UNIVERSITÀ DEGLI STUDI DI BERGAMO

DOCTORAL THESIS

Essays in Systemic Risk and Contagion

Author:

Riccardo PIANETI

Supervisor:

Prof. Giorgio CONSIGLI

Co-supervisor:

Prof. Giovanni URGA

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

Ph.D. School in Economics, Applied Mathematics and Operational Research

October 2013

Declaration of Authorship

I, Riccardo Pianeti, declare that this thesis titled, "Essays in Systemic Risk and Contagion" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date:

"Charm is the ability to insult people without offending them; nerdiness the reverse."

Nassim Nicholas Taleb

Abstract

Essays in Systemic Risk and Contagion

by Riccardo PIANETI

This work contributes to the timely debate about the consequences of the materialization of financial instability in the global economic and financial system. The topic of measuring and forecasting systemic risk, together with the related implications for policy makers, is explored from different angles. First, we propose a method to estimate forward-looking probabilities of joint default, with an application to the recent European debt crisis. We find evidence of increasing systemic risk and danger of default contagion from early 2007 and more significantly from late 2011 onwards. Second, a novel modelling framework to measure systemic risk in a unified approach, relying on an extended information basis across both financial and macroeconomic aggregates, is proposed and tested using data from 1995 to 2011. Third, we analyse in particular the late 2000s crisis and the European debt crisis, by means of a novel modelling set-up to test for contagion versus excess interdependence. The empirical application reveals that the 2007-09 financial crisis characterized as a persistent period of financial distress, whereas the recent debt crisis has to be understood as a short-lived phenomenon, having been prompted by volatility spillovers, which do not display trend in the long-term. Finally, we propose an empirical study to measure the reaction of the Monetary Authorities to systemic risk, and highlight important differences between Central Banks' monetary conducts during the recent period of financial turmoil.

Acknowledgements

I would like to express my sincere gratitude to all the people who supported me through the journey of my studies, and in particular:

To my supervisors Prof. Giorgio Consigli and Prof. Giovanni Urga for their advice, trust and commitment.

To my mentor Martin “Belvo” Belvisi for his intriguing insights and endless passion.

To my co-author Prof. Rosella Giacometti for useful comments and discussions.

To the director of the Ph.D. School, Prof. Marida Bertocchi, for promoting me and pushing me to my best.

To Matteo Crippa, Gianluca Forzenigo, Alexios Ghalanos, Adriana Gnudi, Dr. Gustaaf Houtman, Vincenzo Ludovico Maini, Dominique Remars, Emanuele Spoti and Dr. Lorenzo Trapani to have shown me the way with their advice and educated view.

To my fellow Ph.D. colleagues, in particular Marco Jean Aboav, Hami Amiraslani, Michele Bergamelli, Simona Boffelli and Capt. Kaizad Doctor.

To Mia, Marta and my parents, Graziano and Maria, for their love and constant support.

To Jason, Kristian and Roberta, for their special friendship.

Contents

List of Tables

List of Figures

Abbreviations

AIC	**A**kaike **I**nformation **C**riterion
BIS	**B**ank for **I**nternational **S**ettlements
BoE	**B**ank **o**f **E**ngland
BSMs	**B**anking **S**tability **M**easures in Segoviano and Goodhart (2009)
CBO	**C**ongressional **B**udget **O**ffice
CBPP	**C**overed **B**ond **P**urchase **P**rogramme
CCA	**C**ontingent **C**laims **A**nalysis
CDS	**C**redit **D**efault **S**wap
CEPR	**C**entre for **E**conomic **P**olicy **R**esearch
CIMDO	**C**onsistent **I**nformation **M**ultivariate **D**ensity **O**ptimizing methodology in Segoviano (2006)
CISS	**C**omposite **I**ndicator of **S**ystemic **S**tress in Hollo et al. (2012)
CoVaR	**Co**nditional **V**alue **a**t **R**isk in Adrian and Brunnermeier (2011)
CPI	**C**onsumer **P**rice **I**ndex
CSFB	**C**redit **S**uisse **F**irst **B**oston
CVA	**C**redit **V**alue **A**djustment
DCC	**D**ynamic **C**onditional **C**orrelation model in Engle (2002)
DIP	**D**istress **I**nsurance **P**remium in Huang et al. (2009)
ECB	**E**uropean **C**entral **B**ank
ECM	**E**rror **C**orrection **M**odel
EM	**E**merging **M**arkets

