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MASTER'S THESIS

Sovereign credit risk drivers in a spatial perspective

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Declaration of Authorship

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Prague, January 5, 2018

Signature

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Abstract

This thesis analyses what drives sovereign credit risk when contagion is controlled for. CDS spreads are used as a measure of credit risk and bond yields are used to estimate interconnectedness of the examined countries. The main contribution lies in the use of high–frequency data and a robust wavelet based estimator in addition to spatial econometric model. The aim of this thesis is to test for presence of contagion and to evaluate which fundamentals are decisive for market perception of sovereign credit risk. Another goal is to evaluate the possibility of a structural break caused by the Greek debt restructuring.
The results show that the restructuring did bring change. Contagion is present during the post–crisis period and it diminishes as the economies recover. Similarly, fundamentals are of higher importance in the post–crisis period when compared with the following period.

JEL Classification	C22, C31, C33, G01, G32, G33
Keywords	spatial econometrics, CDS spreads, sovereign credit risk, financial contagion, realised covariance

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Abstrakt

Tato práce analyzuje, co ovlivňuje kreditní riziko států, za zohlednění přenosů rizika. Pro měření kreditního rizika jsou použity Credit Default Swap (CDS) spready a úroky vládních dluhopisů jsou použity k odhadu provázanosti zkoumaných států. Hlavní přínos této práce spočívá v použití vysokofrekvenčních dat a robustních metod jako doplňku k prostorovému ekonometrickému modelu. Cílem práce je testovat přítomnost přenosů rizika a vyhodnotit, které ekonomické indikátory jsou rozhodující pro tržní ohodnocení kreditního rizika. Dalším cílem je vyhodnotit možnou přítomnost strukturální změny způsobené restrukturalizací řeckého státního dluhu.

Výsledky analýzy potvrzují tuto strukturální změnu. K přenosu rizika dochází v období po krizi a jeho efekt se ztrácí při ekonomickém oživení. Význam ekonomických indikátorů je vyšší v období po krizi oproti následujícímu období.

Klasifikace JEL	C22, C31, C33, G01, G32, G33
Klíčová slova	prostorová ekonometrie, CDS spready, kreditní riziko státu, nákaza, realizovaná kovariance

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Acronyms

AIC Akaike Information Criterion

BC Bipower Covariance Estimator

bp basis point

CAPM Capital Asset Pricing Model

CDS Credit Default Swap

CPI Consumer Price Index

ECB European Central Bank

EU European Union

GDP Gross Domestic Product

GMM Generalised Method of Moments

GNI Gross National Income

JWTSCV Jump Wavelet Two-Scale Covariance

JWTSRV Jump Wavelet Two Scales Realized Variation

MLE Maximum Likelihood Estimation

MODWT Maximum Overlap Discrete Wavelet Transform

MRK Multivariate Realized Kernel

PCA Principal Component Analysis

PIIGS Portugal, Ireland, Italy, Greece and Spain

RC Realized Covariance Estimator

SAR Spatial Autoregressive Model

S-CAPM Spatial Capital Asset Pricing Model

SEM Spatial Error Model

SLX Spatial Lag of X Model

SWEAP South–West Euro Area Periphery

TSCV Two Scales Realized Covariance

TSRV Two Scales Realized Variation

Master's Thesis Proposal

Author	Bc. Josef Záhlava
Supervisor	PhDr. Petr Gapko, Ph.D.
Proposed topic	Sovereign credit risk drivers in a spatial perspective

Motivation Understanding of credit risk drivers is of substantial importance for policy makers to take proper steps in its evaluation and management. To understand the forces behind credit risk, it is crucial to properly specify the models to be estimated. Drivers of sovereign credit risk can be explored with a simple (panel) regression. However, due to economies' interconnectedness, the regression results can be biased as economically close countries tend to influence each other also in terms of credit risk. Generally, sovereign credit risk drivers have been investigated by many studies but the spatial impact has not been given sufficient attention. Therefore, I am willing to extend the current state of research by extending the investigation into spatial perspective.

For my analysis I will use daily data on credit default swap (CDS) rates which are commonly considered to be an appropriate measure of credit risk in the literature. (e.g. Tang and Yan (2010), Pesaran et al (2003), Eder and Keiler (2012)). To estimate the interconnectedness of the countries, I will work with data on interest rates at high frequency. With higher frequency data, it is possible to get more information from the data while cleaning the estimates from negative effects of microstructure noise and jumps with use of sophisticated estimators. "The proportion of co-jumps relative to the covariance increased during 2012 - 2015. Hence, the impact of co-jumps on correlations increased, and appropriately estimating co-jumps is becoming a crucial step." (Baruník and Vácha 2016).

Hypotheses

Hypothesis #1: Macroeconomic conditions drive sovereign credit risk.

Hypothesis #2: The drivers' impact is biased by cross-country correlation.

Hypothesis #3: The impact of cross-country correlation as well as the other drivers changed significantly during the crisis.

Methodology First part of the thesis will be dedicated to literature review. I will investigate recent studies of sovereign credit risk determinants and used methodology. I suspect that the explanatory variables' impact evaluation using panel data is biased by interconnectedness of financial sectors between countries. This will be taken into account during construction of the econometric model. Additionally, I will divide the data into sub-periods to see if the impact was different in different sub-periods.

Second part will focus on the data and choice of proper estimators. I will use high frequency data on interest rates to estimate interconnectedness of financial sectors between countries. Using this data, I will estimate cross-country correlations to obtain spatial weights matrix which will be subsequently used in the final spatial estimation. I suspect the simple correlation estimates to be biased by presence of jumps and co-jumps. Therefore, I will investigate the data to explore the presence of jumps and co-jumps and based on results of this investigation I will choose proper estimator based on current literature regarding this topic. Using the estimator with the lowest expected bias given the structure of the used data, I expect to obtain credible correlation estimates for the spatial analysis.

Since I want to work with daily data on CDS to measure credit risk, further steps are needed before final estimation as macroeconomic indicators are updated at lower frequencies. To tackle this issue I will work with wavelet reconstruction and averaging or other appropriate framework to obtain quarterly measures of credit risk levels to cope with the frequency mismatch in the data. This way I will have all variables for the estimation with the same (quarterly) frequency and be able to estimate the effects.

In the final estimation, I will use chosen model from the spatial econometrics framework to evaluate macroeconomic conditions' impact on sovereign credit risk having controlled for the interconnectedness of the countries' financial sectors. Choice of the model will be subject to further theoretical analysis. I will use the cross-country pairwise correlation estimates to construct the spatial weights matrix in the model. Subsequently, I will regress the calculated quarterly credit risk levels on chosen macroeconomic indicators.

In the absence of cross-country correlation bias, the correlation coefficient of the spatial parts of the model will be insignificant. If it will be significant, it means that the estimates in simple panel estimation would be biased and countries' interconnectedness must be controlled for. Subsequently, I will compare these results with results of an estimation not taking countries' interconnectedness into account to see the size of possible bias.

Expected Contribution I will conduct an empirical analysis of sovereign credit risk drivers. I will work with daily data on CDS spreads to get as much information about sovereign credit risk as possible. Using sophisticated estimators, I will evaluate true cross-country correlations to construct spatial weights matrix for further analysis based on the spatial econometrics framework. In contrast to previous analyses, I will control for the countries' interconnectedness in the estimation to obtain unbiased estimates of macroeconomic conditions' impact on sovereign credit risk. The results will provide information on importance of taking countries' interconnectedness into consideration when performing analyses and will improve general understanding of the forces behind sovereign credit risk. Also, this work differs from current literature with its aim to demonstrate the possibility of employment of elaborate estimators working with high-frequency data and using their results in broader context, in this case spatial econometric models working with macroeconomic conditions.

Outline

1. Motivation: there are analyses of credit risk drivers but they do not take countries' interconnectedness into account. Spatial autocorrelation can be of substantial importance to results of econometric analyses which I suspect to be this case.

2. Studies on sovereign credit risk drivers: I will briefly describe how recent studies evaluate drivers of sovereign credit risk.

3. Data: I will explain how I will choose proper estimators and subsequently construct the spatial weights matrix and quarterly levels of sovereign credit risk based on high-frequency data.

4. Methods: I will explain existing spatial econometric models and choose one that will suit this case the best.

5. Results: I will discuss the results of my estimations and compare them pairwise between chosen sub-periods as well as with results of other studies.

6. Concluding remarks: I will summarize my findings and their implications for future research.

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Supervisor

Chapter 1

Introduction

Understanding what drives sovereign credit risk is important for both policymakers and market participants. Appropriate specification of the problem, and consequent specification of models is necessary for proper understanding of the topic. Drivers of sovereign credit risk can be explored with structural models using panel data. However, as a result of economies' interconnectedness, the estimation results can be biased as economically close countries tend to influence each other in various economic aspects, including credit risk. This phenomenon is often referred to as spillovers or contagion, and is present especially during crisis and post–crisis periods. Generally, sovereign credit risk drivers have been investigated by many studies but the impact of spillovers and contagion has not been given sufficient attention. This thesis aims to extend the current state of research by extending the investigation into spatial perspective, i.e. include spillovers and contagion into the models.

The objective of this thesis is to investigate drivers behind sovereign credit risk while controlling for spillover effects and contagion. This topic is analysed using a dataset covering 14 European countries over the 2009–2016 period. Data on CDS spreads are used as a measure of sovereign credit risk. To control for spillover effects and contagion, spatial econometrics framework is employed. To model the interconnectedness of the examined countries, robust wavelet based covariance estimator is used on daily data of 10–year sovereign bond yields. To our knowledge, the approach of adding information based on high–frequency data has not been used before in related literature.
Correlations estimated with this estimator are consequently used in the spatial component of the econometric model. Macroeconomic indicators are used as

explanatory variables in the model. The dataset is split into two parts — before and after the Greek sovereign debt restructuring — and separate models are estimated. It is found that fundamentals (represented by macroeconomic indicators) have lower explanatory power to sovereign credit risk in times of economic prosperity, i.e. after the Greek sovereign debt restructuring. Similarly, spillover effects and contagion, represented by the spatial component of the model, lose their importance when moving from the first sub–period to the second sub–period.

The rest of the text is organised as follows: Chapter 2 provides an overview of literature regarding topics related to the topic of this thesis. Chapter 3 builds on the literature and describes the steps taken in empirical research. In Chapter 4, the used data are described. The results of the used econometric model are presented and discussed in Chapter 5. Chapter 6 concludes.

Chapter 2

Literature Review

This chapter provides a summary of selected studies regarding the topic of sovereign credit risk as well as spatial approach to the problem resulting mainly from the presence of contagion and interconnectedness of markets.

2.1 Sovereign Credit Risk

A substantial amount of literature was published on the topic of credit risk recently. The analysis of credit risk has become a hot topic especially since the emergence of the 2007–2009 crisis. More importantly, the perception of credit risk as well as findings regarding the drivers behind it have changed ever since. It is worth noting that corporate credit risk has received more attention than sovereign credit risk. Nevertheless, sovereign credit risk has also been broadly analysed since its role has changed during the crisis due to the interconnectedness of sovereigns and financial systems, and stabilisation programmes introduced by governments. This section summarises existing literature related to this topic which helped us understand the problem and provided us with ideas to pursue when writing this thesis. The chapter starts with an introduction of the topic of sovereign credit risk and its measures and follows up with empirical analyses viewing the topic from various perspectives, e.g. different types of determinants of sovereign credit risk or different groups of sovereigns.

As mentioned above, corporate credit risk has been subject to many studies. Corporate credit risk is simpler to assess as it can be modelled using detailed and accurate firm–level information. A typical example is data regarding capital structure which makes no sense on the country level. Crouhy *et al.* (2000)

analysed and compared various credit risk models used in business. On top of firm–level information, macroeconomic variables are often used to explain part of the credit risk, e.g. Bonfim (2009) uses macroeconomic variables together with firm–specific characteristics to model default probabilities. The inclusion of macroeconomic variables not only leads to more precise results, but macroeconomic variables also show to be of stronger influence than firm–level information. Pesaran *et al.* (2006) added a global perspective to this topic and developed a new approach to modelling of conditional credit loss distributions. The approach is constructed by linking firms' asset value changes to a global dynamic macroeconomic model allowing for firm–specific reaction to the business cycles. Both local and global business cycles are considered in the model as well as their interconnectedness. Koopman *et al.* (2009), on the other hand, found little influence of macroeconomic fundamentals on the default dynamics of firms. More specifically, the authors suggest that the models seem to be dynamically misspecified and having controlled for this misspecification, the significance of macroeconomic variables drops sharply.

Augustin (2014) has summarized knowledge on the topic of sovereign CDS premia and related topics like spillovers, contagion or frictions. This paper provides an introduction into existing literature on the topic of sovereign CDS's as well as basic characteristics of the market. It provides the reader with insight into the topic and sources of detailed information on particular sub–topics. Similarly, Packer & Suthiphongchai (2003) provided introduction into the topic of sovereign credit risk, and on top of a brief explanation of the function and structure of CDS's, the authors used a dataset of CDS's covering the period of 1997 — 2003 to compare sovereign, corporate, and bank CDS's from various perspectives. The sharp upswing in use of derivatives since the mid 90's is also worth mentioning. In the used sample, quotes on sovereign CDS's accounted for 7.4% of all quotes. On the other hand, sovereign CDS's were the most concentrated in activity as they exhibit highest mean quotes per name. The authors discovered differences in sovereign CDS's as opposed to corporate and bank ones. In the sub–group of highly rated debtors, sovereign CDS premia tended to be lower. This can be accounted to the presence of strong sovereigns in the sample who would probably be rated even above AAA if it was possible. Another suggested explanation works with differences in liquidity. This difference diminishes when moving towards the sub–groups with lower rating. For ratings below BB, the difference turns to the opposite direction as sovereign

CDS's reported higher premia than CDS's of corporates with the same rating. The authors suggest that this is due to uncertainty regarding the situation following a sovereign default.

Cantor & Packer (1996) was the first study to use Moody's and Standard and Poor's ratings of sovereigns and quantify the determinants behind. The authors covered a sample of 49 countries over 1987 — 1995 and used ratings as a measure of sovereign credit risk. The authors stressed the importance of sovereign credit assessment as it not only influences the sovereigns themselves, but also borrowers of the same nationality. The study quantified the influence of macroeconomic indicators on the sovereign rating. Most of the used variables (e.g. Gross Domestic Product (GDP), per capita income, inflation etc.) turned up significant and of expected signs. Fiscal and external balances, however, did not seem to have any impact on the rating. This may be due to the fact that market forces do not allow poorly rated sovereigns to enter weak positions in the first place and therefore the effect of fiscal and external balances diminishes. The authors also investigated the relationship between ratings and yields. According to their estimation, 92% of the variation in spreads can be explained by ratings. Together with other estimations carried out in the study, the result suggests that the ratings not only summarize the information covered by macroeconomic indicators, but also contain additional information which is quite expectable since the rating agencies do not rely solely on these indicators. All in all, the authors confirmed the relation between macroeconomic indicators and credit risk as well as additional information provided by ratings which is of importance regarding assessment and pricing of sovereign credit risk.
Recent studies on credit risk have focused on CDS spreads as a measure of credit risk, but ratings have remained being an important indicator. Aizenman *et al.* (2013a) have looked for links between rating as a primary indicator of credit risk and their link to CDS spreads in European countries during pre–crisis and crisis period. With the arrival of the 2007 — 2009 crisis, disputes over the efficacy of credit ratings have returned and the authors attempted to contribute to this discussion by shedding light on the link between ratings and credit pricing of sovereigns. Using a dataset covering all 27 European Union (EU) countries except Luxembourg during the period from January 2005 to August 2012 the authors find that the relationship between credit rating changes and actual sovereign spreads is complicated and non–linear and depends on the level of rating. Moreover, during the crisis, differences in this relationship have emerged

among sub–groups of European countries. The authors have confirmed that rating changes influence CDS spreads even having controlled for fundamentals. In the pre–crisis period, EU countries showed similar responses in CDS spreads to changes in rating, while during the crisis differences emerged. In particular, Portugal, Ireland, Italy, Greece and Spain (PIIGS) started to be significantly more sensitive. In general, the response was the strongest at the lowest levels of rating and then followed an inverted U–shaped curve. Interestingly, no contagion from PIIGS' downgrades of rating to other EU countries was discovered. As for the link between ratings and CDS spreads, the authors suggested the crisis had caused a shift in sovereign credit risk pricing towards increased importance of economic fundamentals, and divergence of the perception of risk between market and rating agencies.

