. In section 2 the empirical data is described. Section 3 contains the correlation analysis, including the contemporaneous, dynamic and threshold correlation. The results of the different VAR models, full sample, two periods (1985-1999 and 1999-2012) and bull/bear market, are presented in Section 4. In Section 5 the different copula models are proposed, followed by the copula model that best describes the dependence structure between the CCI and the stock market. In Section 6 the conclusions and suggestions for further research are presented.

2 Data

The CCI is constructed and published by the European Commission for all EU (European Union) and EA (Euro Area) countries. The survey is conducted on a monthly basis, in the second and third week of each month. The results are published on the last working day of the month. The questions in the consumer confidence survey are organized around four topics: the households' financial situation and the general economic situation. The exact questions that respondents are asked to answer are:

Q1: *How do you expect the financial position of your household to change over the next 12 months? It will… : get a lot better (++), get a little better (+), stay the same (=), get a little worse (-), get a lot worse (--), don't know (N)*

Q2: *How do you expect the general economic situation in this country to develop over the next 12 months? It will… : get a lot better (++), get a little better (+), stay the same (=), get a little worse (-), get a lot worse (--), don't know (N)*

Q3: *How do you expect the number of people unemployed in this country to change over the next 12 months? The number will… : increase sharply (++), increase slightly (+), remain the same (=), fall slightly (-), fall sharply (--), don't know (N)*

Q4: *Over the next 12 months, how likely is it that you save any money?: very likely (++), fairly likely (+), not likely (-), not at all likely (--), don't know (N)*

The CCI is obtained by calculating the average balance of optimistic and pessimistic answers to these questions expressed in percentages points. The (++) and (--) answers each get weight 1, while the (+) and (-) answers get weight ½. The (=) and (N) answers are not included in the calculation, which gives them weight 0. Each subindex is computed as

$$CCI_i = \left((++)_i + \frac{1}{2}(+)_i \right) - \left((--)_i + \frac{1}{2}(-)_i \right), \qquad \text{with } i = 1,\dots,4. \tag{1}$$

The overall CCI is the unweighted average of the subindices of the four questions:

$$CCI = \frac{1}{4}\sum CCI_i \,. \tag{2}$$

Among the different countries the national surveys and transmission of the results are conducted according to a common timetable, and they make use of the same harmonized questionnaires. The principle of harmonization aims to produce a set of comparable data. The survey results are seasonally adjusted[1], to smooth out influences of events that take place at the same time every year, such as Easter, Christmas, public holidays, or the receipt of extraordinary wage bills in a given month of the year.

This analysis considers CCI data running from January 1985 onwards. Before 1985 there was some sort of measuring of consumer confidence, but this was not measured on a monthly basis. The countries I take into account are the following 11 countries: Belgium, Denmark, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain and the United Kingdom (UK). The other EU countries are left out because the CCI measures are too short to conduct a meaningful analysis. To denote the stock market I use the following stock indices for the different countries: BEL20 (Belgium), C20 (Denmark), CAC40 (France), DAX30 (Germany), FTSE ATHEX 20 (Greece), ISEQ[2] (Ireland), FTSE MIB (Italy), AEX (Netherlands), PSI20 (Portugal), IBEX35 (Spain), and FTSE100 (UK). These 'headline' stock indices are used because they are most mentioned in news reports. They are extracted from the database Datastream were they are presented on a daily basis. Because there is not a clear cut when the CCI data is measured I defined the monthly stock market value as the average of the stock index of all the data points in that month. This may give some spurious correlation or causality estimates due to asynchronous observed data. The sample period for Germany, Ireland[3], Italy, Netherlands, and the UK runs from January 1985 to June 2012. The sample periods for the other countries runs as follows: Belgium (1990M01-2012M06), Denmark (1989M12-2012M06), France (1987M07-2012M06), Greece (1997M09-2012M06), Portugal (1992M12-2012M06) and Spain (1987M01-2012M06).

Figure 1 shows the CCI of the Netherlands and the Dutch stock index, the AEX. Here is suggested that the consumer confidence and the stock market of the Netherlands are related to each other. As well as that after a certain period this relationship is stronger than before.

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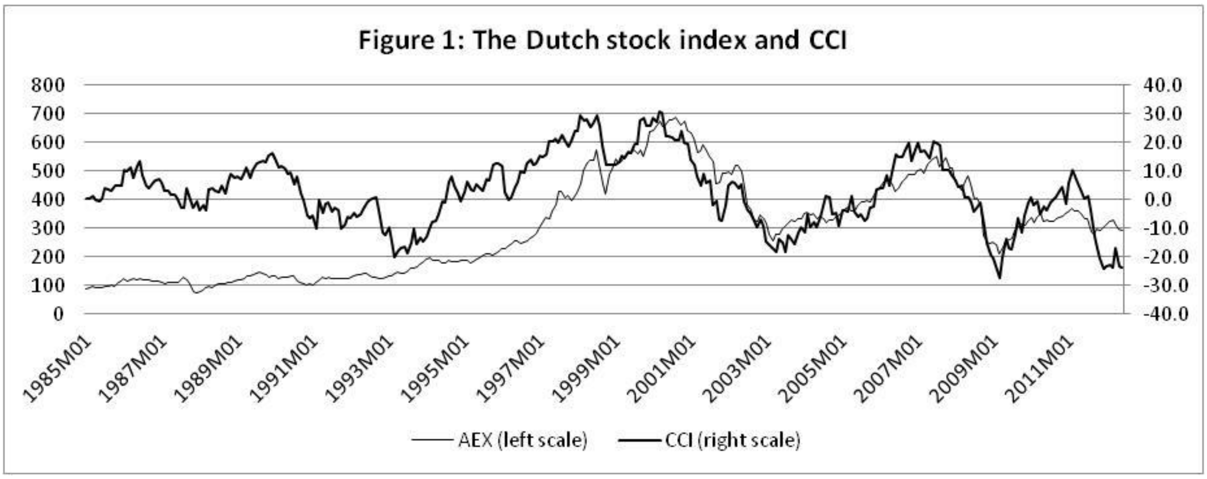
[1] The results are seasonally adjusted by Dainties method. Dainties method is based on the use of filters. A Dainties filter can be defined as a tool that provides a seasonal component. By subtracting this seasonal component from the original observation you obtain the seasonal adjusted observation.

[2] The ISEQ is the only Overall Index I take into account. This is due to the fact that the 'headline' index data, ISEQ 20, is available from 31 December 2004. This would result in a relatively short sample period.

[3] For Ireland the CCI is not measured over the period May 2008 until April 2009.



This figure shows the monthly observations of the Dutch stock index (AEX) and CCI over the period January 1985 until June 2012. The thin black line describes the AEX (left y-axis) and the thick black line plots the CCI (right y-axis). The CCI data serie is obtained from the European Commission database. The AEX index is obtained from Datastream.

The sample statistics of the CCI for the different countries are shown in Table 1. Table 1 shows that the average CCI is negative for all the countries except for Denmark and the Netherlands. Greece has on average the largest negative value for consumer confidence, as well as the largest minimum value. Also Greece has the most volatile consumer confidence amongst the different countries. The large negative values and large volatility of the CCI in Greece is not surprising given the impact of the recent financial crisis in this country. The Netherlands has the largest positive value for consumer confidence. Most of the countries exhibit slight negative skewness and excess kurtosis, indicating a deviation from the normal distribution. When looking at the Jarque-Bera test statistic and its p-value this deviation is confirmed, as I conclude that the assumption of unconditional normality is rejected for most countries, exceptions being Belgium, France, the Netherlands and Portugal.

Table 1: Descriptive statistics of the CCI

	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	UK
Mean	-6.423	7.301	-17.911	-7.929	-38.413	-10.003	-15.070	2.857	-27.927	-13.344	-9.594
Std. Dev.	8.932	7.301	8.434	9.397	17.275	13.806	7.960	12.242	12.928	10.222	8.427
Maximum	16.200	19.000	3.300	10.900	-5.800	19.100	2.500	30.800	-1.300	5.300	7.100
Minimum	-26.500	-11.800	-37.000	-32.900	-83.800	-33.500	-41.500	-27.500	-58.900	-47.600	-35.200
Skewness	-0.024	-0.555	0.039	-0.316	-1.048	0.289	-0.690	0.002	-0.097	-0.864	-0.479
Excess Kurtosis	-0.006	-0.743	-0.459	-0.571	0.399	-0.964	0.282	-0.373	-0.380	1.011	-0.617
Jarque-Bera	0.035	20.148	2.852	10.086	32.986	16.779	26.850	2.039	1.910	49.784	17.872
p-value	0.983	0.000	0.240	0.006	0.000	0.000	0.000	0.361	0.385	0.000	0.000
Observations	270	271	300	330	178	318	330	330	235	306	330

This table shows the descriptive statistics of the CCI for the 11 countries over the period January 1985 until June 2012. The CCI data serie is obtained from the European Commission database. The AEX index is obtained from Datastream.

To ensure stationarity, I transform the variables. I perform different unit root tests to examine if there is a unit root present, hence the time series are non-stationary. Table 2 shows the results of the Augmented Dickey-Fuller (ADF) test and Phillips-Perron test. Panel A provides the ADF test statistic and its p-value as well as the Phillips-Perron test statistic and its p-value for the CCI of the 11 countries. Panel B presents the same test results for the natural logarithm (ln) of the stock indices. The ln transformation is a common transformation when working with economic data that includes a trend, it substitutes an exponential trend by a linear trend. The two tests are conducted including a constant for the consumer confidence indices and including a constant and a trend for the stock indices. Panel A shows that when looking at the ADF test statistics and its p-values the unit root hypothesis cannot be rejected at a 1% significance level for most of the CCI time series, the only exception being Germany. But the Phillip-Perron test indicates that rejection of the unit root is not possible for Germany as well at a 1% significance level. Although, Davidson and MacKinnon (2004) report that the Phillips-Perron test performs worse than the ADF test in finite samples, I still put the same restriction on the CCI for Germany. Because the CCI time series of most of the countries contain a unit root, I(1), I take the first differences of the time series to make them stationary[4]. Panel B illustrates that for all the (ln) stock indices the unit root hypothesis cannot be rejected at a 1% significance level. I also take the first differences of the natural logarithm of the stock indices to make them stationary[4].

Table 2: ADF and Phillip-Perron test

	Panel A										
	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	UK
ADF test statistic	-3.110	-3.423	-3.189	-3.803	-1.029	-2.220	-1.548	-2.030	-1.346	-2.452	-3.081
p-value	0.027	0.011	0.022	0.003	0.743	0.200	0.508	0.274	0.608	0.129	0.029
Phillip-Perron test statistic	-3.138	-3.423	-3.288	-3.197	-0.885	-2.345	-1.791	-2.303	-1.521	-2.491	-3.030
p-value	0.025	0.011	0.016	0.021	0.791	0.159	0.385	0.172	0.521	0.119	0.033
	Panel B										
	BEL 20	C20	CAC40	DAX30	FTSE ATHEX 20	ISEQ	FTSE MIB	AEX	PSI-20	IBEX 35	FTSE 100
ADF test statistic	-1.353	-2.400	-1.522	-2.423	-0.803	-1.615	-1.620	-1.305	-1.503	-1.334	-2.009
p-value	0.872	0.379	0.820	0.367	0.963	0.785	0.783	0.885	0.826	0.877	0.594
Phillip-Perron test statistic	-1.386	-2.332	-1.422	-2.309	-0.455	-1.658	-1.867	-1.166	-1.408	-0.479	-1.902
p-value	0.863	0.415	0.853	0.427	0.985	0.767	0.669	0.915	0.857	0.984	0.651

This table shows the test statistics and p-values of the Augmented Dickey-Fuller (ADF) and Phillip-Perron test of the CCI, shown in Panel A, and of the log stock indices (ln(SI)), shown in Panel B, for the 11 countries over the period January 1985 to June 2012. The tests for the CCI include only a constant. While the tests for the ln(SI) include a constant and a trend.

[4] Table A.1 in the Appendix shows that after taking the first differences of the CCI and of the natural logarithm of the stock indices the time series do not show a unit root any longer.

Furthermore, the Johansen Cointegration Trace test indicates no cointegration at a 1% significance level for all the 11 countries[5]. Which means there is no indication for a long term relationship between the CCI and the stock market.

To make the CCI and stock index variables comparable I standardize them. Variables measured at different scales do not contribute equally to the analysis. Data standardization procedures equalize the range and/or data variability. I standardize the CCI and stock index data series by dividing each variable by its standard deviation. This method produces a set of transformed variables with variances of 1, but different means and ranges.

[5] See Table A.2 in the Appendix for the Johansen Cointegration Trace test results.

3 Correlation

This section describes the correlation analysis for the full data sample, January 1985 until June 2012. The first step in analyzing the relationship between (two) variables is to look at their correlation. Although an observed correlation does not allow one to say anything about causation between the variables, it is a good way to get a first notion of their relationship.

3.1 Dynamic correlation

To get a first impression of the relationship between (changes in) consumer confidence (CCI) and (changes in) the stock market (SI) I look at the contemporaneous correlation between these two time series[6]. The fourth column of Table 3 shows that the contemporaneous correlation (j=0) between the CCI and the associated stock index is positive and significant for all the countries, which means that the stock market and consumer confidence have a tendency to move in the same direction. The contemporaneous correlation estimates have a range from 0.181-0.339, where Belgium features the highest, and Denmark features the lowest contemporaneous correlation estimate. The contemporaneous correlation analysis indicates that there is a positive relationship between consumer confidence and the stock market. But it does not say anything about the direction of this relationship. Does a higher stock price cause an improvement in consumer confidence, or does an improvement in the consumer confidence cause higher stock prices. The causality could also run in both directions.

To obtain an enhanced first impression Table 3 reports also the dynamic cross-correlations. The fifth column shows that besides the significant contemporaneous correlations, the CCI and 1-month lagged stock index are significantly correlated as well for all the 11 countries. Although these correlation estimates are lower than the contemporaneous correlations, except for the Netherlands, this does indicate that the direction of the causality runs from the stock market to the CCI and not the other way around. The few significant correlations in the last two columns also confirm this direction of the relationship. When considering the causality direction from the CCI to the stock market, by looking at the dynamic correlations presented in columns 1-3, there is very low and almost no significant correlations presented. The fact that the contemporaneous correlations are the highest of all, indicates that the stock market has an effect on the CCI almost at the same time, or by all means in a time frame of less than a month.

[6] From now on I will use the terms consumer confidence or CCI and stock market/stock index or SI. In section 2 is explained that I mean by the consumer confidence, the first differences of the Consumer Confidence Index (ΔCCI). The stock market is defined as the fist differences of the natural logarithm of the stock index (Δln(SI)). Both variables are standardized by dividing them by their own standard deviation.

Table 3: Dynamic correlation

	Correlation CCI(t) and SI(t-j)						
j=	-3	-2	-1	0	1	2	3
Belgium	-0.034	0.024	0.080*	0.339***	0.144***	0.029	0.020
Denmark	0.072	-0.057	0.094*	0.181***	0.112**	0.065	-0.004
France	-0.009	-0.032	0.025	0.331***	0.162***	0.055	0.030
Germany	0.059	0.097**	0.071	0.203***	0.150***	0.188***	0.168***
Greece	-0.013	0.025	0.093	0.224***	0.103*	0.117*	0.071
Ireland	0.012	-0.036	-0.001	0.187***	0.172***	-0.132***	-0.005
Italy	0.054	0.016	0.041	0.247***	0.142***	0.091**	0.002
Netherlands	0.071*	-0.004	0.079*	0.248***	0.283***	0.097**	0.106**
Portugal	-0.023	0.052	0.066	0.292***	0.104*	0.018	0.133**
Spain	0.049	0.007	0.138***	0.296***	0.137***	-0.060	0.017
UK	-0.036	0.057	0.062	0.220***	0.152***	-0.030	0.013

This table presents the dynamic correlation estimates of the consumer confidence, CCI(t) and the associated stock market, SI(t-j), of the 11 countries, for j = -3,…,3. The superscripts (***), (**) and (*) indicate statistical significance at a 1%, 5% and 10% level respectively. The sample period runs from January 1985 to June 2012.