EONIA	**E**uro **O**ver**N**ight **I**ndex **A**verage
ERM	European **E**xchange **R**ate **M**echanism
EVT	**E**xtreme **V**alue **T**heory
Fed	**Fed**eral Reserve
FSaR	**F**inancial **S**ystem **at** **R**isk in De Nicoló and Lucchetta (2012)
FX	**F**oreign E**x**change
G10	**G**roup of **Ten**
GARCH	**G**eneralized **A**uto**R**egressive **C**onditional **H**eteroscedasticity model in Bollerslev (1986)
GDP	**G**ross **D**omestic **P**roduct
GUM	**G**eneralized **U**nrestricted **M**odel
HP	**H**odrick-**P**rescott
HQ	**H**annan-**Q**ueen Information Criterion
IIS	**I**mpulse-**I**ndicator **S**aturation
IMF	**I**nternational **M**onetary **F**und
ISDA	**I**nternational **S**waps and **D**erivatives **A**ssociation
KPSS	**K**wiatkowski-**P**hillips-**S**chmidt-**S**hin test for stationarity
Libor	**L**ondon **I**nter**b**ank **O**ffered **R**ate
LR	**L**ong **R**un
LTROs	**L**ong-**T**erm **R**efinancing **O**perations
MS1	**M**odel **S**pecification **1** for Eqs. (2.25)-(2.26)
MS2	**M**odel **S**pecification **2** for Eqs. (2.25)-(2.26)
MS3	**M**odel **S**pecification **3** for Eqs. (2.25)-(2.26)
MSCI	**M**organ **S**tanley **C**apital **I**nternational
NBER	**N**ational **B**ureau of **E**conomic **R**esearch
OECD	**O**rganisation for **E**conomic **C**o-operation and **D**evelopment
OIS	**O**vernight **I**ndexed **S**wap
OLS	**O**rdinary **L**east **S**quares

OTC	**O**ver **t**he **C**ounter
PCA	**P**rincipal **C**omponent **A**nalysis
QE	**Q**uantitative **E**asing
RPIX	**R**etail **P**rice **I**nde**x**
SC	**S**chwarz Information **C**riterion
SES	**S**ystemic **E**xpected **S**hortfall in Acharya et al. (2010)
SMP	**S**ecurities **M**arkets **P**rogramme
SONIA	**S**terling **O**ver**N**ight **I**nterbank **A**verage
SRISK	**S**ystemic **Risk** Index in Brownlees and Engle (2012)
TED spread	**T**-bill **E**uro**D**ollar spread
VaR	**V**alue **a**t **R**isk
ZCB	**Z**ero-**C**oupon **B**ond

Other Conventions

A legend for the employed notation is reported at the end of each chapter. The following standard conventions are used throughout the work:

$\lvert \cdot \rvert$	cardinality of a set
$diag(\cdot)$	diagonal operator transforming a vector into a diagonal matrix
$\mathbb{1}_{\{\cdot\}}$	indicatrix function returning 1 when condition in $\{\cdot\}$ is satisfied and 0 otherwise
v_n	n-th entry of the vector $v \in \mathbb{R}^N$ with $n = 1, \ldots, N$
$A_{n,m}$	(n, m)-element of the $N \times M$ matrix A with $n = 1, \ldots, N$ and $m = 1, \ldots, M$
$A_{\cdot,m}$	m-th column of the $N \times M$ matrix A with $m = 1, \ldots, M$
$A_{n,\cdot}$	n-th row of the $N \times M$ matrix A with $n = 1, \ldots, N$
$\mathbf{1}$	unit column vector
$\mathbb{P}(\cdot)$	probability of an event
$\mathbb{E}(\cdot)$	expected value
$\mathcal{N}(\mu, \sigma^2)$	normal distribution with mean μ and variance σ^2
$\mathcal{T}(\nu)$	t-Student distribution with ν degrees of freedom
$\mathcal{B}(p)$	Bernoulli distribution with parameter p
$\hat{\theta}$	estimate of the unknown scalar or vector parameter θ
ΔX_t	first difference of the time series $\{X_t\}_{t=1,\ldots,T}$ at time t
$X(t, T)$	value of X at time t referred to maturity T

To Mia and Marta

Preface

This thesis presents the product of my work in the fulfilment of the requirements for the degree of Doctor of Philosophy. The work was carried out while at the University of Bergamo during the academic year 2010/11 and while visiting the Centre for Econometric Analysis at Cass Business School, London (UK) during the academic years 2011/12 and 2012/13. In particular, I worked on Chapter 2 in year 1 and 2 and on Chapter 1 and 3 in year 2 and 3.

Academic papers have been drawn from each of the chapters. My co-authors in the papers are: Martin Belvisi (Chapter 3), Prof. Giorgio Consigli (Chapter 2), Prof. Rosella Giacometti (Chapter 1) and Prof. Giovanni Urga (Chapter 2 and 3). The usual disclaimer applies.

Updates, later comments and major revisions of the original work, if any, are reported in the postscript at the end of each chapter.