Another interesting perspective is to investigate the relation between CDS's and underlying assets. Fontana & Scheicher (2016) studied the pricing of Euro area sovereign CDS's and its relation to the underlying bonds on a sample of 10 countries from January 2006 to June 2010. The authors first analysed both instruments and the spread determinants separately and then studied the basis — the difference between CDS spread and bond spread. The authors noted that the 2007 — 2009 crisis has changed the perception of developed countries' sovereign bonds, and at least partially assigned the repricing of the sovereign debt to changes in investor risk appetite during and after the crisis. This change in risk appetite was also found to be one of the major drivers of the increase in CDS premia (an unprecedented upsurge of CDS's was experienced by the end of 2008 and early 2009). Nevertheless, the authors noted that the sovereign CDS market had remained strongly less liquid than the bond market, which implies the possibility of so called flight to liquidity effects, especially in times of crisis. This is, according to the authors, one of possible explanation of the existence of the aforementioned basis. The authors have discovered some differences in the determinants of CDS spreads and bond spreads. For both spreads, it was confirmed that they are related to corporate CDS premia, and that global risk appetite influences the spreads. Interestingly, the ratio of bonds outstanding over GDP was significant only for bond spreads. The authors also employed lead–lag analysis of CDS and bond spread changes. While before the crisis, no cointegration was discovered (probably due to low activity at the CDS market in that period), it was present for all analysed countries in the sub–period starting in September 2008. Nevertheless, the order (i.e. at what market the price discovery takes place and which market adjusts) differed among countries. Overall, the study showed presence of arbitrage opportunities, not easily exploitable nevertheless. Also, it showed similar patterns in the behaviour of sovereign bond and CDS spreads, which indicates that our choice of sovereign bond spreads cross–correlations as a measure of economic proximity in the empirical model is suitable. Similarly, Afonso *et al.* (2012) investigated spread between bond spreads and CDS spreads and impact of rating announcements on the spread. This study found causality between ratings and spreads. Also, spillover effects were confirmed, especially in the Euro area countries. Spillovers from lower rated countries to higher rated countries were of major importance compared to the opposite direction. Moreover, countries with recent history of downgrade(s) showed persistence effects in the perception of their risk measured by CDS and bond spreads.

Many studies conclude that during the crisis, market perception of sovereign credit risk and its determinants have changed. The publications most frequently analyse possible determinants of sovereign credit risk, mostly economic fundamentals and related indicators. Pokorná & Teplý (2011) discussed these changes and stressed the increase in importance of fundamentals impact on CDS premia as a measure of sovereign credit risk. During the crisis, European governments participated in various programs to stabilise financial systems which influenced their fiscal position and consequently market perception of their credit risk. Aizenman *et al.* (2013b) analysed the relation between sovereign risk pricing and fiscal space (ratio of debt and deficits to tax revenues) together with other economic indicators on a sample of 50 countries over 2005 — 2010. Also, the authors tried to evaluate whether the sovereign risk was overpriced in some regions. Regarding this issue, they focused on South–West Euro Area Periphery (SWEAP) countries. The study confirmed importance of fiscal space as well as other fundamentals in risk pricing. The models accuracy, however, fell sharply during the crisis. Also, the study showed that even having controlled for the fundamentals, sovereign spreads for Euro countries (including SWEAP) were substantially lower than for the rest of the world. On the other hand, the spreads for SWEAP countries were strongly above average the whole time and rising even in the times of global trend of decline in 2010. Moreover, the study showed divergence of SWEAP countries from other country groups during the crisis which calls for closer attention in this thesis since some of the SWEAP countries are present in our sample as well. Beirne & Fratzscher

(2013a) analysed the drivers behind sovereign credit risk during and after the crisis. The authors used sample of 31 advanced and emerging market economies over the 2000 — 2011 period to analyse links between risk measures and economic fundamentals looking for explanation of market overreactions such as contagion. Even though the dataset covers more countries, the authors focused on the subset of Euro–area countries. Like other studies, this one found that economic fundamentals had little importance in explanation of sovereign credit risk before the crisis and their influence had been growing ever since. Moreover, the authors found that cross–country spillovers had declined during the crisis and pure contagion was confirmed only in several short periods. These findings together with the estimations carried out in the paper lead the authors to the following conclusions: Cross–country spillovers were of negligible importance and importance of "pure contagion" was very limited. Changes in fundamentals and corresponding fundamentals contagion, on the other hand, proved to be major drivers of sovereign credit risk during the crisis. The increase in importance of fundamentals during the crisis may be attributed to change in market agents' perception of those fundamentals since in the pre–crisis period, their importance was lower, whereas regional contagion and cross–country spillovers played a more important role. These findings suggest closer attention is paid to possible changes in importance of contagion over time in the empirical part of this thesis since our dataset covers crisis and post–crisis period. It is plausible that in the post–crisis period, cross–country spillovers have started gaining importance again. This will be subjected to further analysis.

Dieckmann & Plank (2012) documented the upsurge in sovereign CDS market liquidity during the crisis as a result of government–funded stabilization programs and related private–to–public risk transfer. This study extended the research on sovereign CDS's as majority of publications regarding this topic focused on emerging markets, whereas Dieckmann & Plank (2012) worked with a sample of 18 developed economies — members of Western European sovereign CDS market and covered period from January 2007 to April 2010. The study showed increase in cross–sectional correlation of CDS's among European sovereigns with emergence of the crisis. This finding supports our hypothesis of spatial autocorrelation of sovereign credit risk. We see investigation of this topic as one of the main contributions of this thesis.
In further analysis, the authors used Principal Component Analysis (PCA) and confirmed importance of fundamentals (such as health of financial system, gov-

ernment exposure to the financial system etc.) to the perceived sovereign credit risk (quantified by CDS spread). Moreover, they quantified the phenomenon of government absorption of private sector risk which is generally believed to occur, especially in times of crises. Another interesting finding was higher sensitivity of Euro–area countries (compared with non–Euro countries) to the health of financial system due to their lower flexibility of monetary policy. This finding is of importance for this thesis as our dataset includes Euro area countries as well. Similarly, Ang & Longstaff (2013) studied systemic sovereign credit risk by analysing data on the U.S. sovereigns and selected Euro area countries. The used framework allowed the authors to distinguish between systemic as well as country–specific shocks which resulted in finding that systemic risk was strongly more present in the Euro area compared to U.S. sovereigns. Importance of financial market indicators for the sovereign credit risk, on the other hand, was confirmed in both cases. Taking into consideration similar economic state of the analysed countries, these results suggest that macroeconomic fundamentals are of lesser importance compared to financial markets indicators. For better understanding of the consequences of the crisis, Ali & Daly (2010) analysed default rates on a country level. The authors use a macroeconomic credit model to conduct comparative analysis of the USA and Australia. The motivation for 'the choice of these two countries is the difference in to what extent they were affected by the crisis. The results showed different default rates resulting from the same set of macroeconomic variables. Also, Australian economy proved to be less sensitive to adverse macroeconomic shocks compared to the US economy.

2.2 Spatial Perspective

As suggested above, contagion and spillover effects are expected to occur in the field of sovereign credit risk. Various studies show the usefulness of spatial econometric approach in various fields but heretofore, the field of finance did not receive sufficient attention. This section starts with review of publications on theoretical point of view on the topic of spatial econometrics and then proceeds to its applications in fields close to the topic of this thesis. It is worth noting that to our knowledge, sovereign credit risk was not analysed using such approach. Therefore, this section summarises empirical studies regarding only credit risk of other entities. Elhorst (2014) discussed existing models in the field of spatial panel econometrics — static as well as dynamic models. Apart from general description of existing models, the author also provided sources of information about them. The author described the differences in models estimating demand for cigarettes, which is distant from topic of this thesis, but still provides useful insight into the topic of spatial econometrics. Building on this study and its sources regarding specific models, the best model given the topic and data will be chosen. For further extension of the theoretical knowledge of spatial econometrics, LeSage & Pace (2009) was studied. This book provides thorough explanation of the theoretical fundamentals together with plausible estimation techniques and their advantages and disadvantages. This book is used as the main source of 'technical' knowledge for the model construction in the empirical part of the thesis. Additionally, Elhorst (2014) and Anselin *et al.* (2008) are used regarding panel data extension of the originally cross–sectional setting of the models. The analysis of Barunik & Vacha (2016) then serves as a source of information on estimators' performance when choosing proper correlation estimator for the spatial weights matrix in the empirical part of this thesis. This study investigated influence of noise, especially jumps and co–jumps on various estimators of covariance or correlation. The authors proposed a wavelet based estimator and compared its performance with other estimators under varying conditions regarding presence of jumps.

As for applied work, Fernandez (2011) explored the possibilities of using the concept of spatial econometrics in the field of finance. As the author states, spatial dependency has been studied in various fields of study but in the case of finance, it has not received adequate attention. The author worked with a sample of more than 100 South–American companies over 1997 — 2006 and a Spatial Capital Asset Pricing Model (S-CAPM) — a spatial extension of the original Capital Asset Pricing Model (CAPM). Most importantly, the paper described the principles of spatial econometrics and theoretical background of its application. The author confirmed the existence of spatial dependency in general, but when looking at each country separately, the evidence differed. Nevertheless, this paper provides a solid introduction into the concept of spatial econometrics along with basics of its theoretical background as well as its potential importance in the field of finance. By applying the concept of spatial econometrics on CDS's, Keiler & Eder (2013) studied credit risk and spillover effects on a sample of chosen 15 important financial institutions over 2004 — 2009. The authors introduced a new approach to the analysis and modelling of credit risk by employment of the concept of spatial econometrics. This approach allows to control for and measure spillover effects by extending the general regression model with an autocorrelation term specified by a weighting scheme. Consequently, the analysed risk charge can be decomposed into its constituent parts according to the theory: systemic, systematic and idiosyncratic. The systematic component, which refers to the risk resulting from fundamentals, and idiosyncratic (specific) component were subject to various analyses. What is innovative in the employment of spatial econometrics is the separation and measurement of the systemic component which stems from contagion as a result of interconnectedness of the financial institutions. This study showed that spillover effects are present due to institutional interconnectedness of a significant magnitude, both statistically and economically. Specifically, up to one fifth of credit risk changes are due to systemic risk. These results not only show the importance of systemic risk but also imply that misleading results can be obtained when the interconnectedness of the institutions is neglected. This article analysed credit risk of financial institutions and estimated the interconnectedness of these based on their equity correlations. This approach can be used in a similar manner in this thesis with proper selection of an indicator to measure interconnectedness of sovereigns. Similarly to the study of Keiler & Eder (2013), CDS spreads are used in this thesis as a measure of credit risk.

There are also other ways to control for spatial correlation in models than spatial econometrics as described in this section. For example, Fernandes & Artes (2013) inspected spatial correlation in credit risk, specifically its impact on credit risk scoring using data on approx. 9 million Brazilian SME's. The authors defined a variable measuring local risk and included it in their scoring models. The authors first estimated spatial correlations using distance and then incorporated it into the model to control for the effects. However, this study confirmed importance of spatial dependence which seems favourable for our hypothesis. Another example is Barro & Basso (2010) who studied contagion in a portfolio of bank loans by a dynamic analysis of credit risk having controlled for relations among the debtors, which is achieved by a spatial interaction model. The authors generated networks using information about economic sector and geographical location to model business connections. Results of the model show fat tails of the loss distribution resulting from the component modelling of counterparty risk. This result speaks for presence of contagion effect yielding increased credit risk.

2.3 Covariance Estimator

Barndorff-Nielsen & Shephard (2004a) extended the concept of realised variance to multivariate environment and introduced the so called "realised covariance". By providing a new asymptotic distribution theory, their framework allows to examine high–frequency correlations. The main drawback of this theory is in the assumption of zero jumps and no noise. Therefore, real–world data contaminated with both jumps and micro–structure noise lead to biased results. To deal with this issue, various approaches have been introduced. One of them is in sparse sampling which reduces bias its robustness is redeemed by removal of a large amount of data without any use. Empirically, bias increases with increased sampling frequency as a result of higher presence of micro–structure noise (Barunik & Vacha 2016). Therefore, quite counter–intuitively, smaller amount of data leads to more precise estimations. Other possible approach is in development of robust estimators using all available data.

Zhang (2011) introduced Two Scales Realized Covariance (TSCV) estimator as a multi–variate extension of Two Scales Realized Variation (TSRV) estimator presented by Zhang *et al.* (2005). This estimator deals with noise and reduces bias while using all the data by sub–sampling. Griffin & Oomen (2011) confirmed the dependence of bias of realised covariance estimators on the level of micro–structure noise. Also, the authors developed a consistent and efficient covariance estimator dealing with micro–structure noise and non–synchronous trading. Barndorff-Nielsen *et al.* (2011) developed a multivariate realised kernel to robustly estimate covariation of log–prices. This estimator was examined both in Monte Carlo study and in real–world data application on US equity data.

These approaches, however, dealt mostly with presence of noise and did not consider presence of jumps and co–jumps which can strongly influence the estimated covariance. Keiler & Eder (2013) discussed the problem of correlation estimates biased by shocks in their construction of spatial weights matrix. Specifically, the authors analysed CDS spreads and used equity correlations for the spatial weights matrix. They argued that the presence of jumps (or shocks) influencing both CDS spreads and equity correlations is problematic. Based on the spatial econometric framework of LeSage & Pace (2009), this causes endogeneity of the spatial weights matrix and consequently inconsistency of the model. Keiler & Eder (2013) dealt with this issue by lagging the correlations. In their analysis, the jumps are corrected for in order to obtain estimates of the underlying correlations unaffected by the jumps. Nonetheless, the CDS's are directly linked to the bonds whose yields are used for calculation of the correlation. This implies possible presence of endogeneity even having controlled for the jumps. Hence, lagged matrices are used in the model.

The presence of jumps without adequate approach can lead to process misspecification and severe consequences. As a result, jumps and co–jumps have been addressed with increased attention lately (Barunik & Vacha 2016). Barndorff-Nielsen & Shephard (2004b) introduced an approach building on the difference between realised variance and bipower variation. Aït-Sahalia & Jacod (2009) introduced new test for jump detection in discretely sampled processes comparing volatility on different scales. Another possible approach lies in usage of individual intraday returns and their relation to daily volatility. Such approaches were presented in Andersen *et al.* (2007) or Lee & Mykland (2007). Lee & Mykland (2007) used their jump test on S&P Index and found relationship between jumps and general market news announcements. Similarly, Andersen *et al.* (2007) had started with Monte Carlo analysis and then proceeded to use their estimator on S&P futures returns and confirmed the importance of accounting for jumps when analysing the data. Andersen *et al.* (2010) came up with an empirical framework which works with high–frequency data on the basis of realised variation measures and non–parametric jump detection statistics. This framework assesses distributional properties of the data and uses a sequence of moment based tests to detect location and size of intraday jumps. Additionally, Andersen *et al.* (2012) developed two variance estimators robust to jumps building on MinRV and MedRV measures. Finally, Barunik & Vacha (2015) introduced a jump robust realised variance estimator building on wavelet decomposition for detection of jumps and two–scale estimation of variance robust to noise. This estimator was further extended to multivariate environment to estimate covariances in Barunik & Vacha (2016).