3.2 Threshold correlation

To say something about the asymmetry of the relationship between the CCI and the stock market I look at a so called 'threshold correlation'. As threshold I take the median of the CCI and the stock return. I calculate the correlation between the CCI and the stock market when the CCI and stock index are both below their median, and the correlation when the CCI and stock index are both above their median, these results are presented in Table 4. As a robustness check Table 5 shows the correlations when I look at the median threshold separately for the CCI and the stock market. Hence, looking at the correlation between the CCI and stock index when the CCI values are under/above the CCI median, regardless of the stock index values. The same method performed for the stock index as the threshold, regardless of the CCI value.

To test if the correlation under the median is significantly different from the correlation above the median Fisher's transformation of the correlation coefficient is used:

$$r' = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right), \tag{3}$$

where r denotes the correlation coefficient. This transformation produces a function that is normally distributed. Thereafter I test whether the two correlations are significantly different from each other, hence if there is asymmetry present in the data, by calculating the z-statistic for the difference between the two *r'* values:

$$Z = (r_1' - r_2') / sqrt(1/(N_1 - 3) + 1/(N_2 - 3)), \tag{4}$$

where N_i denotes the number of observations involved in the correlation, i = 1,2.

According to the p-values presented in Table 4, the hypothesis that the correlations between the CCI and the stock market when the CCI and the stock returns are both under and above their median do not differ from each other, cannot be rejected. This indicates that there is no asymmetry present in any of the 11 countries. Although, when looking at the threshold correlations itself, it is shown that 8 out of the 11 countries have a higher correlation when the CCI and the stock returns are both under their median then when they are both above their median, exceptions being Greece, Italy and Portugal. When looking at the CCI and stock market median separately as the threshold in Table 5, it shows that also the correlations under the median, both for the CCI and the stock market, are higher for most of the countries. Only in some cases this difference in correlation under and above the median is confirmed by the low p-value, which results in the rejecting of the hypothesis of no difference between these correlations. In the case of the CCI median as the threshold, there is a significant difference in correlation for France and Germany, at a 10% and 5% significance level respectively. Looking at the stock returns median as the threshold, it is shown that only Portugal has a significant difference in correlation at a 5% significance level.

Although there is almost no significant evidence for asymmetry I can suggest that in lesser periods the consumer confidence and the stock market are moving closer together by looking only at the contemporaneous correlation estimates. Later in this research I will explore this difference in more detail by looking at the difference in the relationship between the CCI and the stock market during bull and bear markets.

Table 4: Threshold correlation, both CCI and SI under/above their median

	Threshold correlation			
	Under median	Above median	z-statistic	p-value
Belgium	0.369	0.251	0.814	0.416
Denmark	0.281	0.249	0.210	0.834
France	0.337	0.105	1.596	0.111
Germany	0.208	0.033	1.180	0.238
Greece	0.194	0.254	-0.314	0.753
Ireland	0.178	0.045	0.864	0.388
Italy	0.131	0.338	-1.463	0.143
Netherlands	0.168	0.141	0.187	0.852
Portugal	0.188	-0.035	1.241	0.215
Spain	0.214	0.167	0.319	0.749
UK	0.179	0.210	-0.219	0.827

This table presents the threshold correlation estimates and the associated z-statistics and p-values for comparing the correlation between the CCI and the stock market when the CCI and the stock index are both under their median and when they are both above their median for the 11 countries. The sample period runs from January 1985 to June 2012.

Table 5: Threshold correlation, separately for CCI and SI under/above their median

	CCI				SI			
	Under median	Above median	z-statistic	p-value	Under median	Above median	z-statistic	p-value
Belgium	0.249	0.276	0.234	0.815	0.349	0.237	-0.992	0.321
Denmark	0.248	0.090	-1.325	0.185	0.150	0.111	-0.316	0.752
France	0.332	0.115	-1.858	0.063	0.337	0.151	-1.612	0.107
Germany	0.210	-0.093	-2.490	0.013	0.255	0.113	-1.190	0.234
Greece	0.220	0.158	-0.418	0.676	0.140	0.077	-0.419	0.675
Ireland	0.174	0.184	0.081	0.936	0.177	0.136	-0.340	0.734
Italy	0.154	0.290	1.163	0.245	0.220	0.276	0.484	0.628
Netherlands	0.290	0.104	-1.586	0.113	0.258	0.069	-1.584	0.113
Portugal	0.273	0.073	-1.562	0.118	0.345	0.092	-2.024	0.043
Spain	0.272	0.168	-0.888	0.374	0.305	0.147	-1.361	0.173
UK	0.263	0.109	-1.299	0.194	0.212	0.125	-0.725	0.468

This table presents the threshold correlation estimates and the associated z-statistics and p-values for comparing the correlation between the CCI and the stock market when the CCI is under and above its median, and when the stock index is under and above its median, for the 11 countries. The sample period runs from January 1985 to June 2012.

4 VAR models

After looking at the correlation estimates I look at VAR (vector autoregression) models for the CCI and SI and perform a Granger causality test to obtain a more thorough understanding of the relationship between the CCI and the stock market of the 11 countries. The time series of the CCI is said to Granger-cause the stock index if it can be established that the CCI values provide statistically significant information about future values of the stock index, and vice versa. Although the Granger test provides further insight in the relationship between the two variables, the possibility of misleading results occurring from a common type of situation has to be kept in mind when interpreting the results (Granger, 1980). The test is performed both ways, CCI to SI and SI to CCI, to determine in which direction the causality effect is moving. The test is conducted on the basis of the following VAR models:

$$\Delta \ln(SI)(t) = \alpha_s + \sum_{i=1}^{k} \beta_s(i) \Delta \ln(SI)(t-i) + \sum_{i=1}^{k} \gamma_s(i) \Delta CCI(t-i) + u_s(t) \tag{5}$$

$$\Delta CCI(t) = \alpha_c + \sum_{i=1}^{k} \beta_c(i) \Delta CCI(t-i) + \sum_{i=1}^{k} \gamma_c(i) \Delta \ln(SI)(t-i) + u_c(t), \tag{6}$$

where *CCI* is the consumer confidence index, *SI* denotes the stock index, *u* is the disturbance term and *k* is the lag length. The null hypothesis that is tested in the Granger causality test is whether there is no Granger causality present in the tested direction, hence whether $\gamma_s(i)$ in (5) are jointly zero, and $\gamma_c(i)$ in (6) are jointly zero. When selecting the number of lags used in model (5) and (6) I first look at the SC (Schwarz information Criterion) lag order selection criterion. The SC indicates that I have to take k = 1 for all the 11 countries. Besides looking only at the SC for selecting the number of lags, I also perform the Portmanteau test to look if there is autocorrelation present in de residuals. I start with looking at the VAR(1) model, because the SC indicates k = 1. From that point I start increasing the number of lags in the VAR model until there is no more autocorrelation present in the residuals at a 5% significance level. Table 6 shows the results for the SC and the Portmanteau test. In this research I continue by using the number of lags selected by the Portmanteau test.

Table 6: Lag selection

	Lag order criteria	Autocorrelation residual test
	SC	Portmanteau
Belgium	1	1
Denmark	1	2
France	1	1
Germany	1	2
Greece	1	1
Ireland	1	2
Italy	1	3
Netherlands	1	4
Portugal	1	1
Spain	1	2
UK	1	1

This table presents the number of lags that are selected for each of the 11 countries. The first column shows the results when looking at the Schwarz information Criterion (SC). The second column presents the number of lags when looking at the Portmanteau test for the presence of autocorrelation in the residuals. The selected number of the Portmanteau lags comes from the procedure of increase the VAR model until there is no more autocorrelation present in the residuals at a 5% significance level. The sample period runs from January 1985 to June 2012.

4.1 Full sample results

First I am analyzing the Granger causality of the full sample, January 1985 until June 2012. Table 7 reports the p-values of the test statistics for the Granger causality test in both directions, CCI to SI and SI to CCI. There is no Granger causality present from the CCI to the stock indices for all the countries. This confirms the findings of the dynamic correlations analysis. However, for the majority of the countries the stock indices Granger cause the CCI, the only exception being Portugal. For Belgium, France, Germany, Ireland, Italy, the Netherlands, Spain and the UK I find statistically significant Granger causality at a 1% significance level, for Denmark at a 5% significance level, and for Greece at a 10% significance level. These results indicate that the publication of the consumer survey data (at the end of each month) does not have a significant effect on the stock market. But the stock market does have, for most of the countries (although for different significance levels), an effect on the consumer confidence.

As a robustness check I also look at the Granger causality for the same number of lags for all the countries, k = 1, 3 and 6. Table A.3 in the Appendix does not show large differences with the results in Table 7.

Table 7: Granger causality full sample

	Granger causality (p-values)	
	CCI to SI	SI to CCI
Belgium	0.615	0.003
Denmark	0.380	0.013
France	0.171	0.002
Germany	0.304	0.002
Greece	0.984	0.070
Ireland	0.761	0.000
Italy	0.918	0.001
Netherlands	0.330	0.000
Portugal	0.407	0.206
Spain	0.442	0.002
UK	0.727	0.001

This table presents the Granger causality p-values for the full sample running from January 1985 to June 2012. The Granger causality test is performed in two directions, from the CCI to the stock indices and from the stock indices to the CCI. The number of lags used are different per country depending of the outcome of the Portmanteau test, see table 6.

When looking at the results of the different VAR models in Table 8, and especially to the signs of the coefficients, it again becomes clear that the causality effect is running from the stock market to the CCI. Mainly in equation (6) this corresponds to the fact that the one month lagged stock indices (SI(-1)) are positive for all the countries, with a range from 0.087 for Portugal to 0.303 for the Netherlands. When looking at the higher lags, which are included only for some countries depending on the outcome of the Portmanteau test, I see that these coefficients are not always positive and they are less high then the SI(-1) coefficients, except for Germany. The one month lagged CCI in equation (5) are all around 0, ranging from -0.081 for France to 0.074 for Spain. The same results are found when looking at higher lags for the CCI. These findings can be interpreted again as evidence that the causality is running from the stock market to the CCI instead of from the CCI to the stock market.

The coefficients of determination (R^2) are all very low, this means that not much variation of the dependent variable can be attributed to differences in the explanatory variables. In most cases model (5) shows a higher R^2 then model (6), except for Ireland and Spain. This is probably due to the fact that the SI(-1) coefficients show a high value in model (5). Hence, the stock index from one month ago has an influence on the stock index now.

Table 8: VAR models full sample

	Belgium		Denmark		France		Germany		Greece		Ireland	
	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI
CCI(-1)	-0.148	-0.031	-0.226	0.035	-0.088	-0.081	0.092	0.006	-0.160	0.001	-0.211	-0.039
	(0.064)	(0.061)	(0.062)	(0.061)	(0.061)	(0.059)	(0.056)	(0.055)	(0.077)	(0.072)	(0.057)	(0.058)
CCI(-2)			-0.161	-0.069			-0.042	0.083			-0.099	-0.025
			(0.062)	(0.061)			(0.056)	(0.055)			(0.056)	(0.057)
SI(-1)	0.194	0.326	0.145	0.300	0.191	0.319	0.088	0.304	0.140	0.395	0.250	0.293
	(0.064)	(0.061)	(0.063)	(0.062)	(0.061)	(0.059)	(0.058)	(0.056)	(0.077)	(0.072)	(0.056)	(0.057)
SI(-2)			0.078	-0.050			0.157	-0.043			-0.143	-0.095
			(0.063)	(0.063)			(0.058)	(0.057)			(0.058)	(0.059)
C	-0.024	0.029	0.002	0.080	-0.002	0.033	-0.024	0.080	-0.054	-0.064	0.004	0.125
	(0.060)	(0.058)	(0.060)	(0.060)	(0.057)	(0.056)	(0.055)	(0.054)	(0.075)	(0.070)	(0.055)	(0.056)
R^2	0.040	0.102	0.074	0.091	0.033	0.091	0.054	0.097	0.035	0.156	0.108	0.080

	Italy		Netherlands		Portugal		Spain		UK	
	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI
CCI(-1)	-0.254	-0.038	-0.114	0.016	0.057	-0.053	-0.161	0.074	-0.174	0.019
	(0.058)	(0.057)	(0.056)	(0.056)	(0.069)	(0.064)	(0.061)	(0.059)	(0.055)	(0.056)
CCI(-2)	-0.068	-0.005	-0.050	-0.020			0.037	0.026		
	(0.059)	(0.058)	(0.057)	(0.056)			(0.061)	(0.059)		
CCI(-3)	0.046	0.010	0.039	0.089						
	(0.057)	(0.057)	(0.057)	(0.057)						
CCI(-4)			-0.046	0.081						
			(0.055)	(0.055)						
SI(-1)	0.197	0.289	0.303	0.342	0.087	0.398	0.211	0.318	0.190	0.194
	(0.057)	(0.057)	(0.057)	(0.057)	(0.069)	(0.064)	(0.062)	(0.059)	(0.055)	(0.056)
SI(-2)	0.085	-0.082	0.018	-0.095			-0.108	-0.184		
	(0.059)	(0.059)	(0.061)	(0.061)			(0.062)	(0.060)		
SI(-3)	-0.005	0.180	0.061	0.076						
	(0.058)	(0.057)	(0.061)	(0.061)						
SI(-4)			0.147	-0.096						
			(0.059)	(0.059)						
C	-0.048	0.029	-0.062	0.055	-0.040	0.016	-0.018	0.055	-0.023	0.089
	(0.054)	(0.053)	(0.054)	(0.053)	(0.066)	(0.061)	(0.057)	(0.055)	(0.054)	(0.055)
R^2	0.086	0.102	0.123	0.125	0.014	0.148	0.055	0.116	0.052	0.040

This table shows the VAR model results presented in (5) and (6) for the full sample running from January 1985 to June 2012. The number of lags used are different per country depending on the outcome of the Portmanteau test, see table 6. Standard errors are presented in parentheses.

4.2 Two period results (1985-1998 1999-2012)

To analyze the stability and linearity through time of the relationship between the CCI and the stock market I perform the Granger causality test over two different periods in the time. Figure 1 shows for the Netherlands a quite clear cut at 1999, after 1999 the CCI and the stock index seem to move closer together then the period before 1999. In addition, the euro introduction was in 1999. Not the actual euro currency, the coins and banknotes entered circulation on 1 January 2002. But from 1 January 1999 onwards the euro was introduced to world financial markets as an accounting currency. This is the reason why I take the following two periods into account when comparing the Granger causality nowadays and in former times: 1985-1998 and 1999-2012.

Because of the quite clear cut in the movement of the CCI and stock index of the Netherlands at 1999 shown in Figure 1, I first examine if the cointegration between these two time series has changed in the two periods. Table A.4 and A.5 in the Appendix show that the Johansen Cointegration Trace test for the CCI and ln(SI) indicates no cointegration at a 1% significance level for all the countries, exception being Greece in the first period. This could be explained by the fact that the Greece time series runs from September 1997. Consequently, in the first period only 15 observations are included, which is too short a period to obtain statistically significant results.

The contemporaneous correlation results in Table 9 show that most countries have an increased correlation between the CCI and the stock market in the second period, 1999-2012. The exceptions here are Italy, Spain and the UK. The average correlation is 0.194 in 1985-1998, and 0.273 in 1999-2012. This is a small but visible increase. While Greece had the lowest correlation in the first period, the UK has the lowest correlation in the second period. The highest correlation in the first period is in Spain, while the highest correlation in the second period is in France. Although the average contemporaneous correlation between the CCI and SI is higher in the second period. The dynamic correlations in Table A.6 in the Appendix show that in this second period most of the correlations between the 1 month lagged SI and the CCI are not significant anymore.