Introduction

The way in which recent financial crises have evolved and spread out at a global level has drawn the attention of academics, regulators and policy makers on methods able to assess the systemic risk affecting the financial system.

A first strand of research defines systemic risk as the risk of financial distress within the international banking sector, with the idea that systemic instabilities propagate through the financial channel and that the soundness of the financial system is epitomized by the financial health of big institutions. Taking this view, standard risk management techniques are applied to measure financial instability within the banking sector, with the scope of providing an assessment of the financial tension in the whole system. Notable contributions along this line are: Lehar (2005), Huang et al. (2009), Segoviano and Goodhart (2009), Acharya et al. (2010), Adrian and Brunnermeier (2011), Brownlees and Engle (2012) and Jobst and Gray (2013)[1]. In particular, Lehar (2005) focuses on both asset correlations and interlinkages within the interbank market to analyse insolvency risk over a one-year horizon. Huang et al. (2009) measure systemic risk by means of the Distress Insurance Premium (DIP), defined as the premium required to cover distressed losses for a given pool of banking institutions. Segoviano and Goodhart (2009) introduce a set of Banking Stability Measures (BSMs) based on the multivariate distribution of banking

[1]A different methodological approach is the one using network theory to measures the degree of interconnectedness of the banking sector. See inter alia IMF (2009), Haldane and May (2011) and Billio et al. (2012).

defaults, which is estimated via the Consistent Information Multivariate Density Optimizing methodology (CIMDO) in Segoviano (2006). Acharya et al. (2010) introduce the Systemic Expected Shortfall (SES) of a bank as the expected shortfall on the bank equity value, conditioned on the materialization of a loss triggered by a systemic event. Adrian and Brunnermeier (2011) propose the concept of Conditional Value at Risk (CoVaR), defined as the financial sector's Value at Risk (VaR) given that an institution has incurred in a VaR loss. Brownlees and Engle (2012) introduce the Systemic Risk Index (SRISK), determined by the expected capital shortage a financial firm would experience in case of a systemic event, defined as a substantial market decline over a given time horizon. Finally, the approach in Jobst and Gray (2013) utilizes Contingent Claims Analysis (CCA) to assess credit risk at the single financial institutions level and generate an aggregate estimate of the joint default risk as a conditional tail expectation using multivariate Extreme Value Theory (EVT)[2].

There is a second line of research within the systemic risk literature, which embraces a global economic and financial perspective, inferring from both the market dynamics and the macroeconomic context an indication of the financial instability at the system level. Schwaab et al. (2011) adopt a dynamic state-space model to determine forward crises indicators with underlying macro-financial and credit risk variables. Hollo et al. (2012) introduce the Composite Indicator of Systemic Stress (CISS) for the European financial system, providing an a-posteriori insight into the extent to which financial stress tends to depress real economic activity. De Nicoló and Lucchetta (2012) propose a model framework to forecast both real and financial systemic instabilities via density forecasts for indicators of real activity and financial soundness.

[2]For an analytic survey of the contributions in this line of research, see the paper by Bisias et al. (2012).

This work contributes to both lines of research. Within the first stream of literature, we propose a method to estimate forward-looking probabilities of joint default applicable to multiple financial and/or sovereign entities, which is used to infer early-warning indications of financial systemic instability. We also contribute to the latter line of research by proposing a novel modelling framework to measure systemic risk in a unified approach, which rely on an extended information basis across both financial and macroeconomics aggregates. The methodology is based on the definition of systemic risk stated in the G10 Report on Consolidation in the Financial Sector (G10, 2001), according to which systemic risk is to be associated to a generalized loss in economic value, going hand-in-hand with increasing uncertainty and worsening conditions in the real side of the economy. From the standpoint of the empirical results, we explore recent episodes of financial instability and relate them to the stylized facts mentioned in the G10 definition. We take this analysis a step further, with particular emphasis on the late 2000s crisis and the European debt crisis, by proposing a modelling set-up to test for pure contagion versus excess interdependence during periods of financial distress. The dissection of the two effects has a crucial information content as to how a crisis develops and spreads out.

The study of economic and financial turmoil episodes finds its primary goal in the development of forecasting methodologies for systemic threats, with the ultimate scope of guiding macroeconomic stabilization policies, along with the idea that the identification of key underlying risk factors would pave the way to a cooperative and more effective international response. On the latter aspect, we propose an empirical study to measure the reaction of Central Banks to the building up of systemic instabilities across the past two decades. Concerning with the effort of developing methodologies able to provide early-warning signals of financial turmoil, the proposed joint default probability estimator can be employed for an assessment of the likelihood of the materialization of future systemic threats. This toolkit is applied to sovereign risk in Europe during the recent debt crisis, with the goal of foreseeing systemic instabilities and danger of contagion.