Chapter 3

Model Specification

CDS's are financial instruments that provide insurance against default. Since markets reflect all available information and are forward looking, CDS spreads seem to be a suitable measure of credit risk. Forte & Pena (2009) and Bundesbank (2010) confirmed CDS spreads' superiority as a measure of credit risk. One of the standard approaches to credit risk analysis is construction of structural models. This discipline assumes links between economic fundamentals or other characteristics and credit risk. Moreover, this thesis extends the current research on sovereign credit risk by incorporating spatial dependence term into the models. This chapter describes the theoretical background used as well as specific steps taken when specifying the model used in this thesis. The chapter is organised as follows: section 3.1 provides an introduction into the topic of spatial econometrics, section 3.2 describes the steps taken when constructing spatial weights matrix, an essential component of the model, section 3.3 discusses model selection and model averaging techniques used to specify the final model. Finally, section 3.4 discusses use of robustness check.

3.1 Spatial Econometrics

Spatial econometrics is a sub–field of econometrics which, on top of classic relationship between the dependent variable and explanatory variables, introduces the concept of spatial dependence. In other words, a spatial dimension is added to the data and models are altered according to it. Based on the spatial dimension, interdependence between the cross–sectional units is allowed in some form. This implies that altered data generating processes are assumed when building models. The most commonly used models combine conventional regression model approach with the spatial autoregressive structure (Anselin 2013). There are three main types of models that incorporate the concept of spatial dependence into conventional econometrics: Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Spatial Lag of X Model (SLX), all of which are briefly described below.

All of these models assume some form of spatial dependence. This dependence is quantified by spatial weights matrix $\mathcal{W}$ which is exogenous and is incorporated into corresponding components of the model. This matrix represents the ties between the cross–sectional units. In its simplest form, its elements can be set to 1 for neighbouring countries and 0 otherwise. More complex structure estimating proximity of the cross–sectional units can be used. Finally, the matrix needs some form of standardisation in order to keep the data generating process non–explosive. In the case of this thesis, the economic proximity of the countries is modelled using correlation estimates of 10–Year sovereign bonds. The whole procedure is described in section 3.2.

SAR accounts for spatial autocorrelation of the dependent variable. This model is formalised in equation (3.1). The parameters to be estimated in this model are β, σ, and λ. If λ is estimated to be equal to zero, the spatial autoregressive component is eliminated and only the conventional data structure is left. This model assumes spatial autocorrelation of the dependent variable which means that cross–sectional units influence each other in terms of the dependent variable. A typical example of such data structure is profits of related companies, say business partners. If a company's performance drops, it can have a negative effect on its business partners, as the volume of trade with those partners is likely to decrease.

$$\begin{aligned} y &= \lambda \mathcal{W} y + X\beta + \epsilon \\ \epsilon &\sim N(0, \sigma^2 I_n) \end{aligned} \tag{3.1}$$

SEM assumes spatial dependence between the residuals. This approach models heterogeneity. This model is formalised in equation (3.2). The approach of this model is similar in assumptions to panel data models in a sense that heterogeneity is assumed to be present, i.e. each cross–sectional unit has an individual intercept. This is not feasible when working with cross–sectional data, but in a spatial setting, the vector of individual intercept can be treated as a spatially structured random vector (LeSage & Pace 2009). In panel data structure, heterogeneity is originally assumed and therefore, this approach loses its importance.

$$\begin{aligned} y &= X\beta + u \\ u &= \rho \mathcal{W} u + \epsilon \\ \epsilon &\sim N(0, \sigma^2 I_n) \end{aligned} \tag{3.2}$$

Finally, SLX, is based on presence of externalities. As the model name suggests, spatial lag of X — the explanatory variable(s) — is included, i.e. explanatory variables of other cross–sectional units can influence the dependent variable. A typical example of such setting are prices of real estate. If a house is located in a neighbourhood with expensive, nice houses with carefully trimmed gardens, its price will be higher than the price of an otherwise same house in neighbourhood full of trash with rats coming from neighbour's garden (Anselin 2003). This model is formalised in equation (3.3).

$$\begin{aligned} y &= X\beta_1 + \rho \mathcal{W} X \beta_2 + \epsilon \\ \epsilon &\sim N(0, \sigma^2 I_n) \end{aligned} \tag{3.3}$$

The models can be combined into a more complex structure. Combining these models, different spatial weights matrices can be used for each type of spatial dependence considered.

Elhorst (2014) provided extension of the originally cross–sectional setting to spatial panel data structure. It is important to note that since originally, spatial weights were cross–sectional. This means that for panel estimation, the weights must be assumed to be constant which is not likely under the presence of structural changes. This applies to this thesis due to the aforementioned Greek debt restructuring. This event is likely to have changed the nature of international interdependence of financial systems. Moreover, in the early years of the examined period, the countries were recovering from the effects of the crisis which again could have influenced the interdependence since contagion and spillover effects are usually stronger in crisis and post–crisis times. These facts support the idea to split the dataset into sub–periods and observe differences.

As a result of two–directional property of the spatial autocorrelation, problem of spatially lagged errors arises. The heterogeneity of one cross–sectional unit enters the explanatory variable of other cross–sectional units via the spatial autocorrelation term. This implies joint dependence of the dependent variable and the error term in each observation period. This issue can be dealt with in two ways: Maximum Likelihood Estimation (MLE) estimation with complete distributional specification or Generalised Method of Moments (GMM) estimation using instrumentation(Anselin *et al.* 2008).

The general model used in this thesis is specified in equation (3.4). It is a SAR model, i.e. it accounts for spatial autocorrelation of the dependent variable. Heterogeneity is assumed to be controlled for by the nature of the panel data treatment method itself. Given the topic of this thesis, there is no reason to expect direct influence of spatial lags of explanatory variables on the dependent variable. The inclusion of spatial lags of the dependent variable, on the other hand, allows for incorporation and evaluation of systemic risk (Keiler & Eder 2013).

$$\begin{aligned} y &= \lambda \mathcal{W} y + X\beta + \epsilon \\ \epsilon &\sim N(0, \sigma^2 I_n) \end{aligned} \tag{3.4}$$

As suggested above, there are two possible approaches to estimation of the model: MLE and GMM. The common approach for estimation of spatial models is MLE. This approach is well developed for cross–sectional spatial models and Anselin *et al.* (2008) provided its extension to panel data setting. Assuming normality, log–likelihood functions are derived and consequently optimised. Inference relies on asymptotic normality. Spatial lag terms can be incorporated into the log–likelihood function to adjust to spatial panel data setting. Numerical procedure of estimation and inference follows. For the assumption of normality necessary for MLE estimation is often unlikely to hold, an alternative approach is convenient. One such alternative is GMM estimator; the presence of endogeneity of the spatial lag component in the model can be solved via instrumentation with the use of spatial lags of the explanatory variables as instruments (Kelejian & Robinson 1993), (Kelejian & Prucha 1998). This way, the endogenous spatial lag of the dependent variable is instrumented, and the model can be consistently estimated using iterative spatial three–stage least squares estimator. See Anselin *et al.* (2008) for further explanation of the methods.

3.2 Construction of Spatial Weights Matrix

One of the main focuses of this analysis is the estimation of the spatial weights matrix. The basis for the construction is in estimation of cross–country correlations from daily data on 10–year bond yields. Highly robust Jump Wavelet Two-Scale Covariance (JWTSCV) is engaged due to the presence of jumps, co–jumps, and noise in the data. This estimator uses wavelet decomposition for jump detection, and subsequently, for two–scale estimation of the correlation of the jump–adjusted process. This section builds on the work of Barunik & Vacha (2016) and other studies mentioned in section 2.3.

Consider an observed logarithmic price process Y_t. Assume this process consists of an underlying logarithmic price process X_t and a microstructure noise term ϵ_t with zero mean and finite variance and independent of the logarithmic price process. This is specified in equation (3.5).

$$Y_t = X_t + \epsilon_t \tag{3.5}$$

As specified by Protter (1990), the quadratic return covariation of (X_t^1, X_t^2) denoted by $QV_{1,2}$ can be decomposed into integrated covariance of the price process ($IC_{1,2}$) and the co–jump variation ($CJ_{1,2}$). Hence, the quadratic covariation matrix $\mathbf{QV}$ as specified in equation (3.6) holds quadratic variance terms on the diagonal and quadratic covariation on the off–diagonal components.

$$\mathbf{QV} = \begin{pmatrix} QV_{1,1} & QV_{1,2} \\ QV_{2,1} & QV_{2,2} \end{pmatrix} = \begin{pmatrix} IC_{1,1} + CJ_{1,1} & IC_{1,2} + CJ_{1,2} \\ IC_{2,1} + CJ_{2,1} & IC_{2,2} + CJ_{2,2} \end{pmatrix} \tag{3.6}$$

The realised covariance estimator in its simple form specified by Andersen *et al.* (2003) and Barndorff-Nielsen & Shephard (2004a) over a fixed time period $[0, T]$ is defined in equation (3.7)

$$\widehat{RC}_{1,2} = \sum_{i=1}^{N} \Delta_i Y_{t,1} \Delta_i Y_{t,2} \tag{3.7}$$

where $\Delta_i Y_{t,j}$ is the i-th return of the process j in period t. Such estimator is a consistent estimator of quadratic covariation as $N \to \infty$ under assumption of no jumps and no microstructure noise. Both Andersen *et al.* (2003) and Barndorff-Nielsen & Shephard (2004a) provide details regarding this result. This means that estimator (3.7) measures the covariation of the observed price process rather than that of the underlying price process which leads to bias under presence of jumps and noise. Regarding noise, robust estimators of the underlying process covariance were introduced e.g. by Barndorff-Nielsen *et al.* (2011) or Zhang (2011). These estimators, however, assume zero jumps which requires additional steps regarding the jumps, e.g. detection of the jumps and adjustment of the observed data.

JWTSCV uses wavelet decomposition of the price process for its analysis. The wavelet decomposition extends the scope of analysis by introducing frequency domain (most analyses are set in time domain). Due to heterogeneity in trading horizons of various market participants, it is reasonable to expect that frequency domain, as opposed to time domain, brings additional information. Moreover, wavelets were already used for jumps detection by Xue *et al.* (2014).

The quadratic covariation can be decomposed by continuous wavelet transform as specified in equation (3.8) which allows for identification of contribution of each wavelet scale to the total quadratic covariation.

$$QV_{1,1} = \frac{1}{C_\psi} \int_0^\infty \left[\int_{-\infty}^\infty W_{j,k}^1 W_{j,k}^2 dk \right] \frac{dj}{j^2} \tag{3.8}$$

where $W_{j,k}$ is continuous wavelet transform with respect to a wavelet $\psi_{j,k}(t)$. The term inside the brackets represents contribution of covariation at scale j to the total quadratic covariation. The outer integral puts all the scales together (Barunik & Vacha 2016).

The continuous form estimator can be transposed to discrete time setting which is important since discrete data are being analysed. Instead of continuous wavelet transform, a non–subsampled discrete version can be used. JWTSCV proposed by Barunik & Vacha (2016) uses Maximum Overlap Discrete Wavelet Transform (MODWT). This wavelet transform uses scales representing frequency bands. In the discrete case, $W_{j,k}$ represents vector of wavelet coefficients at scale j at an intraday observation k where $j = 1, 2, ..., \mathcal{J}^m$, where $\mathcal{J}^m$ is the maximal wavelet decomposition level and $k = 1, 2, ..., N$. JWTSCV uses wavelet coefficients on levels 1 through $\mathcal{J}^m$ and additionally wavelet scale coefficients at level $\mathcal{J}^m$. Therefore, a matrix of $\mathcal{J}^m + 1$ vectors is used. The discrete version of the wavelet estimator of quadratic covariance of processes $(1, 2)$ over a fixed period is specified in equation (3.9). Similarly to the continuous version, it estimates covariance at separate scales (frequency bands) which are then summed to obtain total quadratic covariation estimate.

$$\widehat{QC}_{1,2} = \sum_{j=1}^{\mathcal{J}^m+1} \sum_{k=1}^{N} W^1_{j,k} W^2_{j,k} \tag{3.9}$$

where $W_{j,k}$ are MODWT coefficients at scale j for $k = 1, 2, ..., N$ intraday observations. This estimator can be considered as equal to the estimator from equation (3.7) and it converges in probability to the quadratic covariation (Barunik & Vacha 2016). This estimator, however, assumes no jumps and zero noise.

The use of wavelet decomposition in JWTSCV is also important in the topic of jump detection. The MODWT coefficients are used for construction of a threshold and subsequently compared to it for detection of jumps. This allows for construction of a jump–adjusted process which allows for loosening of the assumption of zero jumps in further estimation of integrated covariation. For this, MODWT coefficients of the first scale are used as in this particular scale, jumps are expected to influence the coefficients. The threshold ξ is calculated as specified in equation (3.10).

$$\xi = \frac{\sqrt{2} median\{|W_{1,k}|\}}{0.6745} \sqrt{2 log N} \tag{3.10}$$

where $W_{1,k}$ is the vector of MODWT coefficients at the first scale and N is the number of intraday observations. Locations k at which the coefficient exceeds the threshold ξ are considered to be locations of jumps (Barunik & Vacha 2016).

Size of jump at location k is then estimated as specified in equation (3.11).

$$J_t = \Delta_i Y_t \cdot \mathcal{I}(|W_{1,k}| > \xi) \tag{3.11}$$

Such estimated jumps can then be subtracted from the original process to obtain jump–adjusted process which converges in probability to the continuous part (Fan & Wang 2007). Hence, the assumption of no jumps is fulfilled using the jump–adjusted process. Moreover, the estimated jumps can be used to estimate the co–jump variation. This is, however, of no interest regarding the topic of this thesis.

Second issue to be dealt with is the presence of microstructure noise. For this, JWTSCV builds on TSCV as proposed by Zhang (2011). Specifically, TSCV is calculated using MODWT coefficients of the jump–adjusted process on every wavelet scale separately to obtain contributions of the scales to the total integrated covariance. These separate scale components are then summed to obtain the total integrated covariation. The two scale estimator is specified in equation (3.12) and its components in detail in equation (3.13).

$$\widehat{IC}_{1,2}^{JWTSCV} = sum_{j=1}^{\mathcal{J}^m+1}\left(\widehat{IC}_{1,2}^{G,J}(j) - \frac{n_G}{n_S}\widehat{IC}_{1,2}^{WRC,J}(j)\right) \tag{3.12}$$

where $n_G = (N-G+1)/G$ and $n_S = N$.

$$\begin{aligned}\widehat{IC}_{1,2}^{G,J}(j) &= \frac{1}{G}\sum_{g=1}^{G}\sum_{k-1}^{N} W_{j,k}^1 W_{j,k}^2 \\ \widehat{IC}_{1,2}^{WRC,J}(j) &= \sum_{k-1}^{N} W_{j,k}^1 W_{j,k}^2\end{aligned} \tag{3.13}$$

Note that the component $\widehat{IC}_{1,2}^{WRC,J}(j)$ is the same as the estimator originally specified in equation (3.9) and $\widehat{IC}_{1,2}^{G,J}(j)$ is virtually the same but averaged on a grid of size N/G. This estimator converges in probability to the integrated covariance of the processes (Barunik & Vacha 2016). This estimator is used in this thesis to calculate correlations from which the spatial weights matrix is consequently constructed. Diagonal elements of the integrated variation matrix ($\widehat{IC}$) are integrated variances of separate processes. Therefore, correlations can be obtained from the matrix as specified in equation (3.14).

$$Corr(X_i, X_j) = \frac{\widehat{IC}_{i,j}}{\sqrt{\widehat{IC}_{i,i}\,\widehat{IC}_{j,j}}} \tag{3.14}$$

The presented framework represents the essence of this thesis. Analysis and robust estimation of high–frequency data in combination with the spatial econometrics framework is its main contribution. To the knowledge of the author, such framework has not yet been used in the topic of sovereign credit risk.

3.3 Model Selection and Model Averaging

Another step in our analysis is the choice of suitable explanatory variables. Some of the explanatory variables may turn out to be irrelevant. Sequential elimination of statistically insignificant variables based on t–test performed after the model estimation and re–estimation of the model is not statistically valid. Hence, a more complex approach needs to be engaged.