Table 9: Correlation and Granger causality two periods, 1985-1998 1999-2012

	Correlation		Granger causality (p-values)			
	1985-1998	1999-2012	1985-1998		1999-2012	
	Estimate	Estimate	CCI to SI	SI to CCI	CCI to SI	SI to CCI
Belgium	0.238***	0.382***	0.649	0.009	0.828	0.038
Denmark	0.116	0.213***	0.414	0.087	0.088	0.056
France	0.244***	0.417***	0.121	0.080	0.795	0.012
Germany	0.120*	0.266***	0.644	0.496	0.034	0.001
Greece	0.046	0.256***	0.085	0.239	0.489	0.110
Ireland	0.165**	0.213***	0.241	0.057	0.883	0.000
Italy	0.266***	0.215***	0.439	0.033	0.327	0.022
Netherlands	0.170**	0.302***	0.667	0.014	0.595	0.000
Portugal	0.156*	0.353***	0.446	0.140	0.688	0.862
Spain	0.327***	0.252***	0.612	0.005	0.125	0.204
UK	0.287***	0.132**	0.418	0.051	0.145	0.003

This table presents in columns 1-2 the contemporaneous correlation estimates of the CCI and the associated stock index of the 11 countries. The superscripts (***), (**) and (*) indicate statistical significance at a 1%, 5% and 10% level respectively. Columns 3-6 report the p-values of the Granger causality test in two directions, from the CCI to the stock indices and from the stock indices to the CCI. The number of lags used are different per country depending on the outcome of the Portmanteau test, see table 6. Column 1, 3 and 4 show the results for the sample period January 1985 until December 1998. Column 2, 5 and 6 show the results for the sample period January 1999 until June 2012.

Table 9 also shows the results of the Granger causality test for years in the past and in former times. Columns 3 and 4 cover the period from January 1985 until December 1998. The results indicate that

Greece is the only country with Granger causality that runs from the CCI to the stock index at a 10% significance level. This could again be explained by the fact that the Greece time series only has 15 observations in the first period, which is too short a period to obtain statistically significant results. Furthermore, for Greece there is no Granger causality from the stock index to the CCI in this period. Also, Germany and Portugal show no Granger causality from the stock index to the CCI. Whereas, I find statistically significant Granger causality that runs from the stock index to the CCI for Belgium and Spain at a 1% significance level, for Italy and the Netherlands at a 5% significance level, and for Denmark, France, Ireland and the UK at a 10% significance level. Columns 5 and 6 show the results for the second period, January 1999 until June 2012. In this period there is no Granger causality present from the CCI to the stock indices for most of the countries again, except for Germany at a 5% significance level and for Denmark at a 10% significance level. Also, there is no Granger causality present from the stock indices to the CCI for Greece, Portugal and Spain. For the other countries the stock index does Granger cause the CCI: Germany, Ireland, the Netherlands and the UK at a 1% significance level, and Belgium, Denmark, France and Italy at a 5% significance level.

Although the average contemporaneous correlation increased considerably in the second period, the results from the Granger causality test do not indicate that there is an overall difference between the two periods. The results for the Granger causality running from the CCI to the stock market stay more or less the same for both periods. The Granger causality running from the stock market to the CCI changes slightly for some countries. While the p-values of the Granger causality test for Portugal (0.140) and Spain (0.005) indicated the presence of causality in the first period, this significant causality is not present anymore in the second period, with p-values of 0.862 for Portugal and 0.204 for Spain. For Germany it is the other way around. In the first period there is no Granger causality present from the stock market to the CCI with a p-value of 0.496, but in the second period there is, with a p-value of 0.001. This is also shown when looking at the VAR model coefficients in Table 10 and 11, for the periods 1985-1998 and 1999-2012 respectively. The SI(-1) coefficients of model (6) show these same changes between the two periods. For example, the lagged stock index coefficient of Portugal in VAR model (6) is in the first period 0.177, while this value in the second period is 0.015. Furthermore, Table 10 and 11 show that in model (6) the one month lagged stock indices are positive for all the countries in both periods. The one month lagged CCI coefficients in model (5) are all negative except for Spain, 0.010, in the first period. In the second period most of these one month lagged CCI coefficients become positive, though small values. Hence, there is an increased positive dependence between the CCI(-1) and SI in the period 1999-2012 in contrast with the period 1985-1998. The R^2 results are more or less the same here as they are for the full sample results, very low for all the countries.

Table 10: VAR models 1985-1998

	Belgium		Denmark		France		Germany		Greece		Ireland	
	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI
CCI(-1)	-0.008	-0.041	-0.215	-0.095	-0.127	-0.123	0.083	-0.054	0.028	-1.123	-0.214	-0.131
	(0.098)	(0.091)	(0.104)	(0.088)	(0.088)	(0.079)	(0.079)	(0.079)	(0.279)	(0.594)	(0.078)	(0.097)
CCI(-2)			-0.092	0.050			-0.024	-0.046			-0.186	-0.121
			(0.103)	(0.087)			(0.079)	(0.079)			(0.078)	(0.097)
SI(-1)	0.266	0.369	0.257	0.377	0.166	0.353	0.079	0.293	0.146	0.368	0.148	0.349
	(0.099)	(0.092)	(0.117)	(0.099)	(0.094)	(0.084)	(0.080)	(0.080)	(0.117)	(0.249)	(0.062)	(0.078)
SI(-2)			-0.045	-0.085			0.027	-0.002			-0.071	-0.148
			(0.121)	(0.103)			(0.081)	(0.081)			(0.064)	(0.080)
C	-0.054	0.134	0.009	0.093	0.013	0.094	-0.005	0.135	-0.153	0.195	0.083	0.214
	(0.083)	(0.077)	(0.094)	(0.080)	(0.092)	(0.083)	(0.074)	(0.074)	(0.192)	(0.408)	(0.067)	(0.084)
R^2	0.068	0.138	0.087	0.133	0.031	0.119	0.018	0.088	0.126	0.330	0.102	0.130

	Italy		Netherlands		Portugal		Spain		UK	
	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI
CCI(-1)	-0.246	-0.084	-0.087	-0.010	-0.009	-0.088	-0.354	0.010	-0.189	-0.059
	(0.082)	(0.082)	(0.080)	(0.080)	(0.121)	(0.114)	(0.090)	(0.086)	(0.080)	(0.073)
CCI(-2)	0.023	0.019	-0.032	-0.081			-0.052	-0.076		
	(0.083)	(0.083)	(0.080)	(0.080)			(0.091)	(0.086)		
CCI(-3)	0.017	-0.087	0.017	0.085						
	(0.080)	(0.080)	(0.081)	(0.081)						
CCI(-4)			-0.044	0.031						
			(0.081)	(0.081)						
SI(-1)	0.184	0.345	0.242	0.403	0.177	0.405	0.303	0.374	0.171	0.240
	(0.081)	(0.081)	(0.081)	(0.081)	(0.119)	(0.113)	(0.092)	(0.088)	(0.087)	(0.080)
SI(-2)	0.090	-0.121	0.023	-0.119			-0.103	-0.213		
	(0.086)	(0.086)	(0.092)	(0.092)			(0.095)	(0.090)		
SI(-3)	0.058	0.209	0.008	-0.012						
	(0.083)	(0.083)	(0.093)	(0.093)						
SI(-4)			0.133	-0.081						
			(0.088)	(0.088)						
C	-0.024	0.102	-0.052	0.156	-0.013	0.205	0.023	0.148	-0.011	0.172
	(0.081)	(0.081)	(0.074)	(0.074)	(0.129)	(0.122)	(0.090)	(0.086)	(0.086)	(0.079)
R^2	0.089	0.130	0.080	0.162	0.032	0.160	0.138	0.150	0.044	0.053

This table shows the VAR model results presented in (5) and (6) for the sample running from January 1985 to December 1998. The number of lags used are different per country depending on the outcome of the Portmanteau test, see table 6. Standard errors are presented in parentheses.

Table 11: VAR models 1999-2012

	Belgium		Denmark		France		Germany		Greece		Ireland	
	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI
CCI(-1)	-0.206	-0.018	-0.219	0.105	-0.045	-0.023	0.091	0.053	-0.168	0.047	-0.217	0.019
	(0.084)	(0.082)	(0.079)	(0.083)	(0.085)	(0.089)	(0.079)	(0.076)	(0.081)	(0.068)	(0.083)	(0.068)
CCI(-2)			-0.186	-0.126			-0.075	0.186			-0.049	0.031
			(0.079)	(0.084)			(0.079)	(0.076)			(0.082)	(0.067)
SI(-1)	0.176	0.290	0.110	0.274	0.204	0.268	0.101	0.286	0.144	0.384	0.390	0.180
	(0.084)	(0.082)	(0.077)	(0.081)	(0.081)	(0.084)	(0.084)	(0.080)	(0.090)	(0.075)	(0.104)	(0.085)
SI(-2)			0.119	-0.025			0.268	-0.095			-0.247	-0.021
			(0.076)	(0.080)			(0.084)	(0.080)			(0.106)	(0.087)
C	-0.014	-0.046	-0.006	0.070	-0.010	-0.021	-0.024	0.027	-0.045	-0.090	-0.065	0.044
	(0.084)	(0.082)	(0.079)	(0.083)	(0.073)	(0.076)	(0.082)	(0.078)	(0.081)	(0.067)	(0.088)	(0.072)
R^2	0.046	0.081	0.078	0.101	0.041	0.068	0.105	0.130	0.034	0.162	0.145	0.035

	Italy		Netherlands		Portugal		Spain		UK	
	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI
CCI(-1)	-0.272	0.038	-0.147	0.042	0.104	-0.031	0.053	0.096	-0.144	0.127
	(0.082)	(0.081)	(0.082)	(0.080)	(0.085)	(0.078)	(0.085)	(0.085)	(0.077)	(0.087)
CCI(-2)	-0.185	-0.015	-0.077	0.024			0.055	0.139		
	(0.083)	(0.082)	(0.082)	(0.081)			(0.085)	(0.085)		
CCI(-3)	0.071	0.138	0.038	0.079						
	(0.083)	(0.082)	(0.083)	(0.081)						
CCI(-4)			-0.053	0.102						
			(0.079)	(0.078)						
SI(-1)	0.216	0.218	0.354	0.267	0.015	0.349	0.125	0.255	0.210	0.136
	(0.081)	(0.080)	(0.084)	(0.082)	(0.088)	(0.081)	(0.081)	(0.081)	(0.070)	(0.078)
SI(-2)	0.057	-0.074	0.040	-0.087			-0.095	-0.147		
	(0.083)	(0.081)	(0.087)	(0.086)			(0.079)	(0.079)		
SI(-3)	-0.093	0.147	0.104	0.128						
	(0.080)	(0.079)	(0.086)	(0.085)						
SI(-4)			0.163	-0.105						
			(0.086)	(0.084)						
C	-0.095	-0.045	-0.046	-0.033	-0.067	-0.070	-0.043	-0.017	-0.031	-0.003
	(0.072)	(0.071)	(0.082)	(0.080)	(0.078)	(0.071)	(0.071)	(0.071)	(0.068)	(0.076)
R^2	0.126	0.092	0.160	0.109	0.012	0.113	0.028	0.102	0.066	0.036

This table shows the VAR model results presented in (5) and (6) for the sample running from January 1999 to June 2012. The number of lags used are different per country depending on the outcome of the Portmanteau test, see table 6. Standard errors are presented in parentheses.

4.3 Bull and bear markets

Besides looking at the overall relationship between the CCI and the stock market and analyzing the stability and linearity of this relationship through time, I also explore if the relationship changes in different stages of the economy. Because I am working with stock prices, I look if the relationship between the CCI and the stock market is different in bull markets compared to bear markets. Although there is not a clear definition of bull and bear markets, a bull market is commonly distinguished as a prolonged period of rising stock prices, while a bear market is characterized by falling prices and higher volatility. The stock market changes from a bull to a bear state if prices decline for a substantial period and with a substantial value since their previous (local) peak. This definition does not rule out sequences of negative (positive) price movements during bull (bear) markets. How large price increases or decreases should be, or how long rising or falling tendencies should last is not uniquely specified. Because of the absence of a clear definition the academic literature does not offer a single preferred method to identify bullish and bearish periods. Kole and van Dijk (2010) analyze different methods that have been put forward in the academic literature to indentify and predict bull and bear markets. By looking at their results I choose to use the algorithm described by Lunde and Timmerman (2004) to identify bullish and bearish periods in the stock market data for the 11 European countries. I choose this algorithm because it is a transparent method and Kole and van Dijk (2010) show that this method, although I only use the identification part of the algorithm, results in the best investment performance.

The Lunde and Timmerman (2004) approach focus on local peaks and troughs. Between a trough and a subsequent peak there is a bull market, and between a peak and a subsequent trough there is a bear market. Let λ be a scalar defining the threshold of the movements in the stock index that triggers a switch between bull and bear markets. A bull market occurs when the stock index has increased by at least λ_1 since the last trough. A bear market occurs when the stock index has decreased by at least λ_2 since the last peak. I follow Linde and Timmerman (2004) by setting $\lambda_1 = 0.20$ and $\lambda_2 = 0.15$. Hence, an increase of 20% of the stock index over the last trough indicates a bull market, and a decrease of 15% of the stock market over the last peak specifies a bear market. The algorithm to identify peaks and troughs in a time series is summarized as follows:

1. The last observed extreme value is a peak with stock index value P^{max}. The subsequent period is considered.
   (i) If the stock index exceeds the last maximum, the maximum is updated (if $SI > P^{max}$, then $P^{max} = SI$).
   (ii) If the stock index drops with a fraction λ_2, a trough is found (if $SI < (1 - \lambda_2)\, P^{max}$, then $P^{min} = SI$).
   (iii) If neither of the conditions is satisfied, no update takes place.

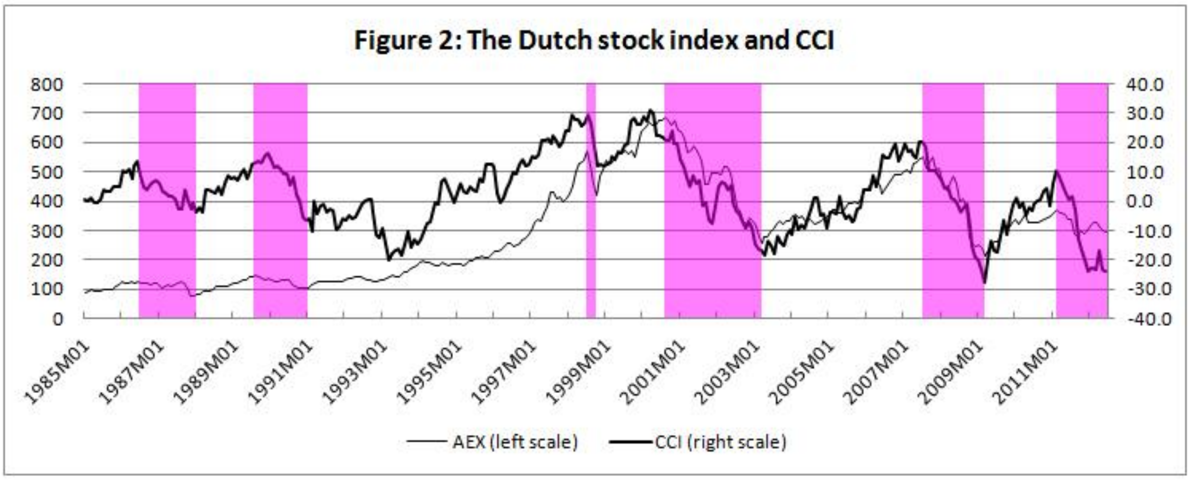
2. The last observed extreme value is a trough with stock index value P^{min}. The subsequent period is considered.
   (i) If the stock index drops below the last minimum, the minimum is updated (if $SI < P^{min}$, then $P^{min} = SI$).
   (ii) If the stock index increases with a fraction λ_1, a peak is found (if $SI > (1 + \lambda_1)\, P^{min}$, then $P^{max} = SI$).
   (iii) If neither of the conditions is satisfied, no update takes place.