The dissertation is divided in three chapters. In Chapter 1, we propose a methodology to estimate the likelihood of the default of one or more entities using current market data. Applying a no-arbitrage argument, we derive a formula for the joint default probability for couple of financial institutions and use it to infer information about the joint default correlations of single entities with a representative protection seller in the credit derivative market. The defaults of the single institutions are then correlated through their common dependence on the protection seller, typically a top tier investment bank, which represents the financial sector, considered in the first line of research mentioned above, as the channel through which financial crises chiefly propagate. We provide an empirical application on sovereign risk in the Euro Area during the recent debt crisis. the proposed methodology is employed to dynamically estimate marginal, joint and conditional default probabilities within the Euro Zone. We test the forecasting capability of the estimated default probabilities using a benchmark stock market index, which marked the timeline of the recent sovereign debt crisis.

In Chapter 2, we propose an indicator to measure systemic risk at a global level. The indicator embodies both the dynamics of international financial and commodity markets, as well as signals from the economic cycle of all the main currency blocks. The indicator can be regarded as a mapping from the set of exogenous economic and financial variables to a risk measure in the $(0, 1)$ space. The calibration is carried out exploiting the rich history of events observed over the period 1995-2011. By introducing a filtered average systemic risk fluctuation, time-varying positive and negative deviations from such average are considered, and monetary interventions by the Federal Reserve (Fed), the European Central Bank (ECB) and the Bank of England (BoE) are related to those deviations. We employ a generalization of the

Taylor rule (Taylor, 1993), which includes a systemic risk factor alongside the canonical inflation rate and output gap variables. The model is estimated in the form of a cointegrated system. Autometrics^{TM} is used for model selection as well as to detect the structural breaks affecting the considered time series. We offer a comparison between the reactions of the three Central Banks to systemic instabilities.

In Chapter 3, we propose a modelling framework to test for contagion versus excess interdependence in the Forbes and Rigobon's (2002) sense. A situation of contagion characterizes as a persistent change in financial linkages between markets, whereas a rise in correlations caused by excess volatility has only a temporary effect. Hence, the first extent is associated to a prolonged episode of market distress altering the functioning of the financial system. On the contrary, a situation of excess interdependence is a short lasting phenomenon. Thus, being able to distinguish between contagion and excess interdependence adds information on the features of a crisis. For this sake, we set up a dynamic factor model in a latent factor framework, with shocks at the global, asset class and country level. The model is specified with dynamic factor loadings, to accommodate time-dependent exposures of the single assets to the different shocks. This also allows us to disentangle the different sources of comovement between financial markets, and to analyse their dynamics during financial crisis periods. We report an empirical application using a sample period which encompasses both the 2007-09 crisis and the current sovereign debt crisis: this is an interesting laboratory to use the proposed framework to explore and characterize financial market dynamics during prolonged periods of financial distress.

Chapter 1

Estimating the Probability of a Multiple Default Using CDS and Bond Data

1.1 Introduction

Recent years have witnessed episodes of financial turmoil, whose intensity has been epitomized by the escalation of credit events occurred during the burst of the crisis. In this chapter, we measure the systemic risk of a financial system by proposing a novel method to estimate the probability of a joint default event for multiple financial and sovereign entities. Systemic risk is thought as the risk of a multiple simultaneous migration of large financial institutions to a situation of financial distress. This definition is in line with the literature which looks at disequilibria within the banking sector to infer an indication on the riskiness of the system as a whole (Lehar, 2005, Huang et al., 2009, Segoviano and Goodhart, 2009, Acharya et al., 2010, Adrian and Brunnermeier, 2011, Brownlees and Engle, 2012, Jobst and Gray, 2013).

The proposed methodology aims at extracting joint default probabilities from bond and CDS market prices. Both bond and credit derivative markets convey information on the default process: the former provides an insight on the *marginal* default probabilities, whilst the latter on the *joint* default probabilities. A similar approach is followed by Giglio (2011). He extracts the joint default probabilities for the reference entity α and the protection seller β in a CDS contract, and then proposes a linear programming model to derive upper and lower bounds for the joint default probability of N banks connected with a network. In this work, we provide point estimates for the joint default probabilities by simulating a system where the single defaults are correlated by means of a credit risk model with a factor model structure. Both the methodologies are in line with the literature on the Credit Value Adjustment (CVA) of derivative contracts in presence of counterparty risk[1]. The importance of adjusting the value of a derivative contract to take into account the likelihood of default of a counterparty in financial derivatives, has also been emphasized within the new Basel III regulatory framework.