One possibility is the method of model selection. This method chooses the best model from the space of models based on a measure of goodness of fit. Akaike Information Criterion (AIC) introduced by Akaike (1998) is a standard tool for model selection (Turkheimer *et al.* 2003). The essence of this approach lies in estimation of all possible models given the data and selecting the best one based on AIC, i.e. the one with the smallest AIC. Using maximum likelihood estimation, AIC can be calculated as described in equations (3.15). Its alternative form for other estimation methods is described in equation (3.16).

$$AIC = -2log\left(\mathcal{L}\left(\hat{\theta}|\mathbf{y}\right)\right) + 2k \tag{3.15}$$

$$AIC = nlog\left(\hat{\sigma}^2\right) + 2k \tag{3.16}$$

where $\mathcal{L}(\cdot)$ is the likelihood function, θ is the unknown parameter vector, k is the number of model parameters, n is the sample size and $\hat{\sigma}^2$ is the estimated variance of residuals. For small samples, correction is needed, as was researched by Sugiura (1978) or Hurvich & Tsai (1989), who came up with corrected AIC — AICc — which is specified in equation (3.17).

$$AICc = AIC + \frac{2k(k+1)}{n-k-1} \tag{3.17}$$

Another, more complex method, is weighted model averaging over space of models which compares the possibilities and comes with possibly the best solution. Frequentist model averaging based on goodness of fit measures provides robust possibility to tackle this issue. However, this approach can get computationally extensive having too many possible explanatory variables. Other possibility is Bayesian model averaging which does not require selecting one individual specification. This method uses weights building on posterior probabilities of the individual models. Bayesian model averaging works with uncertainty of the explanatory variables to be included. Moreover, it can account for the specificity of different estimates coming from different datasets (Havranek *et al.* 2017). This feature is especially convenient in meta analyses which compare various studies. The Bayesian approach is, however, beyond the scope of this thesis.

The case of this thesis, is more straightforward since only one dataset is used. Moreover, the amount of explanatory variables considered is not excessive and therefore, frequentist approach is feasible. All possible model specifications given the dataset are estimated and consequently averaged to come to final model which includes all of the explanatory variables. The method of weighted averaging used in this analysis follows the procedure suggested by Turkheimer *et al.* (2003).

First define the difference between AIC of a particular model i and minimum AIC of all the models considered as Δ_i. (See equation (3.18).) Building on Akaike (1983), the likelihood of model i, given the data and the model space, is then calculated as specified in equation (3.19). Such ratios represent model likelihood ratios. These ratios can consequently be normalised in order to obtain weights w or "Akaike weights" as specified in equation (3.20). These weights can then be used in model averaging.

$$\Delta_i = AIC_i - min(AIC) \tag{3.18}$$

$$\mathcal{L}\left(model_i|\mathbf{y}\right) = e^{-\Delta_i/2} \tag{3.19}$$

$$w_i = \frac{e^{-\Delta_i/2}}{\sum_{j=1}^{M} e^{-\Delta_i/2}} \tag{3.20}$$

The essence of this approach is to weight all models using weights specified in equation (3.20) to obtain estimations of parameters θ_i from all models, rather than the best model selected. Estimates of parameters are calculated as specified in equation (3.21).

$$\hat{\theta} = \sum_{i=1}^{M} w_i \hat{\theta}_i \tag{3.21}$$

Variance estimates of the estimated parameters $Var(\hat{\theta})$ can be obtained with the use of the same weights. Additionally, model misspecification bias needs to be accounted for. Building on specification introduced by Buckland *et al.* (1997), define β_i as specified in equation (3.22). When summing model estimates, their covariance has to be added to the sum of variances, but this covariance term is unknown. The bias β_i can be used in the calculation as its upper bound in order to estimate the variance of the parameters. For details, see e.g. Turkheimer *et al.* (2003). Finally, the variance estimate of the estimated parameters is calculated as specified in equation (3.23).

$$\beta_i = \theta - \hat{\theta}_i E\left(\hat{\theta}_i|\beta\right) = \theta + \beta \tag{3.22}$$

$$Var\left(\hat{\theta}\right) = \left[\sum_{i=1}^{M} w_i \sqrt{Var\left(\hat{\theta}|\hat{\beta}_i\right) + \hat{\beta}_i^2}\right]^2 \tag{3.23}$$

In this thesis, both model averaging and model selection are used and compared. Model averaging, on one hand, shows more complex results, but on the other hand, the variance estimates of the estimated parameters can be over–estimated due to the use of upper bound in the calculation, and therefore the inference need not be precise. Moreover, model selection provides simpler results by specifying which variables are important and which are not.

3.4 Robustness Check

Techniques described in section 3.2 are suitable not only for the construction of the spatial weights matrix but can also contribute to inspection of the dependent variable. Since the used dataset consists of daily data on CDS spreads and the model is constructed using quarterly data, this mismatch needs to be taken care of. This problem can be tackled by using quarterly closes — last values of the daily data for each quarter. This way, all the changes in CDS spread are included. On the other hand, it is reasonable to expect presence of noise and jumps in the data and therefore, robustness checks may be useful and bring additional information. This will be further examined in section 4.1.

Chapter 4

Data Description

The main focus of this thesis is applying financial theory as well as statistical methodology on empirical data. This chapter introduces used data and its characteristics together with the methodology. The used data can be divided into two main categories based on frequency.

The first group consists of daily data provided by *Thomson Reuters* Datastream (2017) and includes time series of CDS spreads on 10–year sovereign bonds and yields of the underlying 10–year sovereign bonds.
The CDS spreads is the main variable of interest. This variable is commonly used as a measure of credit risk. Therefore, it will be used as dependent variable in the models after a transformation to quarterly frequency.
The series of bond yields will be used to estimate financial systems' interconnectedness using a measure of realised covariance and consequently control for this interconnectedness in the models.

Originally, use of intra–day data was planned as higher frequency data carry more detailed information and with the use of sophisticated estimators to cope with jumps and micro–structure noise, it can provide more accurate results. However, such data are virtually impossible to obtain and therefore daily data are used as the "second best" option.

The second group comprises of quarterly data coming from open access databases (Eurostat, OECD, etc.) regarding mostly macroeconomic and financial variables indicating economic and financial conditions of countries from different perspectives. These variables will be used as explanatory variables in the models to examine their influence on sovereign credit risk, or more specifically, market perception of the risk.

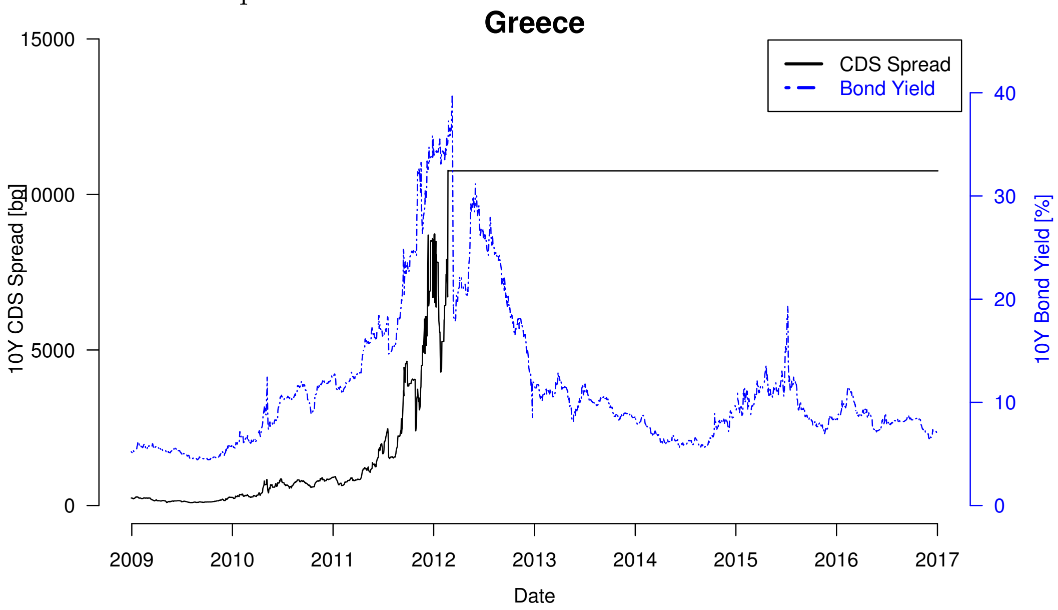
4.1 Daily Data

As indicated in the beginning of this chapter, great deal of work is dedicated to work with higher–frequency data. We are in possession of daily data on CDS spreads on 10–year sovereign bonds and yields of these bonds provided by *Thomson Reuters* Datastream (2017). The dataset covers 17 European countries. The data on CDS cover period of late 2008 until the end of 2016. The dataset regarding bond yields covers longer period as it starts in 2007. This is necessary in order to use lagged data which will be discussed later on. The countries present in the original dataset are the Czech Republic, Germany, France, Greece, Belgium, Denmark, Norway, Spain, the Netherlands, Austria, Italy, Poland, Portugal, Slovakia, the United Kingdom, Finland and Sweden. Nevertheless, the amount of data used in estimations and models is limited as a result of the data availability.

First, Slovakia and Norway are excluded due to large gaps in the data. In this case, the gaps are stemming from absence of sufficiently liquid 10 year sovereign bond. If a 10 year bond is issued in sufficient amount, it is used as a benchmark for 10 year sovereign bond for given country. However, the next year, it has only 9 years to maturity and therefore it cannot be considered as a benchmark for 10 year sovereign bond any more. If no new bonds are issued in sufficient amount, there are no bonds to be used for this time series. As a result, Slovakia has missing time series of over 2 years and Norway of 1 year. Therefore, they are excluded as for the methodology used, it is necessary to have data for all the cross–sectional units to maintain consistency. Nevertheless, these countries can still bring valuable information regarding the data analysis. Hence, they are included in this section even though they are not included in the models.

The second case regards the data on CDS spreads. In this case, the CDS's of Greece had to be excluded since they were not traded since February 23rd 2012 as a result of the newly accepted bailout programme for Greece and consequent implementation of a market–based restructuring of Greek public debt.

Figure 4.1: Greek 10–year Bond Yield and Corresponding CDS Spread



Source: Thomson Reuters

This event lead to 53.5% reduction in the nominal face value of Greek sovereign bonds held by private investors (Monokroussos *et al.* 2012). On this day, the value of Greek CDS spread closed at 10758.84 basis points (bps) and did not change ever since. (see Figure 4.1) Therefore, the time series of Greek CDS is not of interest for the analysis since last five years carry no information.

This event, on the other hand, suggests an extension to this thesis. As mentioned above, the restructuring had caused significant haircut in the value of the debt and Greece lost access to capital market. Long time ahead of this event, the conditions of the haircut, as well as consequent settlements, were being discussed. Even though the event fulfilled the definition of a default, for a long time it was not clear whether the issuers of debt protection (CDS) were going to pay the settlement, as the restructuring could have been approved by the creditors. Nevertheless, the proposed voluntary haircut was drastic in its measures to the investors and was not accepted by many of them. On the other, many feared the case of credit event as a possible cause for bankruptcy of the CDS issuers. This lowered the trust in sovereign CDS's as means of protection against default, and consequently lead to turbulences in the CDS market. In the end, the voluntary haircut was not agreed on and the participation thresholds of 90% for the exchange and amendment had been met. Therefore, credit event was triggered and CDS settlements were paid (Zettelmeyer *et al.* 2013).

As a result, not only did the Greek CDS's stop being traded, but it is also plausible that this event influenced investors' trust in sovereign CDS as a means of protection against default — after a long period of uncertainty during the Greek debt crisis, the settlements were paid, proving that the CDS served their purpose. Taking these events into account, the dataset was split into two periods — before February 23^{rd} 2012 and after. To evaluate possible differences in these two sub–periods, the data were visualised. First, time–plots of log–returns of the bonds yields as well as CDS spreads for all the countries were examined. An example of such plot for Greece might be seen in Figure 4.1. The plots of CDS spreads and bond yields indicate quite a turbulent period until the early 2012 with lower values as well as variances for both time series. The CDS spreads were additionally examined by the Change Point Model (CPM) framework for sequential change detection, testing for both mean and variance changes in the time series. Most of the series shows a structural break in, among other, the first quarter of 2012 or close to it. To discover more, histograms are plotted to visualise and compare distributional properties of log–returns of the CDS spreads between the two chosen sub–periods for each country present in the dataset. The same is done for log–returns of the bond yields.

As for the bond yields, some patterns are clear. All the countries show wider range of values in the second sub–period (from February 23^{rd} 2012 onward). Correspondingly, the second sub–period shows higher variance for all countries. Also, most of the countries (approximately two thirds) have higher peaks around the centre in the first sub–period, suggesting excess kurtosis in the log–returns distribution. Moreover, the rest of the countries have peaks of comparable height in both sub–periods, i.e. no country shows significantly higher peaks in the second sub–period compared to the first one. Slightly over half of the countries show excess kurtosis and more fat tails in the second sub–period compared to the first one. Most of the rest, on the other hand, show similar shape of the histogram in both sub–periods. Almost all the histograms (including both sub–periods) diverge from normal distribution curve (constructed using empirical sample mean and variance) having higher peaks in the centre.

The case of CDS spreads is more complex. The data for the first sub–period for most countries spread over wider range stating presence of larger changes in the values. The few exceptions in this regard are Sweden, Great Britain, and Germany. The case of overall variance corresponds. The data of the first sub–period show higher variance in most cases. The exceptions in this case are Sweden, Great Britain, Germany and Denmark. As can be seen in the histograms, except for Denmark, the countries diverging from the common pattern are the same. All of the countries show increased or at least the same concentration of values around the centre in the second sub–period. This, to some extent, corresponds to the comparison of the shape of the histogram to normal distribution curve (again constructed using empirical sample mean and variance). It is important to stress that none of the countries is even close to normal distribution due to presence of significant peaks in the centre. If the centre is omitted, it can be seen by looking at the rest of the range that the values in the first sub–period are closer to the normal distribution shape for most countries, while fat(ter) tails are observable in the second period.

To further investigate statistical properties of the used daily data on bond yields, realised measures are employed. Main purpose of the use of daily data on bond yields is to estimate cross–country realised correlations as a measure of interconnectedness of the economies. This can be measured in various ways. Since different estimators have different properties regarding robustness and precision, decision on particular methodology to be used stems from investigation of presence of jumps (and co–jumps) and noise.

Basis of the analysis presented in this section lies in the concept of realised variation measures based on Back (1991), whose work was followed up by e.g. Barndorff-Nielsen & Shephard (2004b) or Andersen *et al.* (2003). To estimate jumps, methodology proposed by Andersen *et al.* (2011) is used. This study proposes a reduced form framework for modelling of realized volatility. The idea is to decompose the total quadratic variation into two components: continuous part — integrated variance, and jumps. By splitting the variation into theese two parts, the "true" underlying variance can be estimated and, more importantly for our case, jumps can be detected. Note that realised volatility measures were primarily developed for work with intraday data and this notation from their definition is kept here to be consistent with the authors. This thesis, however, works with daily data for which the same methodology applies with the exception that daily data are used instead of intraday data and calculate quarterly measures instead of daily measures.