Like Kole and van Dijk (2010) I distinguish whether the market is initially a bull or a bear market by counting the number of times the maximum and minimum has to be adjusted since the first observation. If the maximum has to be adjusted three times first instead of the minimum three times first, I consider the market to be bullish initially, otherwise the market is initially bearish.

Table 12: Number and duration of bull and bear markets

		Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	UK
bull	number	3	8	7	10	6	8	8	6	6	8	5
	avg. duration	55	22.4	26.7	25.1	13.2	28.8	21.8	37.3	19	21.6	53.2
	med. duration	50	19.5	23	17	9	28.5	18.5	22.5	10	16.5	39
	std. dev. duration	32.8	17.2	12.1	21.7	12.6	21.6	14.5	28.8	20.6	19.6	44.4
	total number of observations	165	179	187	251	79	229	174	224	114	173	266
bear	number	4	7	8	9	7	7	8	6	7	9	4
	avg. duration	26	13	14	8.7	14	12.4	19.4	17.5	17.1	14.7	15.8
	med. duration	18	14	12	6	4	12	20	17.5	20	16	10.5
	std. dev. duration	20.5	8.8	10.1	5.5	15.3	6.3	11.2	9.0	12.3	10.6	16.8
	total number of observations	104	91	112	78	98	87	155	105	120	132	63

This table shows for the bull and bear market the number of spells, their average and median duration and the standard deviation of the duration. It also reports to total number of observations in all the bull (bear) markets. The algorithm that is used to identify the bull and bear markets is the Lunde and Timmerman (2004) algorithm. The sample period runs from January 1985 to June 2012.



This figure shows the identification of bull and bear market periods in the Netherlands over the period January 1985 to June 2012. The algorithm that is used to identify the bull and bear markets is the Lunde and Timmerman (2004) algorithm. The thin black line plots the Dutch stock market index, the AEX, and the thick black line plots the CCI of the Netherlands. Purple areas indicate bear markets, and white areas correspond with bull markets.

Figure 2 shows the CCI and stock market of the Netherlands, and the state of the market. The purple areas correspond with bear markets, and white areas indicate bull markets. The familiar financial landmarks are all present; the well known bearish periods in 1987 and 1989-1990, the burst of the IT-bubble in 2000 and the resent credit crunch started in 2007. Besides these big bearish periods, there is a shorter period with sustained declines in the AEX, August 1998-October 1998, which possibly is a consequence of the Russian financial crisis that was going on at that time. The figure shows that during bear (bull) markets the CCI ad the stock market move together in a downward (upward) slope. The recession in 1992/93 is not identified as a bear market. While the stock market stays more or less the same in this period, the CCI declines significantly. Figure A.1 in the Appendix reports for the other 12 countries the bull/bear market identification graphs. All the countries show more or less the same bear markets that are described for the Netherlands, exceptions being a few small bear periods that are illustrated for some countries.

Table 13: Dynamic correlations bull and bear markets

	Correlation CCI(t) and SI(t-j)					
	Bull markets			Bear markets		
j=	-1	0	1	-1	0	1
Belgium	-0.018	0.224***	0.081	0.084	0.380***	0.146*
Denmark	0.062	0.110*	0.193***	0.157*	0.219**	0.024
France	0.031	0.220***	0.127**	-0.034	0.361***	0.099
Germany	-0.054	0.075	0.001	0.065	0.073	0.022
Greece	-0.039	0.011	0.123	0.047	0.207**	-0.036
Ireland	-0.075	0.101*	0.141**	-0.003	0.171*	0.151*
Italy	-0.007	0.225***	0.071	0.074	0.213***	0.161**
Netherlands	-0.053	0.022	0.102*	0.000	0.255***	0.352***
Portugal	0.147*	0.197**	0.066	-0.029	0.298***	0.008
Spain	0.169**	0.228***	0.184***	0.034	0.249***	0.038
UK	0.038	0.269***	0.173***	-0.016	0.007	0.166*

This table presents the dynamic correlation estimates of the consumer confidence, CCI(t), and the associated stock market, SI(t-j), of the 11 countries, for j = -1,…,1. The superscripts (***), (**) and (*) indicate statistical significance at a 1%, 5% and 10% level respectively. Columns 1-3 show the correlation estimates for when the state of the economy is considered to be a bull market. Columns 4-6 show the correlation estimates for when the state of the economy is considered to be a bear market. The algorithm that is used to identify bull and bear markets is the Lunde and Timmerman (2004) algorithm. The sample period runs from January 1985 to June 2012.

The contemporaneous correlation estimates in Table 13 show that for most of the countries the bear market correlation estimates are higher than the bull market correlation estimates, exceptions being Germany, Italy and the UK. Also, the average correlation of all the countries when the state of the economy is considered to be a bear market, 0.221, is higher than when the state of the economy is considered to be a bull market, 0.153. However, when looking at the dynamic correlations and Granger causality results there is no similar difference in bull and bear markets recognized. The dynamic correlation estimates in Table 13 show that for most of the countries there is a higher and significant correlation estimate when j = 1 opposed to j = -1 for both the bear and bull markets. This indicates once again that the causality running from the stock market to the CCI is stronger than the other way around. But there is no difference between the bear and bull market dynamic correlation analysis, both states of the economy show more or less the same results. From the Granger causality results shown in Table 14 you can see that none of the countries have Granger causality running from the CCI to the stock market in both bull and bear markets, except for Italy. For Italy there is Granger causality running from the CCI to the stock market in bear markets with a 10% significance level. When looking at the Granger causality test results running from the stock market to the CCI, there is not a clear difference between being in a bull or in a bear market. When the state of the economy appears to be a bear market there is a stock market to CCI causality connection present for Italy, the Netherlands and Spain at a 5% significance level, and Belgium at a 1% significance level. When looking at the Granger causality in bull markets Ireland, Spain and the UK, Denmark and France, and Portugal, at a 1%, 5% and 10% significance level respectively, show a causal connection running from the stock market to the CCI. The VAR model coefficients for the bull and bear markets are shown in Table A.7 and A.8 in the Appendix, respectively.

Table 14: Granger causality Bull and Bear markets

	Granger causality (p-values)			
	Bull markets		Bear markets	
	CCI to SI	SI to CCI	CCI to SI	SI to CCI
Belgium	0.212	0.114	0.974	0.090
Denmark	0.359	0.036	0.303	0.569
France	0.943	0.030	0.283	0.436
Germany	0.137	0.674	0.552	0.492
Greece	0.755	0.304	0.924	0.975
Ireland	0.556	0.004	0.566	0.196
Italy	0.133	0.364	0.082	0.013
Netherlands	0.436	0.215	0.446	0.042
Portugal	0.720	0.079	0.376	0.768
Spain	0.327	0.008	0.498	0.020
UK	0.820	0.000	0.894	0.193

This table presents the Granger causality p-values for the bull and bear markets in two directions, from the CCI to the stock indices and from the stock indices to the CCI. The number of lags used are different per country depending on the outcome of the Portmanteau test, see table 6. Columns 1-2 show the results for when the state of the economy is considered to be a bull market. Columns 3-4 show the results for when the state of the economy is considered to be a bear market. The algorithm that is used to identify bull and bear markets is the Lunde and Timmerman (2004) algorithm. The sample period runs from January 1985 to June 2012.

This result that there is no comprehensible difference between the CCI and stock market when the state of the economy is considered a bull or bear market is somewhat counterintuitive, as I expected to find more significant values of Granger causality in the bear markets than in the bull markets. This is due to the fact that the contemporaneous correlation estimates show higher values in the bear markets. On the contrary, the dynamic correlation estimates do not show different results for being in a bull or a bear market. Next to that, the threshold correlation results in section 3.2 show that there is a higher contemporaneous correlation when CCI and/or stock indices are below their median. Although this is a sign that the CCI and the stock index move closer together in lesser periods, it is not fully comparable to the economy being in a bear market. Because a bear market is the period measured from a peak to a through, whereas the threshold correlation is measured under the median. An explanation for the Granger causality outcome could be that the total number of observations in especially the bear markets is quite small, as can be seen in Table 12. Also the average duration per bear market is fairly small. The small number of total observations in the bear markets and the small number of observations per bear market limit the reliability of the analysis.

5 Copulas

Another method to investigate the relationship between the CCI and the stock indices is to model the dependence by using copulas. Copulas help in the understanding of dependence at a deeper level and are very popular in statistical applications. They allow one to easily model and estimate the distribution of random vectors by estimating the marginals and copula separately. The marginal distribution functions describes the marginal distribution of each component and the copula describes the dependence structure between the components. This method is first introduced by Sklar (1959).

Theorem 1. *Let* $X = (X_1,...,X_n)^{\mathrm{T}}$ *be a random vector with cumulative distribution function* F *and let* F_i *denote the marginal distribution of* X_i*, for* $i = 1,...,n$*. Then there exists a copula* $C:[0,1]^n \to [0,1]$ *such that*

$$F(x_1,...,x_n) = C(F_1(x_1),...,F_n(x_n)). \tag{7}$$

A copula C *of the random vector* X *is thus a function that maps the univariate marginal distributions* $F_1,...,F_n$ *to the joint distribution* F*, and we write* $X \sim F = C(F_1,...,F_n)$*. If the marginals* F_i *are continuous, then* C *in* (1) *is unique and is given by*

$$C(u_1,...,u_n) = F(F_1^{-1}(u_1),...,F_n^{-1}(u_n)) \tag{8}$$

for $u = (u_1,...,u_n) \in R^n$ *where* $F_i^{-n}(u) = \inf\{x : F_i(x) \ge u\}$.

Conversely, given any collection of univariate distributions $F_1,...,F_n$ and any copula C, then F defined by (7) defines a valid joint distribution with marginal distributions $F_1,...,F_n$.

In this paper, I consider a bivariate relationship, namely the relationship between the CCI and the stock market. I use the symbols x and y $(x, y \in R)$ to denote the observations of the random variables X and Y; and u and v $(u, v \in [0,1])$ to denote their marginal cumulative distribution functions (CDFs). The probability density function (PDF) of a bivariate copula $C(u,v)$ is defined as

$$c(u,v) = \frac{\partial C(u,v)}{\partial u \partial v} \tag{9}$$

The density of the bivariate distribution $F(x, y)$ can be written as the product of the copula density and the marginal densities.

$$f(x, y) = c(F_X(x), F_Y(y)) \cdot f_X(x) \cdot f_Y(y) \tag{10}$$

In econometric applications there are currently two groups of copulas in use. The first group we can distinguish, consists of the Normal (Gaussian) copula and the Student *t* copula. The Normal copula is simple to understand and implement. The downside of this copula is that it imposes zero tail dependence and symmetric dependence between booms and crashes. The Student *t* copula allows for heterogeneous tail dependence between pairs of variables, but requires an equal upper and lower tail dependence. Both these copulas are of an elliptical form, and consequently do not

Table 15: Copula models and their properties

	Parameter(s)	Parameter space	Lower tail dependence	Upper tail dependence
Normal	ρ	(-1,1)	0	0
Plackett	γ	(0, ∞)	0	0
Frank	γ	(-∞, ∞)	0	0
Gumbel	γ	(1, ∞)	0	$2\text{-}2^{1/\gamma}$
Rotated Gumbel	γ	(1, ∞)	$2\text{-}2^{1/\gamma}$	0
Clayton	γ	(0, ∞)	$2^{1/\gamma}$	0
Rotated Clayton	γ	(0, ∞)	0	$2^{1/\gamma}$
Student's *t*	ρ, ν	(-1,1) (2,∞)	gT(ρ, ν)	gT(ρ, ν)
Symmetrized Joe-Claytor	τ^L, τ^U	[0, 1) [0, 1)	τ^L	τ^U

This table presents parametric copula models, along with their parameter and tail dependence properties. The Student's *t* copula lower and upper tail dependence is given by: $g_T(\rho,\nu) = 2 \times F_{Studt}\left(-\sqrt{(\nu+1)\frac{\rho-1}{\rho+1}}, \nu+1\right)$.

The symmetrized Joe-Clayton copula is a modification of the 'BB7' copula of Joe (1997), this copula is described in Patton (2006).

allow for different dependencies for different tails. The second group that we can discern consists of the Archimedean copulas. This group of copulas contains for example the Clayton, Gumbel or Frank copula. The Archimedean copulas allow for tail dependence and particular forms of asymmetry. This is due to the flexibility of generator functions, which these copulas follow from. When the number of variables is large, these copulas are quite restrictive because they usually have one or two parameters to characterize the dependence between all variables. Table 15 presents a summary of some common copula models and their properties. For a more detailed description and analysis of copulas Joe(1997) and Nelsen (1999) can be consulted.

5.1 Empirical distribution function

When estimating the copula models I use the full sample period, January 1985 to June 2012. The estimated standard residuals obtained from the estimated VAR models (5) and (6) are transformed using the empirical distribution function (EDF), and I obtain the estimated probability integral transform variable, $\hat{U}_{it}$:

$$\hat{F}_i(\varepsilon) = \frac{1}{T+1}\sum_{t=1}^{T} 1\{\hat{\varepsilon}_{it} \leq \varepsilon\}, \tag{11}$$

$$\hat{U}_{it} = \hat{F}_i(\hat{\varepsilon}_{it}).$$

When estimating the copula in Section 5.3 this results in a semiparametric copula-based model as explained in Patton (2012), using a nonparamemtric model for the marginal distributions, the EDF, and a parametric model for the copula.

5.2 Nonparametric dependence measures

Before focusing on the copula models I am looking at the nonparametric dependence measures[7], quantile, tail and symmetric dependence, to get a better understanding of which copula model is a good fit for the data.

Quantile dependence is a measure of the strength of the dependence between two variables in the joint lower, or joint upper, tails. Quantile dependence provides a more detailed description of the dependence structure of two variables than a scalar measure like linear correlation does. The strength of the dependence between the two variables is estimated by moving from the center

[7] No parametric assumptions are made for the copula and the marginal distribution functions. The dependence estimates are obtained using the empirical copula: $\hat{C}_m(u,v) = \frac{1}{m}\sum_{j=1}^{m} 1\{\frac{R_{1j}}{m} \leq u, \frac{R_{2j}}{m} \leq v\}$, where 1 denotes the indicator function, R_{1j} and R_{2j} are the ranks of the block maxima X^*_{lj} and Y^*_{lj}, respectively, j = 1,…,m and l = n/m.

($q=1/2$) to the tails, and by comparing the left tail ($q<1/2$) to the right tail ($q>1/2$). Following Patton (2012), the quantile dependence is defined as[8]:

$$\hat{\lambda}^{q}=\begin{cases}\dfrac{1}{Tq}\sum_{t=1}^{T}1\{U_{1t}\le q, U_{2t}\le q\}, & 0<q\le 1/2\\ \dfrac{1}{T(1-q)}\sum_{t=1}^{T}1\{U_{1t}>q, U_{2t}>q\}, & 1/2<q\le 1\end{cases} \tag{12}$$

Tail dependence is an extreme events dependence. In this application upper (lower) tail dependence measures the dependence between the CCI and the stock market when both the stock market and the CCI experience very good (bad) times. A nonparametric estimator of tail dependence considered in Frahm, et al. (2005) is the 'log'estimator:

$$\hat{\lambda}^{L}=2-\frac{\log\left(1-2(1-q^{*})+T^{-1}\sum_{t=1}^{T}1\{U_{1t}\le 1-q^{*}, U_{2t}\le 1-q^{*}\}\right)}{\log(1-q^{*})} \qquad \text{for } q^{*}\approx 0 \tag{13}$$

$$\hat{\lambda}^{U}=2-\frac{\log\left(T^{-1}\sum_{t=1}^{T}1\{U_{1t}\le 1-q^{*}, U_{2t}\le 1-q^{*}\}\right)}{\log(1-q^{*})} \qquad \text{for } q^{*}\approx 0 \tag{14}$$

The choice of a threshold q^{*} involves trading off the variance in the estimator (small threshold values) against bias (large threshold values). The method in Frahm, et al. (2005) is used to choose this threshold.