We apply the proposed toolkit to measure the sovereign debt risk in the Euro Zone. In view of the recent crisis, the matter has been addressed by the applied financial literature with many contributions. Zhang et al. (2012) propose a model to estimate the joint default of Euro Area countries. They model the difference between perceived costs and benefits of the single countries' default and correlate them by means of macro-factors as well as by a risk factor common to all the countries. A single country defaults when such difference exceeds a threshold calibrated on CDS data. They estimate marginal, multivariate and conditional probability of default via simulation. Radev (2012) introduces the concept of "change in the conditional joint probability of default" for a pool of EU sovereign entities and banks, as a new

[1] The literature on this topic is too wide to survey here. See the seminal work of Jarrow and Turnbull (1995) and the contribution of Hull and White (2001).

systemic risk measure for the EU area, where the joint default probability is estimated via the CIMDO approach in Segoviano (2006). Here, we measure systemic risk as the probability of a joint default of the EU countries over a 5 years' time horizon. We first infer information about the joint default correlations of the single states with a representative protection seller in the sovereign CDS market. Next, the defaults of the states are correlated through their common dependence on the protection seller, typically a top tier investment bank, which represents the financial sector, considered as the channel through which crises evolve and spread out.

The main findings of the empirical application can be summarized as follows. There is evidence of increasing systemic risk and danger of contagion within the Euro Area from early 2007 and more significantly from late 2011 onwards. The proposed systemic risk indicator proves to be very reactive to changes in market conditions and the magnitude of the estimates is in line with what found by Radev (2012) and Zhang et al. (2012). Marginal and conditional default probability estimates are also provided. We validate the forecasting power of the proposed indicator by comparing it with the dynamics of a benchmark stock market index, which marked the timeline of the recent sovereign debt crisis.

The remainder of the chapter is as follows. Section 1.2 explores the relation between the CDS-bond basis and counterparty risk. In Section 1.3 we set up a theoretical framework to estimate the joint default probability of multiple entities. Section 1.4 proposes the empirical application referred to the Euro Zone and Section 1.5 concludes.

1.2 The Information Content of the CDS-Bond Basis

In this section, we analyse the relation between bond and CDS prices, providing a survey of the literature on the topic. Furthermore, we set up the model framework and present a methodology to infer information on the counterparty risk in a CDS contract.

1.2.1 CDS Premia and Bond Spread

As a first approximation, CDS prices reflect the expected loss of the reference entity given by its default probability and the recovery rate. These factors are actually the same that influence bond spreads: theoretically bond spreads should be equal to CDS premia for the same reference entity (see Duffie, 1999). For the sake of illustration, consider two financial agents α and β and let:

- $r(t, T)$ be the risk-free rate in t for the maturity T.
- $y_\alpha(t, T)$ be the yield at time t on a zero-coupon bond (ZCB) issued by α with maturity date T.
- $s_\alpha(t, T) \equiv y_\alpha(t, T) - r(t, T)$ be the spread over the risk-free rate of the issuance cost of α, prevailing in t and referred to the maturity T.
- $w_{\alpha,\beta}(t, T)$ be the periodic CDS premium to insure against the default of α within the period $[t, T]$ with β as the protection seller.

In equilibrium, a portfolio composed by a ZCB with maturity T and a CDS on that same bond with the same maturity, should replicate a synthetic risk-free asset.

Hence the ZCB yield $y_\alpha(t,T)$ minus the CDS premium $w_{\alpha,\beta}(t,T)$ should be exactly equal to the risk-free rate $r(t,T)$. The invoked equilibrium is ensured by the two following arbitrage strategies[2]:

Strategy 1. *Case* $w_{\alpha,\beta}(t,T) < s_\alpha(t,T)$: the arbitrage strategy in this case consists in buying the bond, financing at the risk-free rate $r(t,T)$ and then buying the CDS by paying the premium $w_{\alpha,\beta}(t,T)$. The portfolio return is $y_\alpha(t,T)-r(t,T)-w_{\alpha,\beta}(t,T) = s_\alpha(t,T) - w_{\alpha,\beta}(t,T) > 0$.

Strategy 2. *Case* $w_{\alpha,\beta}(t,T) > s_\alpha(t,T)$: the arbitrage strategy in this case consists in short selling the bond, investing the proceeds at the risk-free rate of return $r(t,T)$ and selling protection in the CDS market to get the premium $w_{\alpha,\beta}(t,T)$. The portfolio return is $w_{\alpha,\beta}(t,T) + r(t,T) - y_\alpha(t,T) = w_{\alpha,\beta}(t,T) - s_\alpha(t,T) > 0$.