The “naive” realized variation estimator as specified in equation (4.1) does not differentiate between the continuous (integrated) component of quadratic variance and the jump part. The bipower variation estimator proposed by Barndorff-Nielsen & Shephard (2004b) and specified in equation (4.2), on the other hand, converges to the integrated component of quadratic variation. Both equations specify the estimator of variation of asset i at day t with m intraday observations. r denotes logreturn of the price process.

$$RV_{i,t} = \sum_{j=1}^{m} r_{i,t-1+jn}^2 \tag{4.1}$$

$$BPV_{i,t} = \frac{\frac{m}{m-2}}{(\frac{\pi}{2})^2} \sum_{j=3}^{m} |r_{i,t-1+(j-2)n}| \cdot |r_{i,t-1+jn}| \tag{4.2}$$

Hence, the jump component can be identified as a difference between the two estimators. The jump statistic used to measure jump significance as proposed by Andersen *et al.* (2011) is specified in equation (4.3).

$$Z_{i,t} = \frac{\frac{RV_{i,t}-BV_{i,t}}{RV_{i,t}}}{\sqrt{\frac{1}{n}((\frac{\pi}{2})^2 + \pi - 5) max\{1, \frac{TQ_{i,t}}{BV_{i,t}^2}\}}} \tag{4.3}$$

where $TQ_{i,t}$ denotes realised tripower quatricity defined in equation (4.4). The test statistic $Z_{i,t}$ is normally distributed under the null hypothesis.

$$TQ_{i,t} = n\mu_{4/3}^{-1} \left(\frac{n}{n-4}\right) \sum_{j=5}^{m} |r_{i,t-1+(j-4)n}|^{4/3} |r_{i,t-1+(j-3)n}|^{4/3} |r_{i,t-1+(j-2)n}|^{4/3} \tag{4.4}$$

where $\mu_{4/3} = 2^{4/3}\frac{\Gamma(7/6)}{\Gamma(1/2)}$ and $\Gamma(\cdot)$ is the Gamma function.

Using the jump statistic $Z_{i,t}$ and its property of normal distribution, jumps can be located by comparing it to the standard normal distribution quantiles Φ_α. Table 4.1 presents counts of estimated quarterly jumps over the two defined sub–periods (denoted as I and II) as well as the whole sample on 1% and 5% significance levels.

Table 4.1: Estimated Counts of Jumps at 1% Significance Level

	CZ	**DE**	**FR**	**BE**	**DK**	**ES**	**NL**	**AT**	**IT**	**PL**	**PT**	**GB**	**FI**	**SE**
5%														
I	3	0	0	1	1	1	0	1	0	0	2	0	0	0
II	4	2	2	1	2	1	2	3	1	1	0	1	0	3
TOTAL	7	2	2	2	3	2	2	4	1	1	2	1	0	3
1%														
I	2	0	0	0	1	0	0	0	0	0	1	0	0	0
II	1	0	0	0	1	0	0	1	0	0	0	0	0	1
TOTAL	3	0	0	0	2	0	0	1	0	0	1	0	0	1

Based on these results, a robust estimator is employed for the calculation of cross–country realised correlations. Specifically, JWTSCV proposed by Barunik & Vacha (2016) was chosen. This estimator uses wavelet decomposition to identify the statistically significant jumps (and co–jumps) and exploits the ability of TSCV proposed by Zhang (2011) to cope with noise. As a result, it is robust to (co)jumps and noise in the data. It also performs better under such conditions in comparison with other realised covariance measure estimators like Realized Covariance Estimator (RC), Bipower Covariance Estimator (BC), TSCV or Multivariate Realized Kernel (MRK), which is examined in numerical study carried out by the authors in Barunik & Vacha (2016). This estimator, along with results of its application on our data was discussed in detail in Chapter 3.

In the case of CDS's, it is favourable to capture all the information carried by the spreads, i.e. including jumps. Therefore, a different approach is more suitable. Nevertheless, a similar start can be employed in order to gain insights regarding the data structure. The first step is to calculate log–returns of the spreads. The second step is to perform an analysis by using realised volatility measures. Estimation of jumps will be discussed later on. Main insights come from inspection of realised volatility measures (realised variance, bipower variation).

From the plots which are provided in the Appendix, two main groups of countries can be distinguished: The first group, consisting of Austria, Belgium, the Czech Republic, Finland, France, Italy, the Netherlands, Poland, Portugal, and Spain, shows significantly higher values of realised variance in the first sub–period (2009 — 2011) while the second group, comprising Denmark, Germany, Sweden and The United Kingdom, shows higher values in the second sub–period, especially near its end. The properties of the second group slightly differ between realised variance and bipower variation, while the patterns in the first sub–period hold for both estimators. This suggests increased presence of jumps in the second sub–period. Interestingly, the first group is more than twice as large as the second one. Moreover, no clear pattern regarding country size or foreign policy is observable — both groups include members as well as non–members of the Euro–area, which also holds for small and large countries. The SWEAP countries are present only in the first group but, on the other hand, countries from other parts of Europe are present in both groups, which lowers the significance of this separation. Detailed classification and possible separation with the use of classing of economic variables will be presented in Chapter 3. Nevertheless, these results support the hypothesis of change in risk perception (and consequently the drivers of risk evaluation) between the two selected sub–periods.

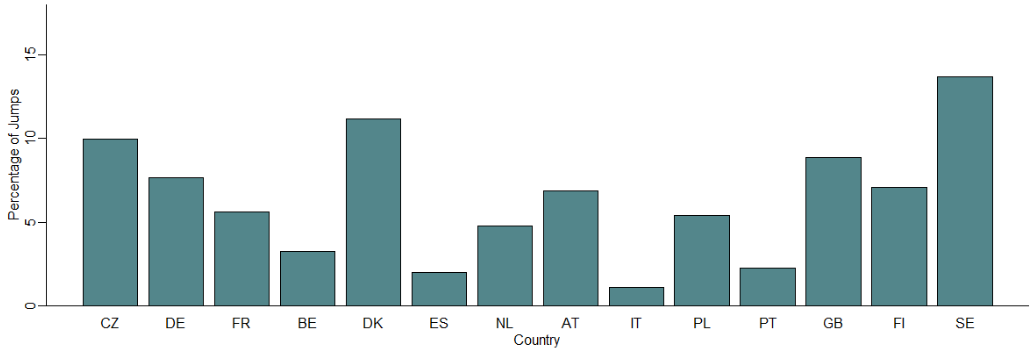
The observed shifts in volatility suggest that the use of robustness checks in the model as proposed in section 3.4 is appropriate. As can be seen in the plots of bipower variation discussed above and as presented in the appendix, the level of volatility of the dependent variable differs across time. Based on this finding, integrated volatility and jump variation of the dependent variable are included in the model as explanatory variables. Moreover, presence of jumps is further examined.

Using MODWT and threshold presented in section 3.2, the daily data of the dependent variable are examined. Based on this measure, relatively large share of observations is considered to be jumps. Estimated percentage of jumps by country are presented in figure 4.2. Based on this amount of jumps, it is reasonable to expect jumps will be present in some of the observations of quarterly close values. As a result, robustness checks are added. The robustness checks of the models are carried out by estimating the same model using quarterly mean and median as the dependent variable.

4.2 Quarterly Data

The second type of data used in this thesis is quarterly data regarding macroeconomic and financial indicators. This data were obtained from OECD (2017), EUROSTAT (2017), and Yahoo (2017). This data will be used as explanatory variables in the models in order to assess the influence of various country–

Figure 4.2: Percentage of Jumps in 10–year CDS Spreads



Source: Thomson Reuters

specific conditions on sovereign credit risk, and possibly find main drivers behind it. The list of used indicators, along with their sources is listed in Table 4.2. Furthermore, Table 4.3 presents basic summary statistics for these variables such as mean, standard deviation or chosen quantiles. The economic reasoning for the inclusion of these indicators into the models is further discussed later in this chapter. All of the data cover the same set of countries over the same time period as the daily data presented in section 4.1. The used data are seasonally adjusted. Moreover, most of the used variables are not stationary and trending is present. Therefore, in the case of non–stationary variables, first differences were used to assure stationarity. These variables are denoted with "_d" at the end of their name. Statistics provided in Table 4.3 describe the calculated differences.

Table 4.2: Candidate Explanatory Variables Description

Variable	Description	Source
CurAccBal_d	Current account balance [% GDP]	OECD
CPI	Inflation rate represented by CPI	OECD
DebtToGdp_d	Government debt[% GDP]	Eurostat
Unemp_d	Unemployment Rate [%]	Eurostat
FinSector	Financial sector size [% GNI]	Eurostat
GDPpcgr	Growth of GDP per capita [%]	OECD
IntlTrd_d	International trade index	Eurostat
MMIR_d	Money market 3M interest rates [%]	Eurostat
IndexLD	Local stock exchange index log–returns	Yahoo Finance
IndProd_d	Industrial production index	Eurostat
RVol	Integrated volatility of 10–year CDS spread	Reuters
JVar	Jump variation of 10–year CDS spread	Reuters

Table 4.3: Candidate Explanatory Variables Summary Statistics

Variable	Mean	Std. Dev.	Min	25%	Median	75%	Max
CurAccBal_d	0.08	1.38	-7.35	-0.66	0.06	0.83	7.54
CPI	1.33	1.29	-1.51	0.30	1.12	2.26	4.70
DebtToGdp_d	0.57	1.83	-7.20	-0.60	0.40	1.43	11.70
Unemp_d	-0.01	0.33	-1.10	-0.20	0.00	0.20	1.20
FinSector	5.16	1.46	2.30	4.20	4.60	6.12	9.30
GDPpcgr	1.06	2.19	-8.22	0.11	1.29	2.31	7.88
IntlTrd_d	1.25	6.03	-27.03	-1.47	1.02	3.90	29.10
MMIR_d	-0.06	0.18	-0.82	-0.10	-0.03	0.02	0.60
IndexLD_d	0.02	0.10	-0.35	-0.04	0.02	0.08	0.26
IntlTrd_d	1.13	5.91	-27.03	-1.54	0.95	3.84	29.10
RVol	0.03	0.02	0.00	0.02	0.03	0.05	0.18
JVar	0.08	1.11	0.00	0.00	0.00	0.00	19.88

extracted 29/10/2017

Selected Explanatory Variables

Main explanatory variables used in the model are macroeconomic indicators chosen based on other studies presented in section 2.1. On top of macroeconomic indicators, volatility of the dependent variable in the previous period is included in the model. Specifically, integrated volatility is estimated using Jump Wavelet Two Scales Realized Variation (JWTSRV) estimator proposed by Barunik & Vacha (2015). Lag of the dependent variable is also included in order to avoid serial autocorrelation of the disturbances.

CDS_10Y: Lag of the dependent variable. As suggested above, this variable is included in order to avoid serial autocorrelation. It is reasonable to expect that previous level of credit risk influences present level of credit risk.

RVol: Lagged integrated volatility of the dependent variable estimated using JWTSRV estimator proposed by Barunik & Vacha (2015). Previous volatility of credit risk may lead to its rise. By using the JWTSRV, integrated volatility can be estimated even under presence of noise and, more importantly, it can be separated from jumps. Calculation of this variable is described in section 3.2. The effect of this variable is expected to be persistent over the years as on one hand, risk stemming from volatility may be higher in the early years when the effects of the crisis were still present, but on the other hand, the volatility is significantly lower in the later years which could yield higher variable coefficient in the model as can be observed from the plots of CDS spreads.

JVar: Jump component of the CDS spread volatility in previous period. As in the case of integrated volatility, jumps can increase future credit risk. The influence of jumps, however, is different from the influence of volatility. Therefore, its separation can provide further information. The jump component is calculated as a sum of squared jumps in the univariate CDS spread time series. The jumps are detected with the use of threshold specified in equation (3.10) in section 3.2.

FinSector: Size of financial sector as a percentage of GNI. As a result of the crisis, financial institutions were unstable and risk of their fall was increased at least in the early years of the time period covered in our dataset. Such fall could influence the economy directly by the potential loss of positions held by a given financial institution and general economic slowdown. Moreover, fear of such effect could force the government into a costly bailout. In such case, size of financial sector relative to country's wealth is an important indicator of government's ability to avoid and, more importantly, survive such scenario. This directly influences the credit risk of the government. The effect of this variable is expected to be stronger in the first sub–period.

GDPpcgr: Growth of GDP per capita. GDP is the most common variable to represent overall economic level of a country. Using GDP per capita, country size is accounted for and the statistic is comparable among countries. Its growth then reflects improvements rather than overall level. This is important as changes in the level of sovereign credit risk are influenced by changes in the economic condition rather than its overall state. The influence of the "baseline" economic condition is included in the unobserved heterogeneity, which is accounted for in both random and fixed effects panel models.

IndProd_d: Industrial production index. This index measures monthly changes in the price–adjusted output of industry. Specifically, it reflects the development of value added in industry. This index should identify turning points in the economic development and therefore reflect the stage of business cycle given country is in. It is used in GDP forecast and, more importantly for this thesis, to form economic and monetary policies. These policies as well as the business cycle stage influence sovereign credit risk through economy as first, economic and monetary policies imply changes in government financial flows and second, financial health of government depends on the real economy which is influenced by the business cycles.

Unemp_d: Unemployment rate. This is one of the real economy indicators. It reflects the situation on labour market, which indicates the condition of the real economy in terms of presence of economic activity or firms' profitability, which influences the taxes paid and therefore financial possibilities of the government.

CPI: Inflation represented by Consumer Price Index (CPI). Inflation reflects price stability which is essential for economic development. Price stability as defined by the European Central Bank (ECB) is a year–to–year increase in the index of consumer prices slightly below 2%. Lower inflation indicates low economic activity and danger of deflation. High inflation, on the other hand, can be a sign of overheating economy or unstable monetary policy and complementary deterioration of the economy. Both cases are present in the dataset which may lead to offsetting of the effects of having inflation that is either too high or too low. Moreover, growth in inflation may be initiated by increased economic activity as well as loss of competitiveness and economic decline. Therefore, expectation of its coefficient in the model is not clear. Given the circumstances, however, one can anticipate that in the first sub–period, inflation was more related to economic decline, while in the second sub–period its increase was more related to increase in economic activity as is usually the case after periods of extremely low inflation. Therefore, the coefficients in the models are expected to differ between the two sub–periods.

IntlTrd_d: International trade volume index. This index monitors country's volume of international trade in goods and services. International trade on one hand enables countries to specialise and thrive through cooperation. On the other hand, high level of internationalisation means increased exposure to credit risk , since a failure of one country affects all members of the chain given their interdependence. This risk can be perceived more strongly in "bad times". Therefore, stronger significance is expected in the first sub–period as opposed to the second sub–period.

CurAccBal_d: Current account balance. Current account of the balance of payments provides information on international transactions in goods, services, and primary and secondary income. It provides a view on international engagement of countries from a different perspective than the aforementioned international trade volume index. The international trade volume index monitors volume of international trade. Current account balance, on the other hand, shows whether given country's export prevails over its import or the other way around. Positive balance means that the country is earning more from export than spending on import, i.e. the balance is calculated as *export - import*. This indicator can be correlated with credit risk as export–oriented countries are more exposed to economic condition of their customer countries. Therefore, economic downturn can spread more strongly among countries that trade together which is definitely the case of the EU. This effect, however, might be included in the spatial autocorrelation component of the model. Therefore, its effect is questionable.

MMIR_d: Money market interest rate. Interest rates represent the price of borrowing. In this thesis, 3–month money market interest rates are used. These rates are one of the shortest rates published. This means these rates reflect liquidity on the money markets. The rates are the same for all Euro–area countries which takes away the information on differences between Euro–area countries. On the other hand, it can provide some information not only for the non–Euro countries, but can also point out some differences between them and Euro countries since Euro–area short–term interest rates are one of the lowest within the group. This difference cannot be assessed by using dummy variables in fixed effects panel data model.

IndexLD: Local stock index log–returns. This is one of the indicators that assesses general economic condition of a country, specifically its capital market representing the private sector.

DebtToGdp_d: Government debt as a percentage of GDP. The case is quite straightforward here. Since CDS's are directly linked to government debt, the influence of debt size relative to the country's wealth on credit risk is obvious. Using first differences to tackle the non–stationarity issue converts this variable into changes of debt, i.e. fiscal balance. This variable can be even more important since fiscal discipline (and avoidance of excessive borrowing) is even more important for credit risk than size of the debt as such.