To get a better understanding about the symmetric dependence, I test for asymmetry jointly. To do this the estimated quantile dependence measures are stacked into a vector of the form:

$$\hat{\lambda}\equiv[\lambda^{q1},\lambda^{q2},\ldots,\lambda^{2p}]' \qquad \text{where } q_{p+j}=1-q_{j}, \quad \text{for } j=1,2,\ldots,p. \tag{15}$$

Then the following test can be conducted:

$$H_0: R\lambda=0 \qquad \text{vs.} \qquad H_a: R\lambda\neq 0 \tag{16}$$
$$\text{where} \quad R\equiv\left[I_p \vdots -I_p\right]$$

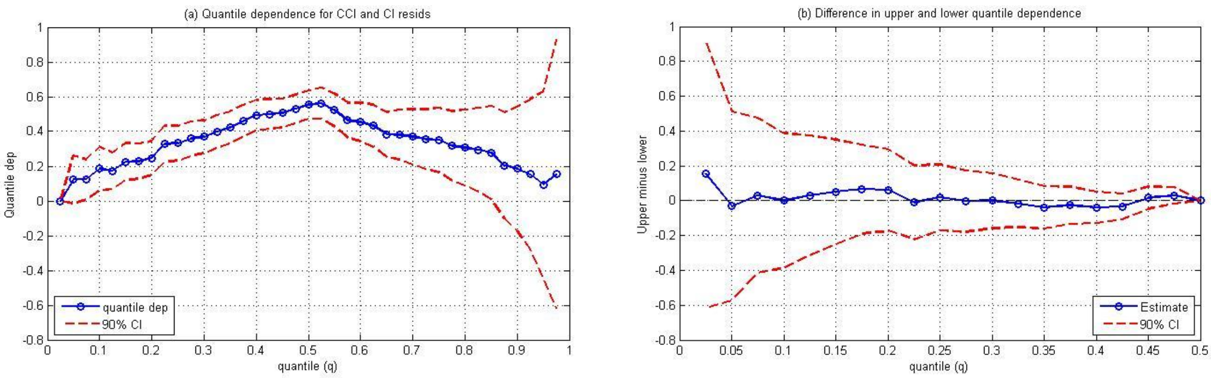
[8] This quantile definition is adapted to positively dependent variables.

Following from Rémillard (2010) that $\sqrt{T}(\hat{\lambda}-\lambda)\xrightarrow{d}N(0,V_\lambda)$ and using that $\hat{V}_{\lambda,S}$ denotes the bootstrap estimate of V_λ, the following holds under H_0:

$$T(\hat{\lambda}-\lambda)'R'(R\hat{V}_{\lambda,S}R')^{-1}R(\hat{\lambda}-\lambda)\xrightarrow{d}\chi^2_p \tag{17}$$

Information about quantile, tail and symmetric dependence is useful because many copula models impose symmetric dependence (Normal and Student t copula), zero tail dependence (Normal and Frank copula), or zero tail dependence in one of their tails (right for the Clayton copula and left for the Gumbel copula).

Figure 3: Quantile dependence results for the Netherlands



This figure shows the quantile dependence results for the Netherlands. Panel (a) presents the estimated quantile dependence between the residuals for the CCI and the SI, along with a 90% bootstrap confidence interval. Panel (b) presents the difference between the corresponding upper and lower quantile along with 90% bootstrap confidence interval for this difference. The sample period runs from January 1985 to June 2012.

Figure 3 presents the quantile dependence results for the Netherlands. Panel (a) shows the estimated quantile dependence plot, for $q \in [0.025, 0.975]$, along with a 90% confidence interval, calculated using a (pointwise) *iid* bootstrap approach. Panel (b) shows the difference between the upper and lower quantile dependence fractions, with as well a 90% bootstrap confidence interval. This figure shows that observations in the upper tail are slightly more dependent than observations in the lower tail from *q* = 0.25 onwards, especially for the smallest quantile *q* = 0.025. Though the confidence interval shows that these upper quantile dependence estimates are not as significant as the rest of the quantile estimates. Figure A.2 in the Appendix shows the quantile graphs for the other 12 countries. There can be seen that all the countries show minor differences between the upper and lower tail dependence, and slightly more difference in the smallest quantiles. Though this difference in tail dependence is shown by the quantile dependence graphs, when looking at the upper and lower tail dependence estimates presented in Table 16, I find that the tail dependence estimates are rather low and also not significant. The 90% bootstrap confidence intervals indicate zero tail dependence for both the lower and upper tail for roughly all the countries. Also, the large confidence intervals yield less precise estimates of the lower and upper tail dependence. This could be expected as Frahm, et al. (2005) states that nonparametric dependence estimates are sensitive in case of small sample sizes like 250 data points. Although the tail dependence estimates do not differ significantly from zero, some estimates are rather substantial, e.g. Belgium, Denmark and the UK.

Table 16: Estimates of tail dependence

	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	UK
	Lower tail dependence										
Estimate	0.162	0.209	0.158	0.090	0.131	0.160	0.095	0.066	0.192	0.099	0.161
90% CI	[0.004, 0.651]	[0.005, 0.690]	[0.002, 0.618]	[0.003, 0.523]	[0.000, 0.708]	[0.003, 0.640]	[0.001, 0.571]	[0.000, 0.521]	[0.004, 0.685]	[0.000, 0.580]	[0.001, 0.639]
	Upper tail dependence										
Estimate	0.166	0.142	0.036	0.032	0.117	0.041	0.267	0.082	0.014	0.049	0.112
90% CI	[0.005, 0.562]	[0.003, 0.632]	[0.000, 0.532]	[0.000, 0.501]	[0.000, 0.722]	[0.000, 0.519]	[0.020, 0.691]	[0.001, 0.550]	[0.000, 0.514]	[0.000, 0.560]	[0.000, 0.587]
p-value for λL=λU	0.500	0.528	0.608	0.541	0.556	0.574	0.399	0.456	0.591	0.558	0.536

This table presents the estimates of the lower and upper tail dependence coefficients for the residuals of the CCI and SI of the 11 countries, along with the 90% bootstrap confidence interval. Also the bootstrap p-value from the test that the upper and lower tail dependence coefficients are equal is presented. The sample period runs from January 1985 to June 2012.

Table 17: Results of joint asymmetric test

	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	UK
chi-squared statistic	0.199	0.041	0.143	0.046	0.203	0.449	1.233	0.284	0.655	0.827	0.085
p-valuea	0.978	0.998	0.986	0.997	0.977	0.930	0.745	0.963	0.884	0.843	0.994

This table presents the χ^2-statistic and its p-value of the joint asymmetric test, for the quantiles {0.025, 0.05, 0.10, 0.975, 0.95, 0.90}, on the CCI and SI residuals. The sample period runs from January 1985 to June 2012.

Besides looking at the lower and upper tail dependence coefficients separately, it is also interesting to see whether the tail dependence coefficients are equal:

$$H_0 : \lambda^L = \lambda^U \quad \text{vs.} \quad H_a : \lambda^L \neq \lambda^U . \tag{18}$$

The p-values for this difference are shown in Table 16. The p-values for all the countries are ranged between 0.399 and 0.608, indicating no rejection of the null hypothesis. Hence, no significant difference in the lower and upper tail dependence coefficients. Implementing the joint asymmetric test on the estimated quantile dependence function for the CCI and the SI residuals, for the quantiles

$q \in \{0.025, 0.05, 0.10, \ 0.975, 0.95, 0.90\}$, result in rather low χ^2 -statistic with very high corresponding p-values for all the 11 countries, shown in Table 17. These high p-values indicate no rejection of the null hypothesis and therefore the dependence structure is symmetric. These results are in line with the results in section 3.2. The analylsis of the threshold correlations indicate that there is no asymmetry present in the CCI and SI data. Although statistically, asymmetry is not the case, there is shown that per country some of the threshold correlations are different from each other, indicating slight asymmetry. When looking at the tail dependence estimates in Table 16 this is shown again. For Denmark, France, Ireland and Portugal the lower tail dependence estimate look rather higher than the upper tail dependence estimate. For Italy it is the other way around, the upper tail dependence estimate seems rather smaller than the the lower tail dependence estimate.

5.3 Copula estimates and tail dependence

In the previous section I conclude that zero tail dependence in both tails and asymmetry in the upper and lower tail dependence can not be rejected for the different countries. Although statistically this is the case, economically speaking there is some tail dependence present for various countries. As well as that the lower and upper tail dependence measures do differ from each other for a number of countries. The copula models considered must contain these same properties, as they are considered the best fit. Table 15 shows that the Normal, Plackett and Frank copula models are a good fit, as zero tail dependence is a feature of these copulas. Also the Student's *t* copula model is considered, as the model allows for non-zero symmetric tail dependence. I also include the symmetrized Joe-Clayton (SJC) copula model, which allows for asymmetric tail dependence and nests symmetry as a special case.

The copula parameters are estimated via maximum likelihood. The difficulty when working with a semiparametric copula-based model instead of a parametric copula model is that the copula likelihood depends on the parameters F_i, and on the marginal distribution parameters. Because of this, standard maximum likelihood methods cannot be applied in this semiparametric case. In such case the estimation of the copula parameter is conducted via the Canonical Maximum Likelihood (CML) method. First the margins are estimated using empirical distributions, then the copula parameters are estimated using an ML approach:

$$\theta_{CML} = \arg\max_{\theta} \sum_{t=1}^{T} \log c\left(\hat{U}_{1t},...,\hat{U}_{nt};\theta\right) \tag{19}$$

Chen and Fan (2006b) provide conditions under which the asymptotic variance of the maximum likelihood estimator of the copula parameter depends on the estimation error in the EDF, but does not depend on the estimated parameters in the marginal distributions.

Table 18 presents the estimated parameters of these copula models allong with the values of the log-likelihood. The estimated parameters of the SJC model are the lower and upper tail dependence estimates. Here the same conclusions are obtained as in Table 16. The lower and upper tail dependies do not differ significantly from each other with a 5% significance level. Although not significant, there are some differences between lower and upper tail dependencies seen. For most of the countries the lower tail dependence is larger, except for Belgium and Italy, which indicates that in lesser times the CCI and the stock market move closer together than in better times. These results are in line with the contemporaneous bull/bear market and threshold correlation results.

According to the log-likelihood values in Table 18, the SJC model is the best copula model for most of the countries, except for Greece where the Student's *t* model is the best copula model fit. The SJC model as the best fit for most of the countries is followed by the Student's *t* and the Normal copula. To analyze if the SJC model is significantly a better fit for the data than the Normal and Student's *t* models I use the pseudo –likelihood ratio (PLR) test described by Chen and Fan (2006b). This test is constructed for model selection between two semiparametric copula-based models. Chen and Fan (2006b) show that for models that are generalized non-nested[9] the likelihood ratio *t* test statistic can be written as:

$$T^N = \frac{T^{1/2}\left\{\overline{L}_{1T}\left(\hat{\theta}_{1T}\right) - \overline{L}_{2T}\left(\hat{\theta}_{2T}\right)\right\}}{\hat{\sigma}_T} \tag{20}$$

where $\hat{\sigma}_T^2 = \frac{1}{T}\sum_{t=1}^{T}\left(\tilde{d}_t + \sum_{j=1}^{n}\left\{\hat{Q}_{2jt}(\hat{\gamma}_{2T}) - \hat{Q}_{1jt}(\hat{\gamma}_{1T})\right\}\right)^2$

$$d_t \equiv \log c_1\left(\hat{U}_t;\hat{\gamma}_{1T}\right) - \log c_2\left(\hat{U}_t;\hat{\gamma}_{2T}\right)$$

$$\tilde{d}_t = d_t - \overline{d}_T$$

$$\hat{Q}_{ijt}(\hat{\gamma}_{iT}) \equiv \frac{1}{T}\sum_{s=1, s\neq t}^{T}\left\{\frac{\partial \log c_i(\hat{U}_s;\hat{\gamma}_{iT})}{\partial u_j}\left(1\left\{\hat{U}_{jt} \leq \hat{U}_{js}\right\} - \hat{U}_{js}\right)\right\}$$

[9] Chen and Fan (2006b) state that two models are generalized non-nested if the set $\left\{(u_1,\ldots,u_d): c_1\left(u_1,\ldots,u_d;\alpha_1^*\right) \neq c_2\left(u_1,\ldots,u_d;\alpha_2^*\right)\right\}$ has positive Lebesgue measure (the volume measure), with α^* the pseudo true value. They test the null hypothesis of generalized nested models by testing H_0: $\sigma_a^2 = 0$. The estimator of σ_a^2 is given by $\hat{\sigma}_a^2 = \frac{1}{T}\sum_{t=1}^{T}\left(\tilde{d}_t\right)^2$.

where the subscript N in T^N is meant for non-nested models. This test statistic is Normally distributed under the null hypothesis that the benchmark copula model is not worse than the candidate copula model. The test is derived under the assumption that the conditional copula is constant.

When two models are generalized nested, the test statistic is defined as:

$$T^Q = 2T\left\{\overline{L}_{1T}\left(\hat{\theta}_{1T}\right) - \overline{L}_{2T}\left(\hat{\theta}_{2T}\right)\right\} \tag{21}$$

where the subscript Q in T^Q is meant for non-nested models. This PLR test statistic has a distribution of a weighted sum of independent $\chi^2_{(1)}$ random variables, the weight is the $(a_1 + a_2) \times 1$ vector of eigenvalues of the matrix W defined as $W = \begin{bmatrix} \Sigma_2 B_2^{-1} & -\Sigma_{12}' B_1^{-1} \\ \Sigma_{12} B_2^{-1} & -\Sigma_1 B_1^{-1} \end{bmatrix}$.

Table 19 presents the results of the PLR test described above. The results show that most of the test statistics are not significant. Only for France, Italy and the UK there can be stated that the Student's *t* model significantly beats the SJC model. Furthermore, there can be seen that the Student's *t* model is always prefered over the Normal model, but not significantly. And for 8 (3 of them are significant) out of the 11 countries the Student's *t* model is also prefered over the SJC model. Table 19 also shows that only in two cases the compared models are considered generalized non-nested, resulting from the Chen and Fan (2006b) test on the null hypothesis that the two models are generalized nested. The reason that not much of the differences in likelihood values in Table 18 are confirmed by the PLR test results and that most of the models are considered generalized nested could be that the three models that are analyzed are quite similar for the central region and the small number of observation. The largest differences between these models occur in the tails, where we have less data to distinguish between the competing specifications. Concluding, it is not really clear which copula model would be the best to model the dependence between the CCI and the stock market.

Table 18: Copula model parameter estimates

	Normal		Plackett		Frank		Student's t		Sym Joe-Clayton	
	Est. Param.	log L	Est. Param.	log L	Est. Param.	log L	Est. Param.	log L	Est. Param.	log L
Belgium	0.285	11.4	2.316	9.7	1.638	9.2	0.286, 0.118	12.3	0.086, 0.188	**13.8**
Denmark	0.111	1.6	1.199	0.5	0.354	0.5	0.084, 0.131	3.1	0.039, 0.016	**3.3**
France	0.292	13.3	2.417	12.6	1.789	12.2	0.299, 0.078	14.0	0.232, 0.011	**15.3**
Germany	0.172	4.9	1.698	5.0	1.065	5.0	0.180, 0.061	5.4	0.106, 0.000	**6.0**
Greece	0.224	4.5	2.035	4.4	1.344	4.0	0.229, 0.206	**6.6**	0.133, 0.069	5.8
Ireland	0.107	1.8	1.336	1.3	0.556	1.3	0.106, 0.083	2.4	0.073, 0.000	**3.3**
Italy	0.213	7.6	1.688	4.5	1.000	4.2	0.177, 0.183	10.5	0.016, 0.151	**11.5**
Netherlands	0.161	4.3	1.606	3.8	0.928	3.7	0.164, 0.030	4.3	0.031, 0.035	**4.6**
Portugal	0.266	8.6	2.233	8.2	1.635	8.1	0.276, 0.030	8.7	0.249, 0.000	**10.8**
Spain	0.270	11.5	2.258	11.1	1.668	11.0	0.278, 0.011	11.5	0.187, 0.017	**11.6**
UK	0.192	6.2	1.799	5.4	1.089	5.0	0.187, 0.136	7.5	0.165, 0.000	**9.0**

This table presents the estimated parameters of the Normal, Plackett, Frank, Student's *t* and symmetrized Joe-Clayton models for the copula of the standardized residuals of the CCI and SI of the 11 countries. The estimated parameters of the Student's *t* and symmetrized Joe-Clayton models are (ρ, ν^{-1}) and (τ^{L}, τ^{U}), respectively. The value of the copula log-likelihood at the optimum is also presented. The best copula model per country according to the log-likelihood value appears in bold type. The sample period runs from January 1985 to June 2012.