However, there is strong empirical evidence that $w_{\alpha,\beta}(t,T) \neq s_\alpha(t,T)$ (see Section 1.4). We then define as *basis* the difference $b_{\alpha,\beta}(t,T) \equiv w_{\alpha,\beta}(t,T)-s_\alpha(t,T)$. Multiple are the factors that give rise to a basis different from zero. O'Kane and McAdie (2001) and De Wit (2006) identify a comprehensive list of drivers which cause the basis to deviate from zero, and distinguish the factors which are technical in nature from the fundamental ones. The theoretical and applied literature on the topic insists in particular on few of them, that are:

(1) The counterparty risk which affects CDS contracts, consisting in the possibility that the protection seller β might not respect its obligations (see inter alia Bai and Collin-Dufresne, 2011),

[2]For the sake of illustration and without loss of generality, we assume a frictionless market where one can borrow and lend at the risk free rate. We will relax this hypothesis later. We also assume that the positions are kept until bond maturity or until the credit event occurs. Otherwise the strategies would face a roll over risk in the financing/investing positions linked to the volatility of $r(t,T)$.

(2) Liquidity reasons that cause investors to prefer a riskless bond to a corporate bond plus a CDS or vice versa (Trapp, 2009),

(3) Market frictions that cause the above Strategies 1 and 2 to be asymmetric, thus undermining the role of arbitrageurs in reverting the basis towards zero (Bai and Collin-Dufresne, 2011).

The case of the basis between sovereign CDS and the corresponding government bonds makes no exception and the influence of counterparty risk, liquidity and funding issues on the basis has been documented inter alia by Fontana and Scheicher (2010).

Other market imperfections might cause the basis to be positive or negative. As an example, we can mention the different reactivity of CDS and bond markets to new information on an issuer. A negative or positive basis can reflect a different degree of adjustment between the two markets that arbitrage strategies correct only in the long run. A large body of literature has shown that CDS corporate markets have a leading position in the price discovery process i.e. the CDS prices variation anticipate the variations in bond prices which react with a temporary lag (see Amadei et al., 2011, and, for the case of EU sovereign risk, Palladini and Portes, 2011).

In the following, we focus on counterparty risk, which is not present in bond contracts, but crucially affects CDS markets. However, CDS contracts traded in the OTC markets are increasingly subject to collateralization agreements, which are intended to mitigate counterparty risk. We take this extent into explicit consideration by disentangling the effect of counterparty credit risk on the basis. Furthermore, in order to take into account the impact of liquidity, instead of modelling an unobservable liquidity process as in Giglio (2011), we normalize the observed quotes by means of the bid-ask spreads, which is a direct measure of the liquidity linked to these contracts. The impact of the cost of funding on Strategy 2 above, is also taken into account. All these adjustments are made explicit in the following section.

1.2.2 Counterparty Risk and the Basis

In section 1.2.1, we claimed that the basis differs from zero because of a number of different factors. The literature on the topic points in particular at counterparty risk, liquidity and funding issues as well as market imperfections. The goal is to disentangle the different components of the CDS-bond basis and ultimately pin down the component that can be referred to counterparty risk. This section presents the methodology employed for this sake.

The concept of basis is built upon the comparison of two contracts, a bond and a CDS, which typically differ from the point of view of the liquidity. We apply a liquidity adjustment to facilitate a direct comparison between CDS and bond spreads.

Investors demand an additional premium for holding a bond, to compensate for the liquidation risk (Amihud and Mendelson, 1986, Chen et al., 2007). Let α be the issuer of a bond, with a spread on the risk free rate denoted as $s_\alpha(t,T)$. We denote the liquidity premium on such bond as $\lambda_\alpha(t,T)$, so that:

$$s_\alpha(t,T) = s'_\alpha(t,T) + \lambda_\alpha(t,T) \tag{1.1}$$

where $s'_\alpha(t,T)$ is the liquidity-adjusted bond spread. We rewrite the above equation as:

$$s_\alpha(t,T) = s'_\alpha(t,T)\left[1 + l_\alpha(t,T)\right] \tag{1.2}$$

where $l_\alpha(t,T)$ is a proportionality factor linking the bond spread with its liquidity-adjusted counterpart. We use the bid-ask spread as a liquidity proxy, to infer information about the liquidity components of the bond spread. $l_\alpha(t,T)$ is estimated as the bid-ask spread expressed in percentage term, that is:

$$l_\alpha(t,T) = \frac{s_\alpha^{bid}(t,T) - s_\alpha^{ask}(t,T)}{s_\alpha(t,T)} \tag{1.3}$$

where $s_\alpha^{bid}(t,T)$ and $s_\alpha^{ask}(t,T)$ are the bond spread linked to the bid and the ask quote of the bond, respectively. The proposed liquidity adjustment assumes that the liquidity premium $\lambda_\alpha(t,T)$ is proportional to the bid-ask spread. In the limit case that the market is characterized by infinite liquidity, it is reasonable to assume that $s_\alpha^{bid}(t,T) = s_\alpha^{ask}(t,T)$, and no adjustment is performed. As the market becomes more and more illiquid, market participants will require to be compensated for the liquidation risk, thus causing the bid price to deviate from the ask price.