The chosen explanatory variables together with the type of model used before model selection and model averaging are formalised in equation (4.5). In the robustness checks, $logCDS$ and $logCDS_{t-1}$ are replaced by quarterly mean and median of their values.

$$
\begin{aligned}
logCDS = & \lambda \mathcal{W} \cdot logCDS + logCDS_{t-1} + RVol\_c\_1s_{t-1} + JVar\_c\_1s_{t-1} + \\
& + CurAccBal\_d_{t-1} + + FinSector_{t-1} + IndProd\_d_{t-1} + \\
& + GDPpcgr_{t-1} + Unemp\_d_{t-1} + IntlTrd\_d_{t-1} + MMIR\_d_{t-1} + \\
& + IndexLD_{t-1} + + CPI_{t-1} + DebtToGdp\_d_{t-1} + u
\end{aligned} \tag{4.5}
$$

Chapter 5

Estimation Results

5.1 Spatial Weights Matrix

The estimator described in section 3.2 is used on daily data of 10–year sovereign bond yields of chosen European countries. By this, correlations of country pairs as well as individual country variances are calculated. Moreover, the dataset is split into two sub–periods to examine possible changes in credit risk drivers after the Greek debt restructuring. The calculated correlation tables for the first sub–period, second sub–period and the whole sample are presented in the appendix in tables A.1, A.2, and A.3, respectively. Graphical representation of the correlations, specifically range of correlations for specific countries, is presented in figures 5.1 for the first sub–period, 5.2 for the second sub–period, and 5.3 for the whole sample. Significant differences can be observed between the two sub–periods in the inter–quartile ranges. In the first sub–period, the range is significantly wider than in the case of the second sub–period. Closeness of the whole–sample correlations to those of the second sub–period stems from different lengths of the two sub–periods — the first sub–period covers only three years while the second sub–period covers five years and therefore puts more weight into the overall result.

Note that the presented correlations are for illustrative purpose only. These correlations describe the situation during the examined period but as specified in section 3.2, the spatial weights matrices are lagged in order to avoid their endogeneity. Specifically, for the second sub–period, spatial weights matrix constructed based on the data from the first sub–period is used and for the first sub–period, historical data not originally included in the dataset are used.

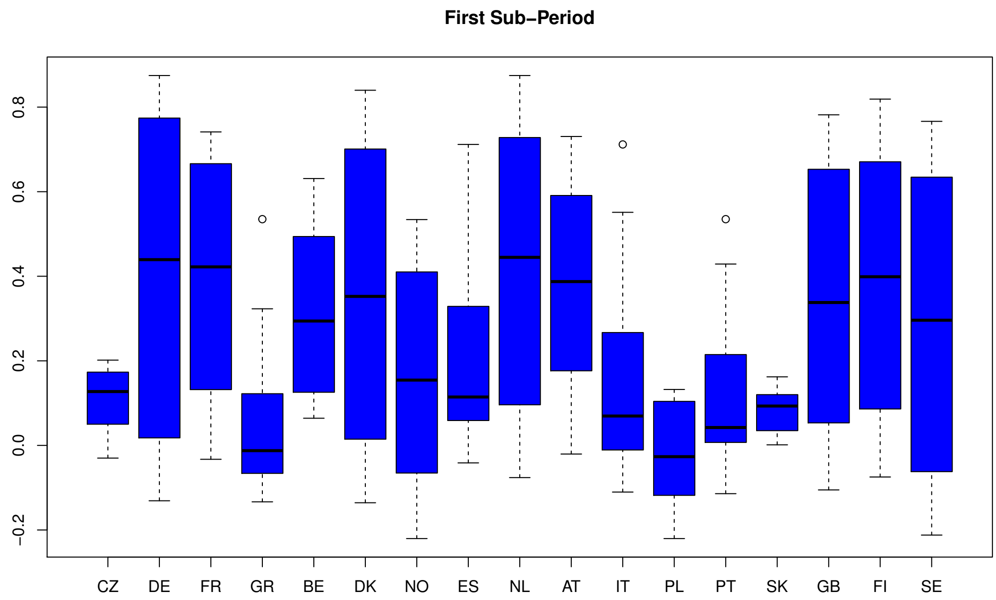


Figure 5.1: Range of Cross–Country Correlations (First Sub–Period)

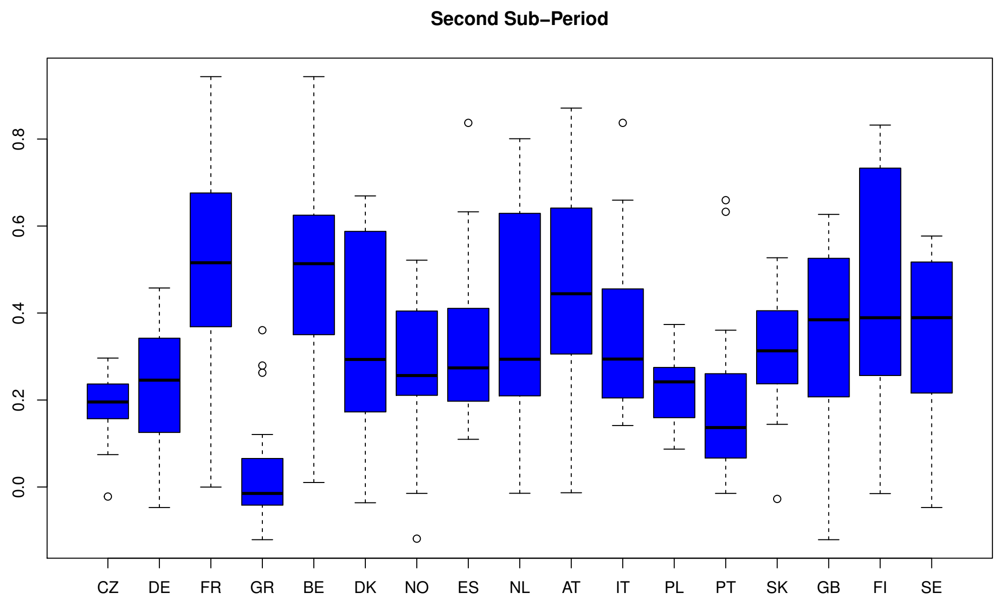


Figure 5.2: Range of Cross–Country Correlations (Second Sub–Period)

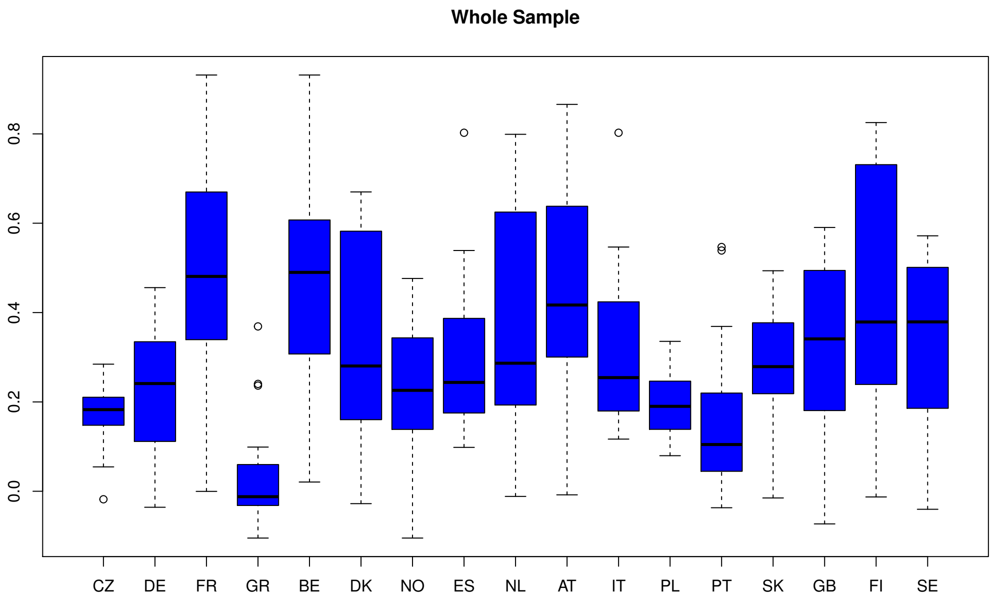


Figure 5.3: Range of Cross–Country Correlations (the Whole Sample)

As specified in section 3.1, the diagonal elements of the matrix are set to 0. Moreover, in order to retain stationarity (given $\lambda \in (-1, 1)$), the spatial weights matrix must be standardised (LeSage & Pace 2009). Having pairwise correlations bound to $(-1, 1)$, the row sum can exceed 1 and the linear combination $\sum_{j=1}^{N} \lambda \mathcal{W}_{i,j} y_j$ representing the contribution of spatial lags can become explosive. In this case, the common approach in this case is row standardisation of the matrix, i.e. each element is divided by corresponding row sum making the row sums of the matrix equal to one (Plümper & Neumayer 2010). This approach, however, diminishes the differences in overall influence of spatial lags on the dependent variable across countries. Having all row sums equal to one results in omission of differences in international engagement of the countries, as measures of economic proximity represented by the correlations are transformed from absolute measures to relative measures. This is not desirable taking into account the differences in size as well as range of pairwise correlations of different countries in the used dataset. Therefore, an approach proposed by Keiler & Eder (2013) is used in this thesis. The elements of the matrix are divided by the maximum absolute eigenvalue of the matrix. This way, the matrix is standardised in order to retain stationarity while preserving the differences in countries' international engagement and consequent difference in impact of spatial lags.

5.2 Spatial Model

As specified above, the correlation matrices were standardised with the use of the maximum absolute eigenvalue. With the use of these matrices, models were estimated for the two chosen sub–periods.
To eliminate the possibility of serial autocorrelation of the errors, lag of the dependent variable is included.
In the case of non–stationary variables, first differences were used. Such variables are denoted with "_d" at the end of their name. In the case of local stock indices, log–returns were calculated.
Moreover, endogeneity is reasonable to be expected for all the explanatory variables. To deal with this issue, all explanatory variables as well as the spatial weights matrices are lagged.

Given the to reasonable expectations of structural break and the change in international interdependence between the two selected sub–periods, the model estimated for the whole sample need not be valid. Therefore, this estimation is not reported.

First, MLE was used to estimate the results. Unfortunately, normality of residuals was rejected by multiple tests. When looking at the histograms, leptokurtic distribution with fat tails was present in all of the models. This is quite typical for financial markets data. As a result, GMM was used for estimation. This method does not require normality for consistence. The GMM estimation yields similar results as MLE but with higher variance of the estimates, i.e. less variables are found to be statistically significant. Nonetheless, this price has to be paid for robustness to the non–normality in data.

Two techniques were used in order to obtain the final results of the analysis: model selection and model averaging. When using model selection, different explanatory variables were chosen for the best model. Lag of the dependent variable is included in all of the models considered for both model selection and model averaging. This is to avoid serial correlation of the residuals which would make the estimation inconsistent. All other variables were subject to model selection. As a result, sharp differences between the two sub–periods can be observed. The results of the estimations for the first and the second sub–period are presented in tables 5.1 and 5.2, respectively.

Table 5.1: Model Selection Results for the First Sub–Period

	Dependent variable: 10–Year CDS Spread			
Baseline Model				
	Estimate	Std. Error	t–stat	p–value
lambda	0.340409	0.114184	2.981	0.00287**
$CDS10Y_{t-1}$	0.744916	0.060497	12.313	0.00000***
$JVar_{t-1}$	4015.195395	2205.800251	1.820	0.06871 .
$FinSector_{t-1}$	25.776056	12.250556	2.104	0.03537*
$GDPpcgr_{t-1}$	-6.469986	2.322493	-2.786	0.00534**
CPI_{t-1}	9.712964	5.611827	1.731	0.08349 .
$MMIR\_d_{t-1}$	88.851031	27.586366	3.221	0.00128**
$IndexLD_{t-1}$	80.681365	36.217493	2.228	0.02590*
$DebtToGdp\_d_{t-1}$	6.881838	2.140169	3.216	0.00130**
R-squared				0.816
AIC				1095.59
Robustness Check: Mean				
	Estimate	Std. Error	t–stat	p–value
lambda	0.164515	0.085572	1.923	0.05454 .
$CDS10Y\_mean_{t-1}$	0.955209	0.047949	19.921	0.00000***
$JVar_{t-1}$	3716.987996	1485.356049	2.502	0.01233*
$FinSector_{t-1}$	19.199516	8.309828	2.310	0.02086*
$GDPpcgr_{t-1}$	-6.071599	1.557138	-3.899	0.00010***
CPI_{t-1}	5.051226	3.912029	1.291	0.19663
$MMIR\_d_{t-1}$	85.945379	17.893626	4.803	0.00000***
$IndexLD_{t-1}$	5.085429	25.241627	0.201	0.84033
$DebtToGdp\_d_{t-1}$	3.782751	1.457792	2.595	0.00946**
R-squared				0.950
AIC				986.26
Robustness Check: Median				
	Estimate	Std. Error	t–stat	p–value
lambda	0.165382	0.089938	1.839	0.06594 .
$CDS10Y\_med_{t-1}$	0.915934	0.049709	18.426	0.00000***
$JVar_{t-1}$	4184.934558	1571.171010	2.664	0.00773**
$FinSector_{t-1}$	19.798325	8.783324	2.254	0.02419*
$GDPpcgr_{t-1}$	-6.501449	1.645972	-3.950	0.00008***
CPI_{t-1}	6.526379	4.100423	1.592	0.11147
$MMIR\_d_{t-1}$	91.968105	18.970619	4.848	0.00000***
$IndexLD_{t-1}$	12.727566	26.662340	0.477	0.63310
$DebtToGdp\_d_{t-1}$	4.847508	1.537314	3.153	0.00161**
R-squared				0.950
AIC				1001.91
Note:		. p<0.1; *p<0.05; **p<0.01; ***p<0.001		

Table 5.2: Model Selection Results for the Second Sub–Period

	Dependent variable: 10–Year CDS Spread			
Baseline Model				
	Estimate	Std. Error	t–stat	p–value
lambda	0.173759	0.099818	1.741	0.08173 .
$CDS10Y_{t-1}$	0.680473	0.033443	20.348	0.00000***
$FinSector_{t-1}$	9.046474	5.948361	1.521	0.12830
$Unemp\_d_{t-1}$	22.066425	5.936524	3.717	0.00020***
CPI_{t-1}	-2.165786	2.082920	-1.040	0.29844
$IndexLD_{t-1}$	26.265415	19.003454	1.382	0.16693
R-squared				0.836
AIC				1824.05
Robustness Check: Mean				
	Estimate	Std. Error	t–stat	p–value
lambda	0.034743	0.061908	0.561	0.57467
$CDS10Y_{t-1}$	0.878587	0.024064	36.511	0.00000***
$FinSector_{t-1}$	12.545191	4.258145	2.946	0.00322**
$Unemp\_d_{t-1}$	12.196905	4.279030	2.850	0.00437**
CPI_{t-1}	-1.889270	1.477614	-1.279	0.20104
$IndexLD_{t-1}$	9.371700	13.616684	0.688	0.49129
R-squared				0.933
AIC				1778.85
Robustness Check: Median				
	Estimate	Std. Error	t–stat	p–value
lambda	0.006990	0.064690	0.108	0.91395
$CDS10Y_{t-1}$	0.889888	0.024673	36.067	0.00000***
$FinSector_{t-1}$	13.194469	4.364381	3.023	0.00250**
$Unemp\_d_{t-1}$	13.307767	4.385621	3.034	0.00241**
CPI_{t-1}	-2.183380	1.516613	-1.440	0.14997
$IndexLD_{t-1}$	7.574180	13.960719	0.543	0.58745
R-squared				0.930
AIC				1810.02
Note:	. p<0.1; *p<0.05; **p<0.01; ***p<0.001			

Explanatory Variables

Size of financial sector relative to nation's wealth remains in both models but decreases in its magnitude as well as significance. In the second period it is included in the best model but is not statistically significant. This is attributable to general recovery from the effects of the crisis. In general, the level of risk in this sector has decreased, and therefore risk of possible bailouts or adverse effects on the economy is lower, and it loses its importance in determination of sovereign credit risk. This variable becomes statistically significant in the robustness checks even in the second sub–period. It is significantly lower than in the case of the first sub–period nevertheless.