Table 19: PLR test statistics, model comparison

	Normal	Student's t	Sym Joe-Clayton
	Belgium		
Normal	-		
Student's t	1.914	-	
Sym Joe-Clayton	2.356	0.442	-
	Denmark		
Normal	-		
Student's t	2.867	-	
Sym Joe-Clayton	3.031	0.165	-
	France		
Normal	-		
Student's t	1.398	-	
Sym Joe-Clayton	-9.141	**-10.539**	-
	Germany		
Normal	-		
Student's t	1.001	-	
Sym Joe-Clayton	-4.003	-5.004	-
	Greece		
Normal	-		
Student's t	4.101	-	
Sym Joe-Clayton	1.937	-2.164	-
	Ireland		
Normal	-		
Student's t	1.199	-	
Sym Joe-Clayton	-3.333	-4.531	-
	Italy		
Normal	-		
Student's t	1.064^{N}	-	
Sym Joe-Clayton	0.580	**-5.256**	-
	Netherlands		
Normal	-		
Student's t	0.180	-	
Sym Joe-Clayton	0.762	0.582	-
	Portugal		
Normal	-		
Student's t	0.171	-	
Sym Joe-Clayton	-14.839	-15.010	-
	Spain		
Normal	-		
Student's t	0.049	-	
Sym Joe-Clayton	-7.346	-7.395	-
	UK		
Normal	-		
Student's t	2.720	-	
Sym Joe-Clayton	1.532^{N}	**-9.509**	-

This table presents the Chen and Fan (2006b) PLR test statisctics to compare three constant copula models, the Normal, Student's *t* and symmetrized Joe-Clayton copula models. A positive test statistic indicates that the model on the left is better than the model on the top. The opposite holds for a negative test statistic. Test statistics that are significant on a 5% significance level are presented in bold. The subscript ^{N} indicate that the models that generalized non-nested, and the PLR test statistic is calculated using equation (20). If there is no subscript present the models are generalized nested and the PLR test statistic is calculated using equation (21).

6 Conclusion

In this thesis I study the relationship between the consumer confidence index (CCI) and stock market of 11 countries in the European Union. Because the CCI is a monthly measured index, the headline stock index prices are transformed to monthly data as well. The Johansen Cointegration Trace test indicates no cointegration. Hence, no long term relationship between the CCI and stock market can be indicated. I therefore only analyse the short term relationship.

I start this research with analyzing the full sample general relationship between the CCI and the stock market by looking at the contemporaneous and dynamic correlations. The contemporaneous correlation analysis indicates that there is a positive relationship between consumer confidence and the stock market. The result that the CCI and the 1-month lagged stock index show significant correlation estimates indicate that the direction of the causality runs from the stock market to the CCI.

Looking at a so called 'threshold correlation' gives a first impression about the asymmetry in this relationship. When using the median of the CCI and the stock return as a threshold, I conclude that there is no significant evidence for asymmetry. Though, in lesser periods the consumer confidence and the stock market are moving closer together compared to better periods. This points to some slight asymmetry, although not significant.

I continue by looking at VAR (vector autoregression) models and performing Granger causality tests, to see if the dynamic correlation results show the right direction of the relationship. Different lag orders are applied for the different countries depending on the outcome of the Portmanteau autocorrelation residual test. The full sample results show indeed that the Granger causality is running from the stock market to the CCI, and not the other way around. The sample period is split in two subsamples, 1985-1998 and 1999-2012, to explore the development of the relationship of the CCI and the stock market through time. The contemporaneous correlation estimates show that most of the countries have an increased correlation between the CCI and the stock market in the second period. Though the CCI and 1-month lagged stock market correlations do not show this difference. Also, the results from the Granger causality tests do not indicate an overall difference between the two periods. Hence, there is a stable relationship between the CCI and the stock market through time. Analyzing the relationship in different stages of the economy is done by splitting the data in bull and bear markets by using the Lunde and Timmerman (2004) algorithm. The Granger causality results show that there is not a clear difference between the state of the economy being bullish or bearish. Although, the contemporaneous correlation show a higher and more significant relationship in bear markets.

At last I use copula models to analyze the dependence between the CCI and the stock market. By looking at some nonparametric dependence measures, quantile, tail and symmetric dependence, I conclude that zero tail dependence in both tails and asymmetry in the upper and lower tail dependence can not be rejected for the different countries. These symmetry results are in line with the threshold correlation results. However, economically speaking there is some slight tail dependence and asymmetry present. Therefore, I choose to include the Student's *t* and the symmetrized Joe-Clayton (SJC) copula models in the analysis besides the copula models that allows zero tail dependence. The log likelihood analysis and the Chen and Fan (2006b) PLR test do not give a clear answer on which copula model (the Normal, Student's *t* or SJC) would be the best to model the dependency structure of the CCI and the stock market.

To summarize, I find that, the stock market has a significant influence on the consumer confidence. Although this correlation slightly changes through time and in different stages of the economy, these differences are not significant.

Lastly, I provide some venues for future research. The financial crisis we are currently facing impacts the South European countries more than the Western European countries. This thesis focuses on 11 countries in the EU separately. It might be interesting to divide these countries in a South and West European part to see whether there is a difference in relationship in CCI and the stock market between these two groups. It might be that the consumers in the Southern parts of Europe might react less adequate to changes in the stock market because of the Southern mentality. If this is the case it might be particularly interesting for international companies which are present all across Europe because they might adopt a different investment strategy in the two parts of Europe. Next to that it might also be interesting to research if there is a difference in relationship between the CCI and the stock market in the EU countries which use the Euro as a currency versus EU countries which do not use the Euro currency as a consumer payment currency (e.g. U.K and Denmark). To research if the consumers in non Euro countries feel less threatened by fluctuations in the stock market. For the identification of bull and bear market periods I use the rules-based Lunde and Timmerman (2004) algorithm. Other identification algorithms, such as regime-switching models that also take signs and volatility into account could lead to other and more meaningful results. With respect to the copula analysis it could be interesting to look at time varying copula models. For example the time varying symmetrized Joe-Clayton copula could provide some interesting results.

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Appendix

Table A.1: ADF and Phillip-Perron test

	Panel A										
	Belgium	Denmark	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	UK
ADF test statistic	-17.710	-19.291	-17.629	-15.911	-14.920	-21.115	-21.638	-18.351	-13.948	-19.311	-20.673
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Phillip-Perron test statistic	-17.710	-19.617	-17.627	-16.319	-14.923	-21.670	-21.661	-18.359	-13.918	-19.251	-20.688
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Panel B										
	BEL 20	C20	CAC40	DAX30	FTSE ATHEX 20	ISEQ	FTSE MIB	AEX	PSI-20	IBEX 35	FTSE 100
ADF test statistic	-11.902	-12.139	-12.771	-13.265	-9.032	-13.666	-8.116	-13.055	-10.375	-12.979	-14.844
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Phillip-Perron test statistic	-12.064	-12.290	-12.791	-13.219	-9.032	-13.613	-14.219	-13.005	-10.325	-12.686	-14.730
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

This table shows the test statistics and p-values of the Augmented Dickey-Fuller (ADF) and Phillip-Perron test for the first differences of the CCI (ΔCCI), shown in Panel A, and first differences of the ln stock indices (Δln(SI)), shown in Panel B, for the 11 countries over the period January 1985 to June 2012. The tests for the ΔCCI include only a constant. While the tests for the Δln(SI) include a constant and a trend. For the ΔCCI and Δln(SI) of all the 11 countries is shown that there is no unit root present, hence these time series are stationary.

Table A.2: Johansen Cointegration Trace test full sample

	Hypothesized No. Of CE(s)	Eigenvalues	Trace Statistic	0.01 Critical Value	Prob.**
Belgium	None	0.045	15.785	19.937	0.045
	At most 1	0.013	3.500	6.635	0.061
Denmark	None	0.057	17.549	19.937	0.024
	At most 1	0.007	1.916	6.635	0.166
France	None	0.039	14.700	19.937	0.066
	At most 1	0.009	2.800	6.635	0.094
Germany	None	0.031	14.090	19.937	0.081
	At most 1	0.011	3.706	6.635	0.054
Greece	None	0.049	8.810	19.937	0.383
	At most 1	0.000	0.063	6.635	0.802
Ireland	None	0.023	11.951	19.937	0.159
	At most 1	0.015	4.799	6.635	0.029
Italy	None	0.021	8.662	19.937	0.398
	At most 1	0.005	1.740	6.635	0.187
Netherlands	None	0.017	8.431	19.937	0.421
	At most 1	0.009	2.806	6.635	0.094
Portugal	None	0.034	10.446	19.937	0.248
	At most 1	0.011	2.501	6.635	0.114
Spain	None	0.021	9.009	19.937	0.365
	At most 1	0.008	2.468	6.635	0.116
United Kingdom	None	0.026	13.317	19.937	0.104
	At most 1	0.014	4.698	6.635	0.030

This table shows the results of the Johansen Cointegration Trace test between the CCI and the ln(SI) for the 11 different countries over the period January 1985 to June 2012. I include a deterministic trend in the data and an intercept but no trend in the CE and test VAR. Furthermore, I include 2 lags for all the countries, except for the UK with 1 lag, selected by the SC (Schwarz information criterion) lag order selections criteria. I look at the Trace test because it is said to be superior in some situations to that of the Maximum Eigenvalue test, by Lüutkepohl, Saikkonen and Trenkler (2001). The trace test indicates no cointegration at the 0.01 level for all the 11 countries. **MacKinnon-Haug-Michelis (1999) p-values.

Table A.3: Granger causality full sample

	Granger causality (p-values)					
	k=1		k=3		k=6	
	CCI to SI	SI to CCI	CCI to SI	SI to CCI	CCI to SI	SI to CCI
Belgium	0.615	0.003	0.478	0.026	0.418	0.022
Denmark	0.458	0.017	0.338	0.037	0.600	0.022
France	0.171	0.002	0.579	0.019	0.897	0.004
Germany	0.839	0.020	0.492	0.003	0.580	0.012
Greece	0.984	0.070	0.963	0.133	0.750	0.092
Ireland	0.364	0.000	0.904	0.000	0.560	0.000
Italy	0.656	0.000	0.918	0.001	0.069	0.015
Netherlands	0.995	0.000	0.620	0.000	0.478	0.000
Portugal	0.407	0.206	0.369	0.138	0.488	0.168
Spain	0.335	0.002	0.438	0.005	0.749	0.041
UK	0.727	0.001	0.357	0.005	0.792	0.012

This table presents the p-values of the Granger causality test for the full sample in two directions, from the CCI to the stock indices and from the stock indices to the CCI, with lags k = 1,3,6. The sample period runs from January 1985 to June 2012.

Table A.4: Johansen Cointegration Trace test 1985-1998

	Hypothesized No. Of CE(s)	Eigenvalues	Trace Statistic	0.01 Critical Value	Prob.**
Belgium	None	0.113	12.637	19.937	0.129
	At most 1	0.000	0.001	6.635	0.974
Denmark	None	0.054	6.600	19.937	0.625
	At most 1	0.007	0.749	6.635	0.387
France	None	0.034	4.965	19.937	0.813
	At most 1	0.002	0.331	6.635	0.565
Germany	None	0.025	6.684	19.937	0.615
	At most 1	0.015	2.442	6.635	0.118
Greece	None	0.773	22.788	19.937	0.003
	At most 1	0.238	3.540	6.635	0.060
Ireland	None	0.068	11.814	19.937	0.166
	At most 1	0.002	0.266	6.635	0.606
Italy	None	0.041	10.691	19.937	0.231
	At most 1	0.023	3.822	6.635	0.051
Netherlands	None	0.027	4.733	19.937	0.837
	At most 1	0.002	0.279	6.635	0.597
Portugal	None	0.078	5.830	19.937	0.716
	At most 1	0.002	0.167	6.635	0.683
Spain	None	0.037	5.285	19.937	0.778
	At most 1	0.000	0.003	6.635	0.955
United Kingdom	None	0.033	5.847	19.937	0.714
	At most 1	0.002	0.316	6.635	0.574

This table shows the results of the Johansen Cointegration Trace test between the CCI and the ln(SI) for the 11 different countries over the period January 1985 to December 1998. I include a deterministic trend in the data and an intercept but no trend in the CE and test VAR. Furthermore, I include 2 lags for all the countries, except for the UK with 1 lag, selected by the SC (Schwarz information criterion) lag order selections criteria. I look at the Trace test because it is said to be superior in some situations to that of the Maximum Eigenvalue test, by Lüutkepohl, Saikkonen and Trenkler (2001). The trace test indicates no cointegration at the 0.01 level for all the countries, exception being Greece. **MacKinnon-Haug-Michelis (1999) p-values.

Table A.5: Johansen Cointegration Trace test 1999-2012

	Hypothesized No. Of CE(s)	Eigenvalues	Trace Statistic	0.01 Critical Value	Prob.**
Belgium	None	0.038	8.627	19.937	0.401
	At most 1	0.015	2.387	6.635	0.122
Denmark	None	0.075	18.364	19.937	0.018
	At most 1	0.035	5.768	6.635	0.016
France	None	0.091	18.565	19.937	0.017
	At most 1	0.019	3.060	6.635	0.080
Germany	None	0.049	12.840	19.937	0.121
	At most 1	0.028	4.649	6.635	0.031
Greece	None	0.034	5.593	19.937	0.743
	At most 1	0.000	0.006	6.635	0.940
Ireland	None	0.028	6.067	19.937	0.688
	At most 1	0.012	1.819	6.635	0.177
Italy	None	0.022	3.582	19.937	0.934
	At most 1	0.000	0.036	6.635	0.850
Netherlands	None	0.063	12.646	19.937	0.128
	At most 1	0.013	2.041	6.635	0.153
Portugal	None	0.025	5.497	19.937	0.754
	At most 1	0.009	1.476	6.635	0.225
Spain	None	0.045	9.725	19.937	0.303
	At most 1	0.014	2.207	6.635	0.137
United Kingdom	None	0.036	8.599	19.937	0.404
	At most 1	0.016	2.604	6.635	0.107

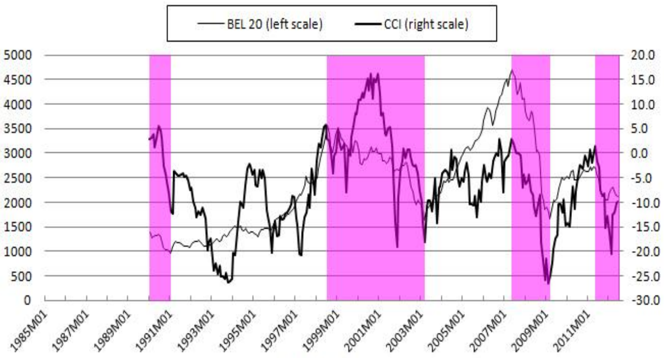
This table shows the results of the Johansen Cointegration Trace test between the CCI and the ln(SI) for the 11 different countries over the period January 1985 to June 2012. I include a deterministic trend in the data and an intercept but no trend in the CE and test VAR. Furthermore, I include 2 lags for all the countries, except for the UK with 1 lag, selected by the SC (Schwarz information criterion) lag order selections criteria. I look at the Trace test because it is said to be superior in some situations to that of the Maximum Eigenvalue test, by Lüutkepohl, Saikkonen and Trenkler (2001). The trace test indicates no cointegration at the 0.01 level for all the 11 countries. **MacKinnon-Haug-Michelis (1999) p-values.