The liquidity-adjusted bond spread becomes:

$$s'_\alpha(t,T) = \left(1 + \frac{s_\alpha^{bid}(t,T) - s_\alpha^{ask}(t,T)}{s_\alpha(t,T)}\right)^{-1} s_\alpha(t,T) \tag{1.4}$$

We apply the same concept to CDS spreads and perform the following adjustment[3]:

$$w'_{\alpha,\beta}(t,T) = \left(1 + \frac{w_{\alpha,\beta}^{ask}(t,T) - w_{\alpha,\beta}^{bid}(t,T)}{w_{\alpha,\beta}(t,T)}\right)^{-1} w_{\alpha,\beta}(t,T) \tag{1.5}$$

The liquidity-adjusted basis is then given by:

$$b'_{\alpha,\beta}(t,T) \equiv w'_{\alpha,\beta}(t,T) - s'_\alpha(t,T) \tag{1.6}$$

[3] In the notation, we follow the market practice according to which, in the case of the bond, the bid and the ask quotes are referred to the bond price so that $s_\alpha^{bid}(t,T) \geq s_\alpha^{ask}(t,T)$, whereas in the case of the CDS they are directly referred to the spread, so that $w_{\alpha,\beta}^{ask}(t,T) \geq w_{\alpha,\beta}^{bid}(t,T)$.

We also take explicitly into account funding issues linked to the implementation of arbitrage Strategies 1 and 2, outlined in Section 1.2.1. We show how the basis might be affected and propose an adjustment. We relax the hypothesis that all the market participants can borrow and lend money at the risk free rate $r(t,T)$. We more realistically assume that they borrow money at the Libor rate $\mathcal{L}(t,T)$ and they can deposit money at the depo rate, denoted as $d(t,T)$. Let us denote with $\delta(t,T)$ the spread of the Libor rates over the depo rates, that is $\delta(t,T) \equiv \mathcal{L}(t,T) - d(t,T)$. When a negative basis is observed, the payoff of Strategy 1 is given by $y_\alpha(t,T) - \mathcal{L}(t,T) - w_{\alpha,\beta}(t,T)$, which, in the case the bond spread is measured over $\mathcal{L}(t,T)$, is still equal to $s_\alpha(t,T) - w_{\alpha,\beta}(t,T)$. On the other hand, in the case of a positive basis, the payoff of Strategy 2 changes to $w_{\alpha,\beta}(t,T) + d(t,T) - y_\alpha(t,T)$, which is equal to $w_{\alpha,\beta}(t,T) - s_\alpha(t,T) - \delta(t,T)$. Such a spread stems from the asymmetry of the strategies in relation to the process of funding[4]. Thus, Strategy 2 will be implemented as long as $b_{\alpha,\beta}(t,T) > \delta(t,T)$. Hence, it might well be that arbitrageurs can not revert a positive basis to 0 because of the presence of funding asymmetries in the implementation of the two strategies. Therefore, we correct the basis as:

$$b''_{\alpha,\beta}(t,T) \equiv w'_{\alpha,\beta}(t,T) - s'_\alpha(t,T) - \delta(t,T) \tag{1.7}$$

where $b''_{\alpha,\beta}(t,T)$ is the basis adjusted by funding and liquidity.

The basis $b''_{\alpha,\beta}(t,T)$ consists in the materialization of counterparty risk in the underlying CDS contract, as any funding and/or liquidity effects has been accounted for. However, as stated in the ISDA Margin Survey (ISDA, 2012), the practice of requiring the counterparty in OTC derivatives to post a collateral against the possibility of a default, has become more and more common. We adapt our formulas to take this extent into account. Realistically, the quote of a CDS is the average of the prices provided by different dealers. We can then imagine that a quota $q_c \in [0,1]$

[4] In normal market conditions $\delta(t,T)$ can be assumed to be positive, however the proposed adjustment does not necessarily requires this hypothesis to hold.