Loss of significance can be observed for inflation as well. Note that the sign of the coefficient has changed from negative in the first sub–period to positive in the second sub–period. This is attributable to the facts discussed in section 4.2 — while in the first sub–period, rising inflation can be a sign of deterioration of the economy, the second sub–period represents low–inflation environment and rise of inflation can mean renewal of economic activity. Nonetheless, this effect is not strong enough to become statistically significant which, as opposed to the size of financial sector, is confirmed by the robustness checks. Inclusion of year 2017 could strengthen it given the general economic growth connected with subtle rise of inflation in the world.

The coefficient of local stock index is quite counter–intuitive. Its sign suggests that rise in local stock index implies increased sovereign credit risk. On the other hand, it is not significant at all in the second sub–period and it loses its statistical significance in the first sub–period in the robustness checks. Therefore, this is probably an anomaly.

The inclusion of unemployment into the model in the second sub–period and its omission in the first sub–period is interesting. It is of expected sign and remains statistically significant in the robustness checks in the second sub–period. Possible explanation is that in the first, post–crisis sub–period, unemployment rose in vast majority of the countries so its influence on sovereign credit risk could have been "consumed" by other factors. In the second sub–period, on the other hand, the pace of recovery was different among countries, and therefore the detection of the link between unemployment and sovereign credit risk was possible.

Finally, a set of variables is only included in the selected model for the first sub–period. These include jump variation of the dependent variable, GDP growth, money market interest rates and size of debt. All of these variables' coefficients are of expected sign and remain statistically significant in the robustness checks. Their link to sovereign credit risk was confirmed. Its theoretical basis was discussed in section 4.2 and therefore it is not necessary to discuss it again. Nonetheless, it is worth noting that these variables have lost their importance when moving on to the second sub–period.

As for jump variation, its presence is quite sparse and its influence was more visible in the more turbulent first sub–period while in the second sub–period, markets did not react as vigorously and the effect faded quickly.
The case of the size of sovereign debt is similar. After recovering from the effects of the crisis, markets tend to care less about the size of debt as the agents regain trust in governments' ability to repay it.
In the case of GDP growth, the difference could reflect the fact that in the first sub–period this variable did vary more than in the second sub–period. Moving to the second, stagnant sub–period, less variation is observable and therefore it cannot be easily linked to sovereign credit risk.
Finally, short–term money market interest rate is somewhat similar to GDP growth in its patterns. While in the first sub–period it was showing more variability, in the second sub–period small or no changes are observable. The rates have reached their historical minima and have remained so for a long time. With such low variability, links are difficult to detect.
Studies such as Beirne & Fratzscher (2013b) or Arghyrou & Kontonikas (2012) carry out a study which finds increased sensitivity of financial markets to economic fundamentals during "bad times" which is in accordance with the results of this thesis. In the second sub–period, less factors are found to be decisive for determination of sovereign credit risk.

Spatial Autocorrelation Term

The main focus of this thesis is to examine the presence of spillover effects represented by the spatial autocorrelation component of the model. Decrease of its size as well as statistical significance can be observed between the two sub–periods. Moreover, the robustness checks report lower importance, again in magnitude as well as in statistical significance. In the first sub–period, the size of the spatial autocorrelation coefficient decreases approximately by half and its significance drops but remains on the edge of statistical significance having $p - value$ of .055 for mean and 0.066 for median. Since some portion of information is lost when using mean or median, presence of spillover effects in the first sub–period can still be confirmed. Its size, however, can be a subject of discussion. In the second sub–period, on the other hand, the drop is more significant: the spatial autocorrelation coefficient turns into so called "insignificant zero" for both mean and median. This means that not only is it statistically insignificant, but its estimate is also close to zero. This speaks for the absence of spillover effects in the second sub–period.

While the results for the first sub–period confirm the presence of spatial autocorrelation of the dependent variable, i.e. spillover effects, the results for the second sub–period rather reject it. This can be explained by the differences in economic conditions between the two sub–periods. Contagion and/or spillovers of credit risk, often referred to as "excess correlation", are known to appear more frequently during crisis. This is confirmed by numerous studies, e.g. De Bruyckere *et al.* (2013) which explores patterns of contagion between banks and sovereigns, Arezki *et al.* (2011) which examines the spillover effects of sovereign rating news during the crisis or Longstaff (2010) which examines subprime credit crisis and contagion in subprime indexes. While in the first sub–period the effects of the crisis were still present and Greek sovereign debt crisis was reaching its peak, the second sub-period was marked by the start of recovery and overall better condition of the economy.

The results presented above were obtained using model selection as described in section 3.3. Additionally, an analysis using frequentist model averaging as specified in the same section was carried out. Its results, however, provide little additional information to those of model selection. Due to the discussed possible over–estimation of estimates' variance, less variables were found to be statistically significant. The patterns, however, remain unchanged. The results of the models obtained using model averaging are presented in the Appendix.

Chapter 6

Conclusion

This thesis analyses sovereign credit risk drivers in a spatial perspective. Specifically, it estimates the influence of macroeconomic indicators on sovereign credit risk while accounting for international interconnectedness and resulting spillovers. It contributes to existing research by adding information from high–frequency data to econometric model which works with quarterly data. Specifically, high–frequency data is analysed with the use of robust wavelet based covariance estimator JWTSCV. These correlations are used in a spatial econometric model to model international spillovers of credit risk. Consequently, quarterly data on macroeconomic indicators are used as explanatory variables assessing what drives sovereign credit risk.

In the first part of the thesis, research related to the topic of this thesis is summarised. While building on the existing literature, theoretical background for all the steps in the analysis is introduced. Fundamentals of spatial econometrics and possible models are introduced. Presentation of robust wavelet based covariance estimator JWTSCV follows. Finally, model selection and model averaging techniques are presented and robustness checks are suggested.

The empirical part shows the main contribution of this thesis. Additional information obtained from high–frequency data analysis is used in the construction of the model. Moreover, contagion and spillovers are accounted for in the estimation.
Daily data on CDS spreads and 10–year sovereign bond yields are analysed to support the decision to use robust covariance estimator and robustness checks. Quarterly close, mean, and median of the CDS spreads are used as the de-

pendent variable. JWTSCV is used to estimate cross–country correlations from daily data on bond yields. A spatial weights matrix is constructed based on these estimates. The spatial weights matrix is standardised by its maximum absolute eigenvalue.
Several macroeconomic indicators are chosen to be used in the model. Finally, econometric model is specified and estimated. The dataset is split into two sub–periods to accommodate for Greek debt restructuring which may have changed investors' attitude towards CDS. Moreover, the first sub–period covers the period of 2009 — 2011 where the effects of the 2007–2009 crisis are still present and Greece is going through sovereign debt crisis.

The models are estimated using GMM. All explanatory variables as well as the spatial weights matrix were lagged in order to avoid their endogeneity. Significant differences are discovered between the two sub–periods. In the first sub–period, more variables are found to be statistically significant when compared to the second sub–period. Lag of the dependent variable is included in all the models and is statistically significant. Apart from the lag, 7 explanatory variables are included in the selected model for the first sub–period: Jump variation, size of financial sector, GDP growth, inflation rate, short term money market interest rate, local stock index log–returns and debt to GDP. All the variables are statistically significant, but local stock index log–returns and inflation rate lose their significance in robustness checks. In the second sub–period, the size of financial sector and unemployment rate are statistically significant. Additionally, inflation rate and local stock index log–returns are included in the selected model but are nowhere near statistical significance. In both sub–periods, the variables' coefficients are of expected sign with the exception of local stock index. This variable, however, turns out to be statistically insignificant in robustness checks.
The spatial autocorrelation component of the model is statistically significant in the first sub–period, while in the second sub–period it is not. These results are in compliance with findings of other studies, which generally report presence of spillovers or contagion and higher sensitivity of credit risk to fundamentals in times of crisis. Model averaging provides little additional information to model selection and essentially the same conclusions are drawn from results of this approach.

To conclude, the empirical research has proved the benefit of the new methodology presented in this thesis. It was shown that additional information stemming from high–frequency data analysis can be added to conventional econometric models to improve their performance. Moreover, international interconnectedness can yield spillovers which have to be accounted for in order to obtain consistent estimates. Finally, in accordance with other studies, importance of fundamentals as well as presence of spillovers and contagion are stronger in crisis and post–crisis period, whereas in times of economic prosperity, the market perception of sovereign credit risk becomes less dependent on fundamentals, and spillovers and contagion become negligible.

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Appendix A

Appendix

A.1 Bipower Variation of 10–year CDS Log–returns

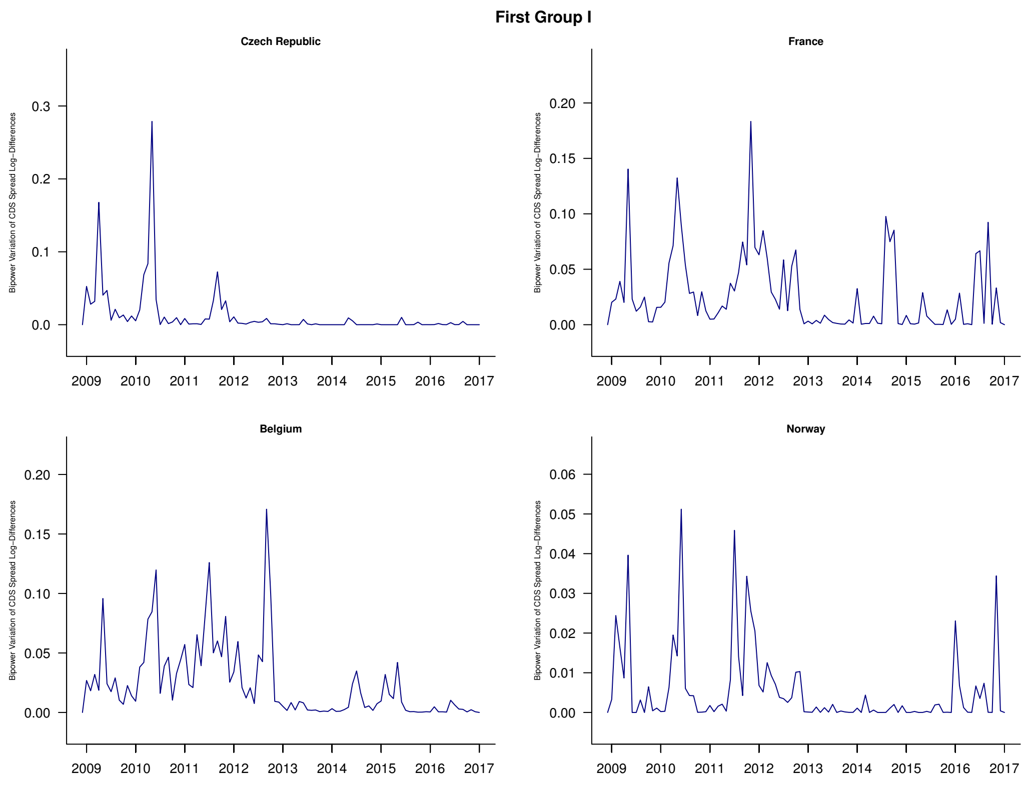

Figure A.1: Bipower Variation of 10–Year CDS Log–Returns I
Source of Data: Thomson Reuters

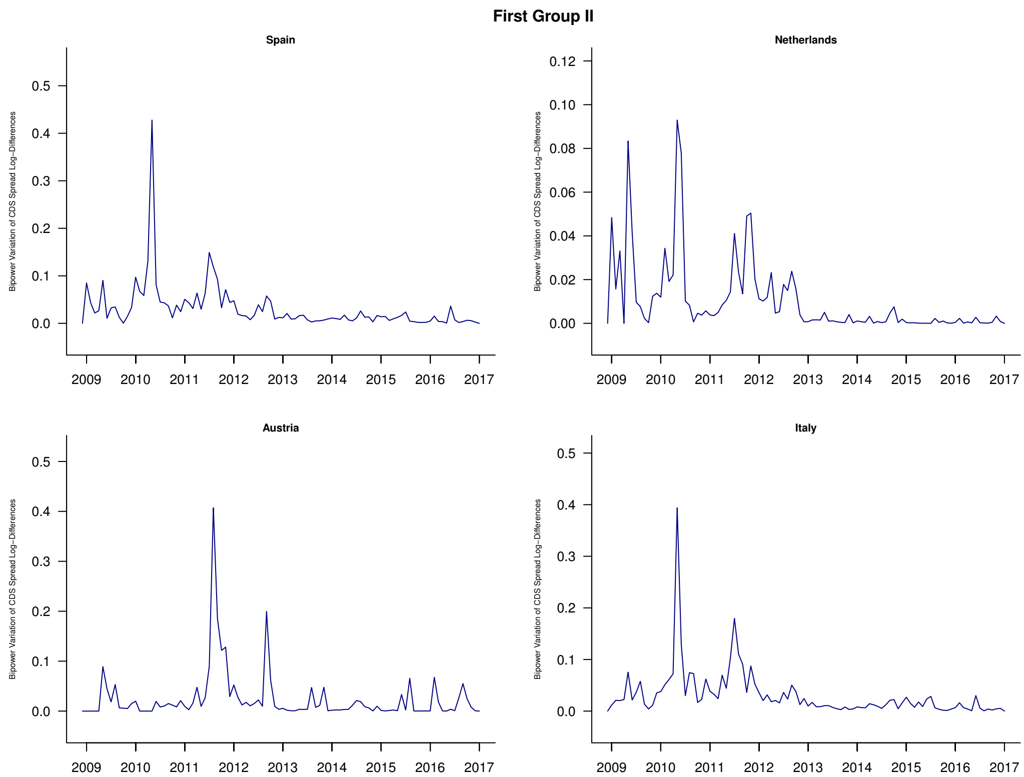

Figure A.2: Bipower Variation of 10–Year CDS Log–Returns II
Source of Data: Thomson Reuters

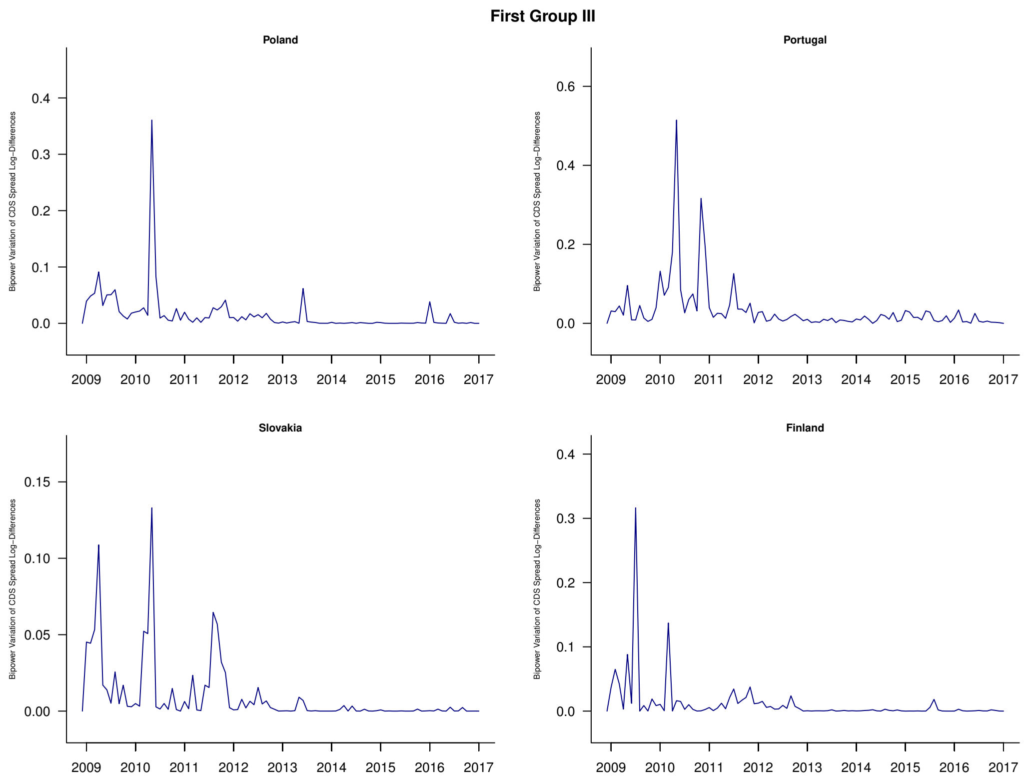

Figure A.3: Bipower Variation of 10–Year CDS Log–Returns III
Source of Data: Thomson Reuters