Table A.6: Dynamic correlations two periods, 1985-1998 1999-2012

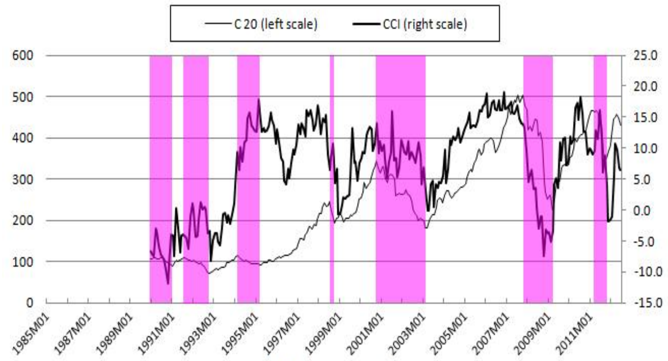
	Correlation CCI(t) and SI(t-j)					
	1985-1998			1999-2012		
j=	-1	0	1	-1	0	1
Belgium	0.047	0.238***	0.261***	0.092*	0.382***	0.090
Denmark	-0.085	0.116	0.193**	0.195***	0.213***	0.074
France	-0.045	0.244***	0.125*	0.096	0.417***	0.195***
Germany	-0.024	0.120*	0.101*	0.147**	0.266***	0.188***
Greece	-0.444**	0.046	0.354*	0.159**	0.256***	0.074
Ireland	-0.050	0.165**	0.136**	0.040	0.213***	0.208***
Italy	0.019	0.266***	0.127*	0.066	0.215***	0.147**
Netherlands	0.028	0.170**	0.231***	0.111*	0.302***	0.317
Portugal	-0.025	0.156*	0.179*	0.099	0.353***	0.054
Spain	0.121*	0.327***	0.139**	0.151**	0.252***	0.123
UK	0.004	0.287***	0.103*	0.133**	0.132**	0.212

This table presents the dynamic correlation estimates of the consumer confidence, CCI(t), and the associated stock market, SI(t-j), of the 11 countries, for j = -1,…,1. The superscripts (***), (**) and (*) indicate statistical significance at a 1%, 5% and 10% level respectively. Columns 1-3 show the correlation estimates for the sample period January 1985 until December 1998. Columns 4-6 show the correlation estimates for the sample period January 1999 until June 2012.

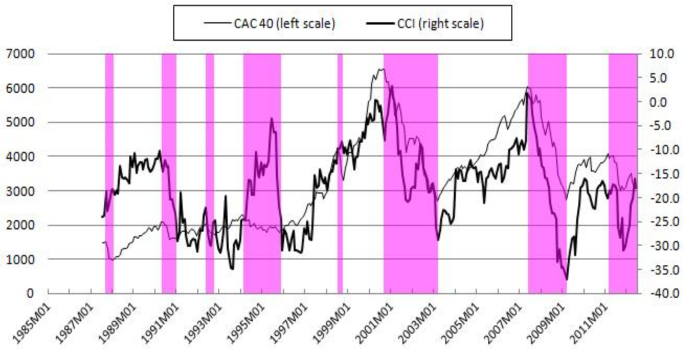
Figure A.1: Identification of bull and bear markets



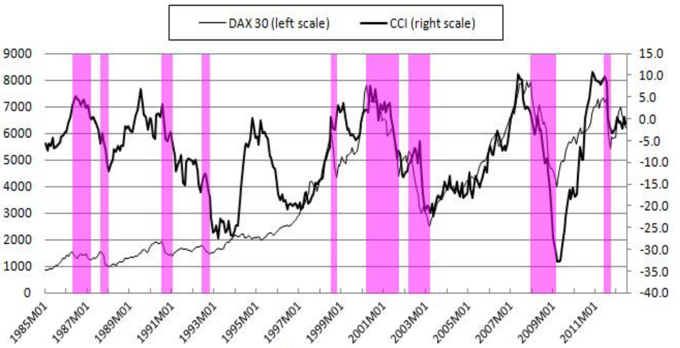
(a) Belgium



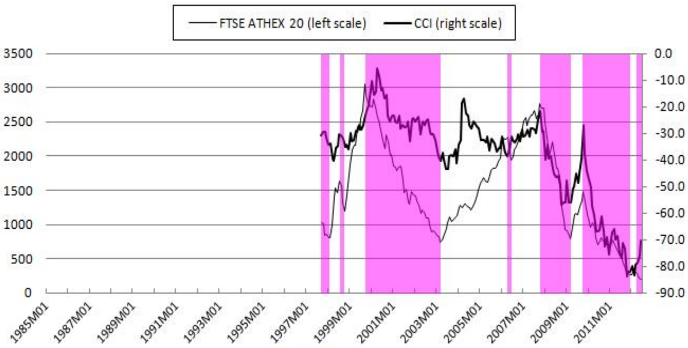
(b) Denmark



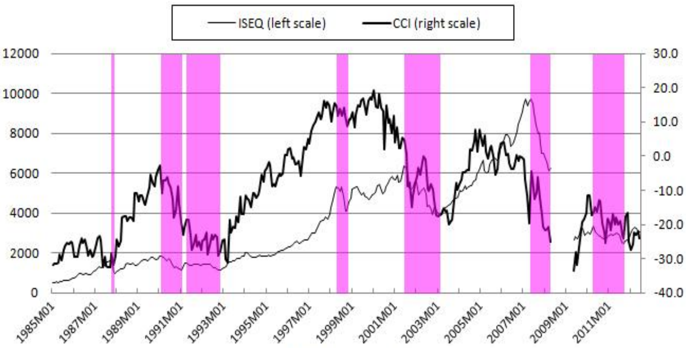
(c) France



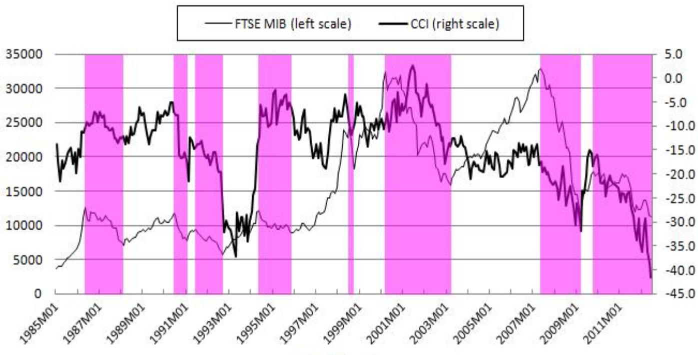
(d) Germany



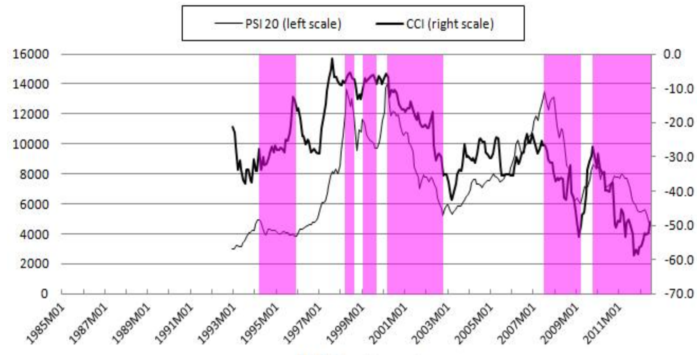
(e) Greece



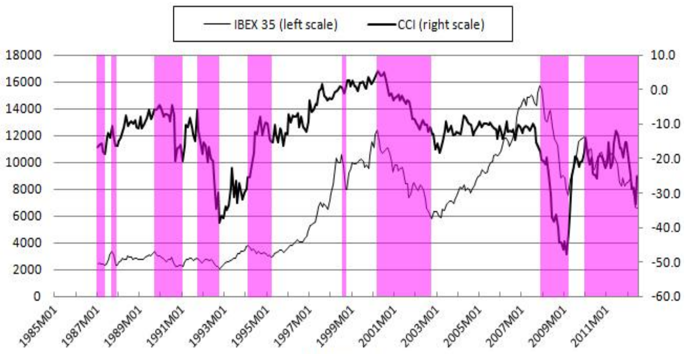
(f) Ireland



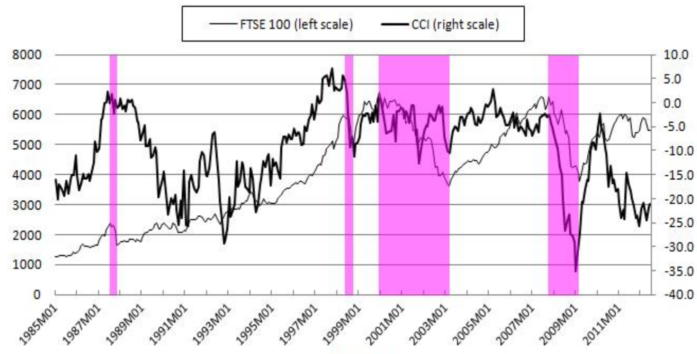
(g) Italy



(h) Portugal



(i) Spain



(j) UK

This figure shows the identification of bull and bear market periods for the different countries over the period January 1985 to June 2012. Some countries have a shorter sample period, depending on the CCI and SI data that is available, which is presented in the Data section. The algorithm that is used to identify the bull and bear markets is the Lunde and Timmerman (2004) algorithm. The thin black line plots the stock market index, and the thick black line plots the CCI. Purple areas indicate bear markets, and white areas correspond with bull markets.

Table A.7: VAR models bull market

	Belgium		Denmark		France		Germany		Greece		Ireland	
	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI
CCI(-1)	-0.191	-0.001	-0.181	0.000	-0.178	0.000	0.059	-0.001	-0.056	-0.001	-0.269	-0.001
	(0.079)	(0.001)	(0.074)	(0.001)	(0.078)	(0.001)	(0.067)	(0.001)	(0.129)	(0.002)	(0.071)	(0.001)
CCI(-2)			-0.188	-0.001			-0.045	0.002			-0.059	-0.001
			(0.071)	(0.001)			(0.066)	(0.001)			(0.071)	(0.001)
SI(-1)	11.340	0.311	13.378	0.038	13.071	0.112	3.396	0.172	6.820	0.335	17.150	0.217
	(7.133)	(0.072)	(5.276)	(0.075)	(5.990)	(0.073)	(4.364)	(0.066)	(6.587)	(0.111)	(5.694)	(0.068)
SI(-2)			2.477	-0.144			-2.326	-0.027			-11.905	-0.098
			(5.171)	(0.073)			(4.229)	(0.064)			(5.818)	(0.069)
C	0.191	0.011	-0.022	0.024	0.189	0.018	0.458	0.018	0.298	0.033	0.351	0.019
	(0.260)	(0.003)	(0.243)	(0.003)	(0.244)	(0.003)	(0.197)	(0.003)	(0.534)	(0.009)	(0.276)	(0.003)
R^2	0.042	0.105	0.090	0.040	0.044	0.014	0.010	0.042	0.018	0.117	0.116	0.057

	Italy		Netherlands		Portugal		Spain		UK	
	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI
CCI(-1)	-0.252	-0.001	-0.141	-0.001	0.215	0.001	-0.319	0.001	-0.216	0.000
	(0.087)	(0.002)	(0.071)	(0.001)	(0.096)	(0.001)	(0.073)	(0.001)	(0.062)	(0.001)
CCI(-2)	0.042	0.001	-0.105	0.001			-0.018	-0.001		
	(0.091)	(0.002)	(0.072)	(0.001)			(0.072)	(0.001)		
CCI(-3)	0.036	-0.003	0.064	0.001						
	(0.083)	(0.001)	(0.071)	(0.001)						
CCI(-4)			-0.056	0.001						
			(0.070)	(0.001)						
SI(-1)	6.648	0.312	4.622	0.145	1.838	0.385	9.527	0.188	20.549	0.188
	(4.674)	(0.082)	(6.751)	(0.072)	(6.537)	(0.088)	(4.737)	(0.080)	(5.512)	(0.062)
SI(-2)	3.079	0.014	1.558	-0.035			9.496	0.032		
	(5.004)	(0.088)	(6.665)	(0.071)			(4.492)	(0.076)		
SI(-3)	1.640	0.143	-2.400	0.087						
	(4.794)	(0.084)	(6.548)	(0.070)						
SI(-4)			13.867	-0.038						
			(6.104)	(0.065)						
C	-0.053	0.017	0.441	0.014	0.189	0.017	-0.085	0.017	-0.083	0.009
	(0.270)	(0.005)	(0.311)	(0.003)	(0.321)	(0.004)	(0.222)	(0.004)	(0.182)	(0.002)
R^2	0.077	0.131	0.073	0.047	0.050	0.173	0.142	0.054	0.073	0.035

This table shows the VAR model results presented in (5) and (6) for the sample running from January 1985 to June 2012 for when the state of the economy is considered to be a bull market. The number of lags used are different per country depending on the outcome of the Portmanteau test, see table 6. Standard errors are presented in parentheses.

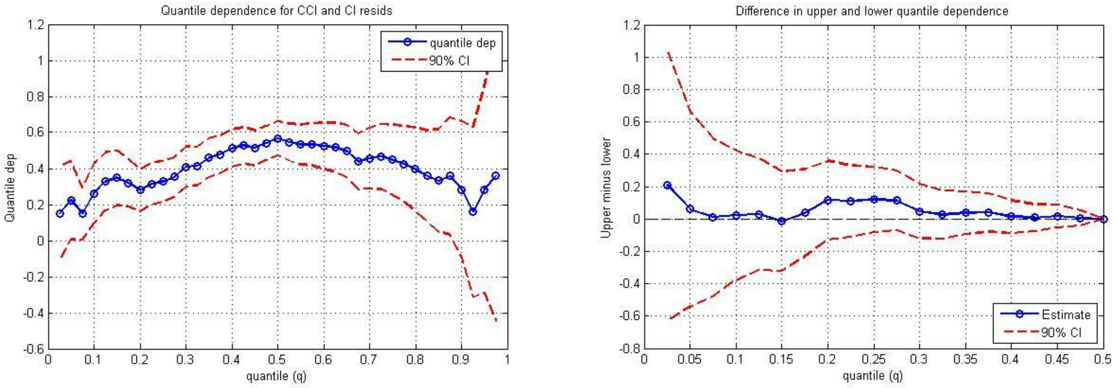
Table A.8: VAR models bear market

	Belgium		Denmark		France		Germany		Greece		Ireland	
	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI
CCI(-1)	-0.102	0.000	-0.258	0.002	0.043	-0.002	0.029	0.001	-0.140	0.000	-0.122	0.002
	(0.109)	(0.002)	(0.123)	(0.002)	(0.107)	(0.002)	(0.128)	(0.003)	(0.104)	(0.002)	(0.120)	(0.002)
CCI(-2)			-0.201	-0.002			-0.120	0.003			-0.159	0.000
			(0.127)	(0.002)			(0.133)	(0.003)			(0.110)	(0.002)
SI(-1)	12.312	0.230	7.514	0.150	4.930	0.216	-0.833	0.205	-0.178	0.165	10.067	0.026
	(7.193)	(0.107)	(7.081)	(0.125)	(6.300)	(0.104)	(5.743)	(0.137)	(5.775)	(0.108)	(6.045)	(0.096)
SI(-2)			-0.267	-0.088			7.319	-0.172			-6.205	-0.151
			(7.259)	(0.129)			(6.117)	(0.146)			(8.811)	(0.140)
C	-0.539	-0.018	-0.184	-0.028	-0.467	-0.025	-1.168	-0.039	-1.097	-0.048	-0.693	-0.028
	(0.384)	(0.006)	(0.423)	(0.007)	(0.370)	(0.006)	(0.513)	(0.012)	(0.534)	(0.010)	(0.472)	(0.008)
R^2	0.030	0.052	0.075	0.062	0.011	0.042	0.039	0.073	0.021	0.028	0.087	0.030

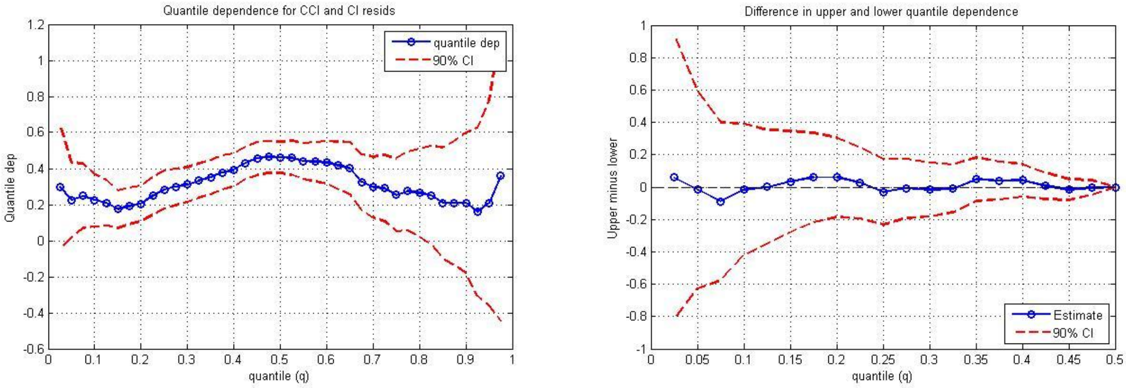
	Italy		Netherlands		Portugal		Spain		UK	
	CCI	SI	CCI	SI	CCI	SI	CCI	SI	CCI	SI
CCI(-1)	-0.312	0.001	-0.106	-0.001	-0.069	-0.001	-0.144	0.001	-0.208	0.000
	(0.094)	(0.002)	(0.126)	(0.003)	(0.099)	(0.002)	(0.102)	(0.001)	(0.127)	(0.002)
CCI(-2)	-0.339	-0.004	0.019	-0.005			0.005	0.002		
	(0.095)	(0.002)	(0.125)	-0.003			(0.104)	(0.001)		
CCI(-3)	-0.028	0.002	-0.002	0.002						
	(0.093)	(0.002)	(0.127)	(0.003)						
CCI(-4)			-0.062	0.000						
			(0.120)	(0.003)						
SI(-1)	9.699	0.118	16.841	0.376	1.787	0.192	7.319	0.132	10.789	0.106
	(4.184)	(0.090)	(5.481)	(0.117)	(6.041)	(0.098)	(5.672)	(0.081)	(8.194)	(0.156)
SI(-2)	8.452	-0.039	-0.718	-0.201			-17.805	-0.320		
	(4.221)	(0.091)	(6.778)	(0.145)			(6.608)	(0.095)		
SI(-3)	-3.600	0.168	5.120	0.165						
	(4.099)	(0.088)	(6.607)	(0.141)						
SI(-4)			2.889	-0.227						
			(6.626)	(0.142)						
C	-0.414	-0.021	-1.102	-0.031	-0.525	-0.022	-0.994	-0.025	-0.551	-0.023
	(0.263)	(0.006)	(0.495)	(0.011)	(0.318)	(0.005)	(0.379)	(0.005)	(0.432)	(0.008)
R^2	0.170	0.084	0.133	0.188	0.005	0.034	0.092	0.106	0.072	0.008

This table shows the VAR model results presented in (5) and (6) for the sample running from January 1985 to June 2012 for when the state of the economy is considered to be a bear market. The number of lags used are different per country depending on the outcome of the Portmanteau test, see table 6. Standard errors are presented in parentheses.

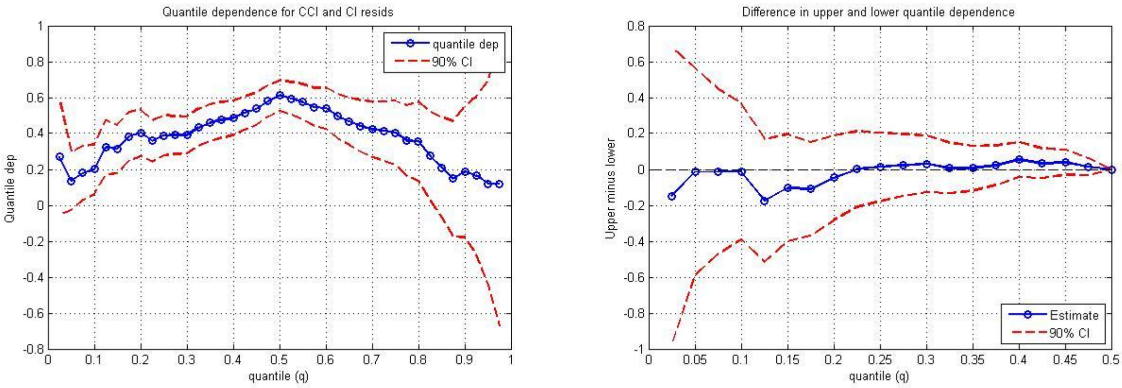
Figure A.2: Quantile dependence results



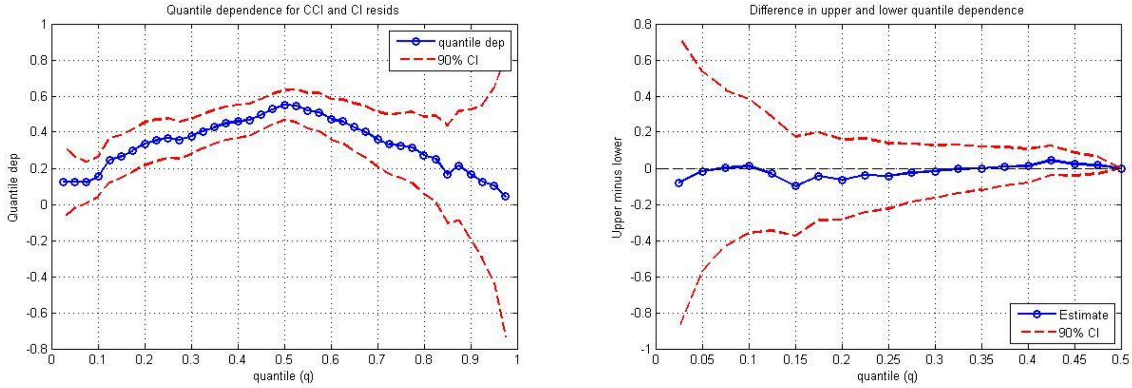
(a) Belgium



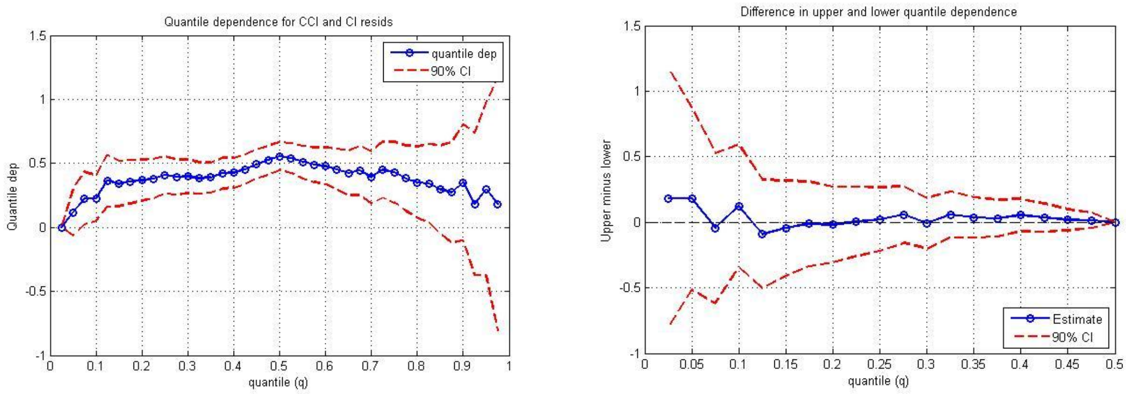
(b) Denmark



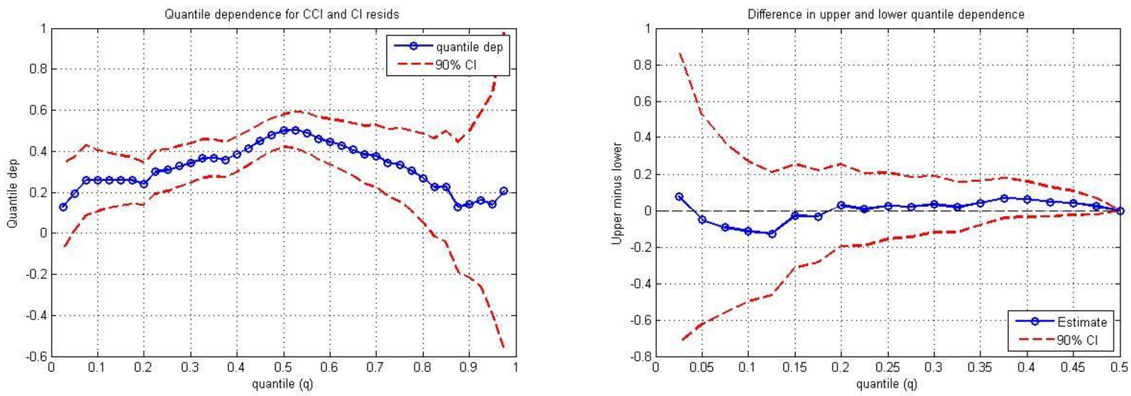
(c) France



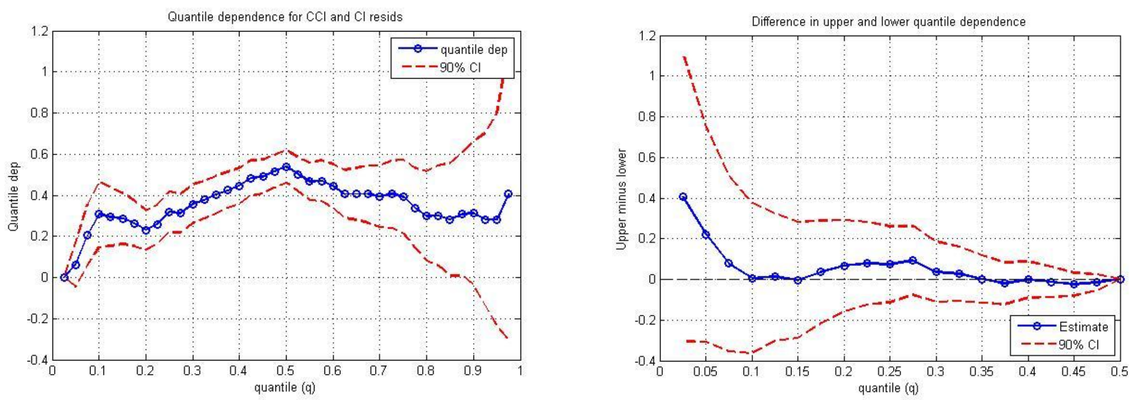
(d) Germany



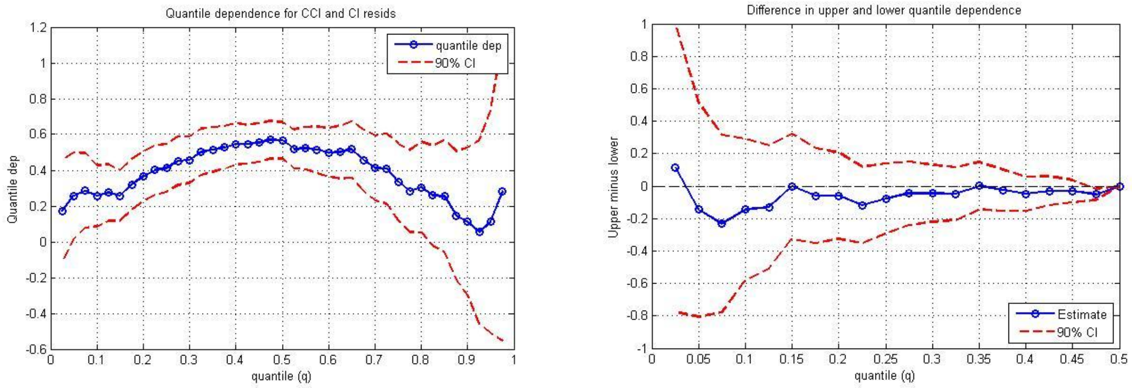
(e) Greece



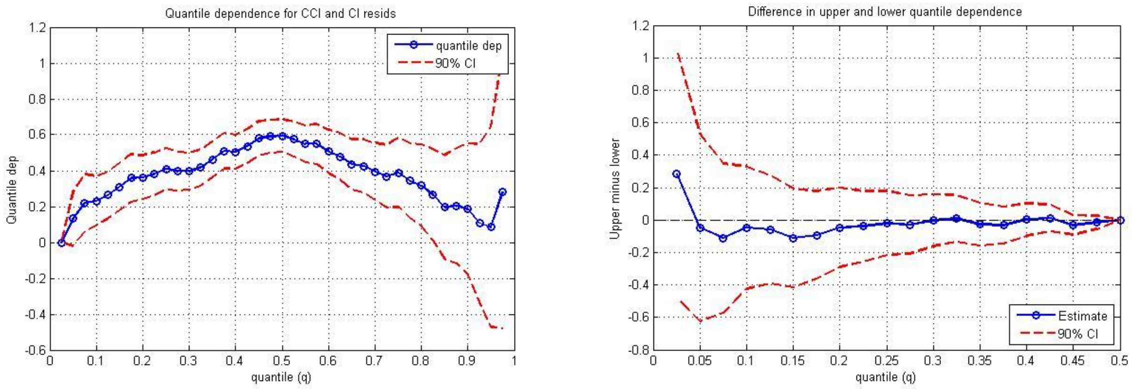
(f) Ireland



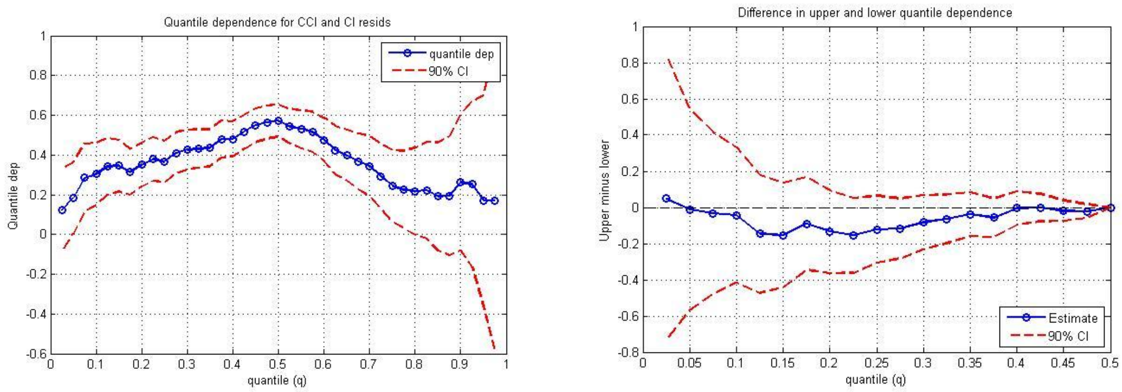
(g) Italy



(h) Portugal



(i) Spain



(j) UK

This figure shows the quantile dependence results for the different countries. The left panel presents the estimated quantile dependence between the residuals for the CCI and the SI, along with a 90% bootstrap confidence interval. The right panel presents the difference between the corresponding upper and lower quantile along with 90% bootstrap confidence interval for this difference. The sample period runs from January 1985 to June 2012.