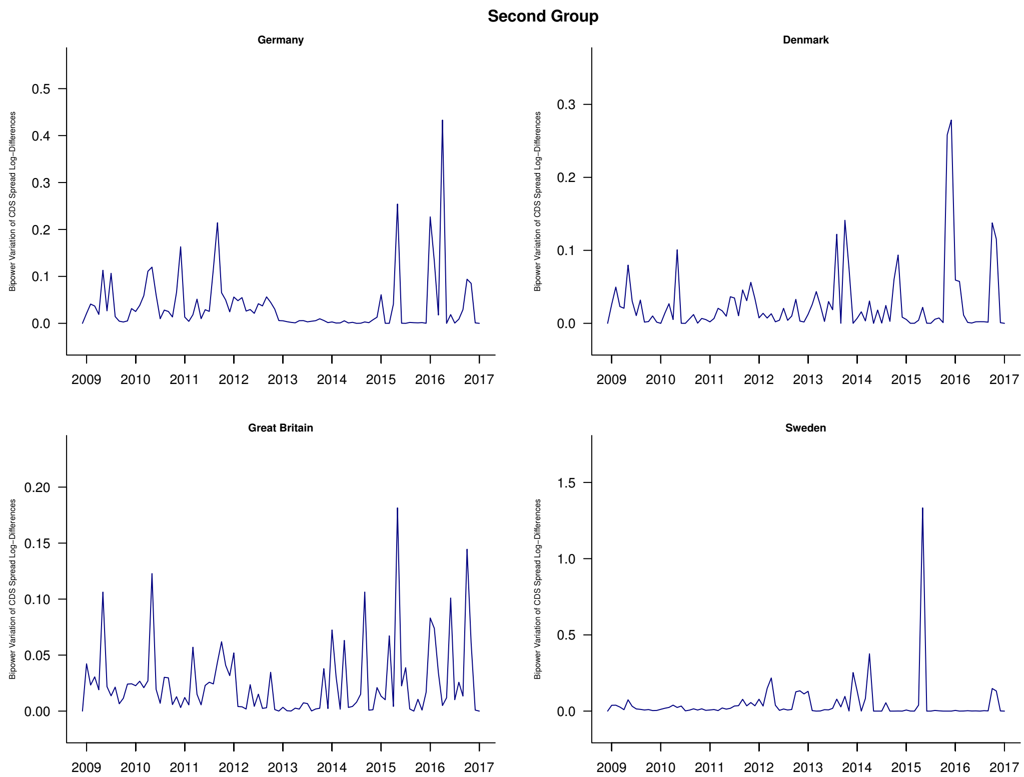

Figure A.4: Bipower Variation of 10–Year CDS Log–Returns IV
Source of Data: Thomson Reuters

A.2 Correlation Matrices

Table A.1: Correlation Matrix, First Sub–Period

	CZ	DE	FR	GR	BE	DK	NO	ES	NL	AT	IT	PL	PT	SK	GB	FI	SE
CZ	1	0.182	0.153	-0.030	0.111	0.170	0.052	0.080	0.202	0.191	0.034	0.110	0.011	0.048	0.148	0.177	0.143
DE	0.182	1	0.727	-0.101	0.370	0.840	0.509	0.033	0.875	0.607	-0.030	-0.131	0.003	0.121	0.782	0.819	0.766
FR	0.153	0.727	1	0.001	0.631	0.628	0.340	0.297	0.741	0.731	0.263	-0.033	0.096	0.111	0.595	0.701	0.505
GR	-0.030	-0.101	0.001	1	0.140	-0.068	-0.133	0.323	-0.064	0.031	0.271	0.104	0.535	0.020	-0.026	-0.051	-0.102
BE	0.111	0.370	0.631	0.140	1	0.269	0.064	0.562	0.437	0.571	0.551	0.064	0.297	0.106	0.291	0.433	0.152
DK	0.170	0.840	0.628	-0.068	0.269	1	0.436	0.054	0.793	0.575	-0.025	-0.136	-0.027	0.133	0.712	0.757	0.690
NO	0.052	0.509	0.340	-0.133	0.064	0.436	1	-0.041	0.453	0.245	-0.089	-0.220	-0.110	0.013	0.385	0.365	0.534
ES	0.080	0.033	0.297	0.323	0.562	0.054	-0.041	1	0.165	0.334	0.712	0.106	0.429	0.064	0.084	0.123	-0.022
NL	0.202	0.875	0.741	-0.064	0.437	0.793	0.453	0.165	1	0.701	0.059	-0.076	0.016	0.133	0.715	0.789	0.713
AT	0.191	0.607	0.731	0.031	0.571	0.575	0.245	0.334	0.701	1	0.239	-0.020	0.083	0.162	0.494	0.617	0.440
IT	0.034	-0.030	0.263	0.271	0.551	-0.025	-0.089	0.712	0.059	0.239	1	0.104	0.374	0.080	0.003	0.053	-0.110
PL	0.110	-0.131	-0.033	0.104	0.064	-0.136	-0.220	0.106	-0.076	-0.020	0.104	1	0.132	0.001	-0.105	-0.075	-0.212
PT	0.011	0.003	0.096	0.535	0.297	-0.027	-0.110	0.429	0.016	0.083	0.374	0.132	1	0.021	0.051	0.034	-0.114
SK	0.048	0.121	0.111	0.020	0.106	0.133	0.013	0.064	0.133	0.162	0.080	0.001	0.021	1	0.056	0.119	0.106
GB	0.148	0.782	0.595	-0.026	0.291	0.712	0.385	0.084	0.715	0.494	0.003	-0.105	0.051	0.056	1	0.640	0.666
FI	0.177	0.819	0.701	-0.051	0.433	0.757	0.365	0.123	0.789	0.617	0.053	-0.075	0.034	0.119	0.640	1	0.603
SE	0.143	0.766	0.505	-0.102	0.152	0.690	0.534	-0.022	0.713	0.440	-0.110	-0.212	-0.114	0.106	0.666	0.603	1

Table A.2: Correlation Matrix, Second Sub–Period

	CZ	DE	FR	GR	BE	DK	NO	ES	NL	AT	IT	PL	PT	SK	GB	FI	SE
CZ	1	0.156	0.296	-0.022	0.278	0.138	0.246	0.158	0.186	0.272	0.201	0.190	0.074	0.224	0.227	0.201	0.188
DE	0.156	1	0.458	-0.047	0.427	0.249	0.235	0.110	0.286	0.339	0.141	0.087	0.027	0.242	0.345	0.352	0.328
FR	0.296	0.458	1	-0.0002	0.943	0.641	0.441	0.453	0.711	0.871	0.504	0.277	0.238	0.527	0.627	0.832	0.577
GR	-0.022	-0.047	-0.0002	1	0.010	-0.036	-0.119	0.263	-0.014	-0.013	0.279	0.121	0.360	-0.027	-0.121	-0.015	-0.047
BE	0.278	0.427	0.943	0.010	1	0.591	0.423	0.447	0.642	0.832	0.502	0.273	0.236	0.525	0.608	0.816	0.529
DK	0.138	0.249	0.641	-0.036	0.591	1	0.262	0.207	0.617	0.585	0.209	0.129	0.059	0.325	0.413	0.669	0.404
NO	0.246	0.235	0.441	-0.119	0.423	0.262	1	0.148	0.233	0.386	0.189	0.251	-0.015	0.317	0.521	0.312	0.505
ES	0.158	0.110	0.453	0.263	0.447	0.207	0.148	1	0.240	0.374	0.837	0.367	0.633	0.285	0.187	0.337	0.216
NL	0.186	0.286	0.711	-0.014	0.642	0.617	0.233	0.240	1	0.698	0.234	0.117	0.085	0.302	0.385	0.801	0.428
AT	0.272	0.339	0.871	-0.013	0.832	0.585	0.386	0.374	0.698	1	0.409	0.255	0.188	0.480	0.584	0.797	0.558
IT	0.201	0.141	0.504	0.279	0.502	0.209	0.189	0.837	0.234	0.409	1	0.374	0.659	0.309	0.183	0.330	0.240
PL	0.190	0.087	0.277	0.121	0.273	0.129	0.251	0.367	0.117	0.255	0.374	1	0.283	0.233	0.254	0.194	0.216
PT	0.074	0.027	0.238	0.360	0.236	0.059	-0.015	0.633	0.085	0.188	0.659	0.283	1	0.144	0.0002	0.129	0.082
SK	0.224	0.242	0.527	-0.027	0.525	0.325	0.317	0.285	0.302	0.480	0.309	0.233	0.144	1	0.384	0.426	0.375
GB	0.227	0.345	0.627	-0.121	0.608	0.413	0.521	0.187	0.385	0.584	0.183	0.254	0.0002	0.384	1	0.530	0.487
FI	0.201	0.352	0.832	-0.015	0.816	0.669	0.312	0.337	0.801	0.797	0.330	0.194	0.129	0.426	0.530	1	0.547
SE	0.188	0.328	0.577	-0.047	0.529	0.404	0.505	0.216	0.428	0.558	0.240	0.216	0.082	0.375	0.487	0.547	1

Table A.3: Correlation Matrix, the Whole Sample

	CZ	DE	FR	GR	BE	DK	NO	ES	NL	AT	IT	PL	PT	SK	GB	FI	SE
CZ	1	0.152	0.284	-0.018	0.265	0.136	0.204	0.143	0.180	0.264	0.175	0.181	0.055	0.205	0.216	0.196	0.185
DE	0.152	1	0.456	-0.036	0.422	0.253	0.212	0.098	0.288	0.340	0.125	0.080	0.021	0.230	0.326	0.355	0.330
FR	0.284	0.456	1	-0.0003	0.932	0.637	0.394	0.421	0.703	0.866	0.468	0.255	0.188	0.494	0.591	0.825	0.572
GR	-0.018	-0.036	-0.0003	1	0.021	-0.028	-0.105	0.240	-0.012	-0.008	0.237	0.099	0.369	-0.015	-0.073	-0.013	-0.040
BE	0.265	0.422	0.932	0.021	1	0.582	0.350	0.437	0.633	0.824	0.488	0.259	0.209	0.492	0.548	0.805	0.513
DK	0.136	0.253	0.637	-0.028	0.582	1	0.240	0.185	0.617	0.583	0.184	0.117	0.043	0.308	0.394	0.670	0.407
NO	0.204	0.212	0.394	-0.105	0.350	0.240	1	0.102	0.206	0.337	0.117	0.160	-0.037	0.251	0.476	0.282	0.473
ES	0.143	0.098	0.421	0.240	0.437	0.185	0.102	1	0.216	0.353	0.803	0.325	0.539	0.247	0.166	0.304	0.187
NL	0.180	0.288	0.703	-0.012	0.633	0.617	0.206	0.216	1	0.693	0.210	0.109	0.065	0.286	0.355	0.799	0.425
AT	0.264	0.340	0.866	-0.008	0.824	0.583	0.337	0.353	0.693	1	0.380	0.238	0.151	0.454	0.542	0.792	0.552
IT	0.175	0.125	0.468	0.237	0.488	0.184	0.117	0.803	0.210	0.380	1	0.336	0.547	0.272	0.137	0.295	0.198
PL	0.181	0.080	0.255	0.099	0.259	0.117	0.160	0.325	0.109	0.238	0.336	1	0.230	0.207	0.196	0.180	0.184
PT	0.055	0.021	0.188	0.369	0.209	0.043	-0.037	0.539	0.065	0.151	0.547	0.230	1	0.109	0.013	0.101	0.046
SK	0.205	0.230	0.494	-0.015	0.492	0.308	0.251	0.247	0.286	0.454	0.272	0.207	0.109	1	0.327	0.403	0.351
GB	0.216	0.326	0.591	-0.073	0.548	0.394	0.476	0.166	0.355	0.542	0.137	0.196	0.013	0.327	1	0.499	0.490
FI	0.196	0.355	0.825	-0.013	0.805	0.670	0.282	0.304	0.799	0.792	0.295	0.180	0.101	0.403	0.499	1	0.546
SE	0.185	0.330	0.572	-0.040	0.513	0.407	0.473	0.187	0.425	0.552	0.198	0.184	0.046	0.351	0.490	0.546	1

A.3 Model Averaging Results

Table A.4: Model Averaging Results for the First Sub–Period

	Dependent variable: CDS10Y			
Spatial Component				
	Estimate	Std. Error	t–stat	p–value
lambda	0.306507	0.139481	2.197	0.02864*
Explanatory Variables				
$CDS10Y_{t-1}$	0.750515	0.067164	11.174	0.00000***
CPI_{t-1}	6.279846	4.426195	1.419	0.15685
$CurAccBal\_d_{t-1}$	0.077456	0.597019	0.130	0.89685
$DebtToGdp\_d_{t-1}$	7.104213	2.218084	3.203	0.00149**
$FinSector_{t-1}$	15.898396	9.945867	1.598	0.11084
$GDPpcgr_{t-1}$	-5.360176	2.321428	-2.309	0.02153*
$IndProd\_d_{t-1}$	-1.517243	1.293019	-1.173	0.24143
$IndexLD_{t-1}$	42.715609	29.019580	1.472	0.14193
$IntlTrd\_d_{t-1}$	0.051394	0.165126	0.311	0.75580
$JVar_{t-1}$	2117.021809	1566.613194	1.351	0.17746
$MMIR\_d_{t-1}$	83.310857	30.839478	2.701	0.00724**
$RVol_{t-1}$	-76.724353	93.938175	-0.817	0.41462
$Unemp\_d_{t-1}$	1.237570	3.601558	0.344	0.73134
Note:	. p<0.1; *p<0.05; **p<0.01; ***p<0.001			

Table A.5: Model Averaging Results for the First Sub–Period

	Dependent variable: CDS10Y			
Spatial Component				
	Estimate	Std. Error	t–stat	p–value
lambda	0.112190	0.104552	1.073	0.28399
Explanatory Variables				
$CDS10Y_{t-1}$	0.683841	0.034084	20.063	0.00000***
CPI_{t-1}	-0.916929	1.186714	-0.773	0.44024
$CurAccBal\_d_{t-1}$	-0.133491	0.298215	-0.448	0.65470
$DebtToGdp\_d_{t-1}$	-0.131633	0.266342	-0.494	0.62146
$FinSector_{t-1}$	5.543110	4.263443	1.300	0.19441
$GDPpcgr_{t-1}$	-0.178153	0.345317	-0.516	0.60624
$IndProd\_d_{t-1}$	-0.622904	0.573450	-1.086	0.27812
$IndexLD_{t-1}$	12.860317	11.476216	1.121	0.26322
$IntlTrd\_d_{t-1}$	-0.012363	0.052670	-0.235	0.81456
$JVar_{t-1}$	0.046326	0.238199	0.194	0.84591
$MMIR\_d_{t-1}$	0.066740	2.125470	0.031	0.97497
$RVol_{t-1}$	7.653656	18.487643	0.414	0.67914
$Unemp\_d_{t-1}$	21.009234	6.148532	3.417	0.00071***
Note:	. p<0.1; *p<0.05; **p<0.01; ***p<0.001			