of such contracts are assisted by a collateral agreements covering the entire nominal amount[5]. Then, the market average quote of a CDS on α, provided by the representative dealer β, can be seen as the weighted average of a contract assisted by a total collateralization and a contract without collateral, so that the liquidity-adjusted CDS quote $w'_{\alpha,\beta}(t,T)$ can be rewritten as:

$$w'_{\alpha,\beta}(t,T) = (1-q_c)w''_{\alpha,\beta}(t,T) + q_c\tilde{w}''_{\alpha,\beta}(t,T) \tag{1.8}$$

where $w''_{\alpha,\beta}(t,T)$ is the quote referred to an uncollateralized CDS contract on α, whereas $\tilde{w}''_{\alpha,\beta}(t,T)$ is the value of a CDS on α, fully assisted by collateral. In absence of market frictions, the latter coincides with the spread on the debt of α, that is $s_\alpha(t,T)$. In the case of no collateralization ($q_c = 0$), the liquidity-adjusted CDS spread $w'_{\alpha,\beta}(t,T)$ coincides by definition with $w''_{\alpha,\beta}(t,T)$, so that no adjustment for collateralization is needed. On the other hand, when the counterparty risk in the CDS is fully collateralized ($q_c = 1$), the CDS quote is perfectly in line with the spread on the corresponding bond, leading to a basis equal to 0. This extent is in clear contrast with what we observe in reality, as market data show in Section 1.4. Let us exclude the possibility of full collateralization by letting $0 \leq q_c < 1$.

Including the effect of liquidity and funding, we have that $\tilde{w}''_{\alpha,\beta}(t,T) = s'_\alpha(t,T) + \delta(t,T)$, so that from the previous equation we get:

$$w''_{\alpha,\beta}(t,T) = \frac{w'_{\alpha,\beta}(t,T) - q_c\left[s'_\alpha(t,T) + \delta(t,T)\right]}{1-q_c} \tag{1.9}$$

Now we define $b'''_{\alpha,\beta}(t,T)$ as the basis which cumulates adjustments for liquidity, funding and partial collateralization, which is given by:

$$b'''_{\alpha,\beta}(t,T) \equiv w''_{\alpha,\beta}(t,T) - s'_\alpha(t,T) - \delta(t,T) \tag{1.10}$$

[5]Alternatively, we can assume that the contracts are assisted by partial collateralization, so that the average quota of nominal amount covered is equal to q_c. From the modelling point of view, the two cases are equivalent.

Substituting in the definition of $w''_{\alpha,\beta}(t,T)$, we get:

$$b'''_{\alpha,\beta}(t,T) = \frac{1}{1-q_c}\left(w'_{\alpha,\beta}(t,T) - s'_{\alpha}(t,T) - \delta(t,T)\right) \tag{1.11}$$

Hence $b'''_{\alpha,\beta}(t,T)$ results in a multiplicative adjustment of $b''_{\alpha,\beta}(t,T)$, defined in Eq. (1.7).

Eq. (1.11) isolates the component of the basis motivated by counterparty credit risk. We thus expect $b'''_{\alpha,\beta}(t,T) \leq 0$. To exclude the effect of market imperfections which might cause the basis to be positive, we define:

$$B_{\alpha,\beta}(t,T) \equiv \left(b'''_{\alpha,\beta}(t,T)\right)^{-} \tag{1.12}$$

where $(\cdot)^{-} \equiv \min(\cdot, 0)$. In what follows, $B_{\alpha,\beta}(t,T)$ is considered as the component of the basis corresponding to counterparty risk.

1.3 A Formula for the Joint Probability of Default

In this section, we first present a methodology for the estimation of bivariate probabilities of default (Section 1.3.1), and then extend the model to the multivariate case (Section 1.3.2).

1.3.1 The Bivariate Case

Consider two risky financial institutions and denote them as α and β. Imagine that at time $t = 0$, a portfolio is built, according to the following uniperiodal strategy:

- Buy a 1-year ZCB issued by α,

- buy a 1-year CDS from β, the protection seller, on the reference entity α,
- finance the positions on the market with a 1-year loan.

Assume that both the ZCB and CDS contracts have \$1 face value and let RR_α, RR_β be the recovery rates of α and β, respectively, so that $\$RR_\alpha$ and $\$RR_\beta$ are the amounts recovered when α and β default. When we exclude market imperfections, such as liquidity and funding issues, and in the presence of non-collateralized counterparty risk, the portfolio value at time $t = 0$ is given by $B_{\alpha,\beta}(0,1)$ (see Eq. 1.12).

At time $t = 1$, a non-zero cash flow equal to $(1 - RR_\alpha)(1 - RR_\beta)$ is generated only when both α and β default. Thus, in an arbitrage-free world, it must hold that:

$$P_{\overline{\alpha},\overline{\beta}}(0,1) = \frac{|B_{\alpha,\beta}(0,1)|}{(1 - RR_\alpha)(1 - RR_\beta)} e^{r(0,1)} \tag{1.13}$$

where $P_{\overline{\alpha},\overline{\beta}}(0,1)$ is the one-year joint default probability for α and β, with $B_{\alpha,\beta}(0,1) \leq 0$ by definition.

The extension of the formula in Eq. (1.13) over the generic time sequence $0 = t_0 < t_1 < \ldots < t_M$ is achieved by exploiting the following recursive relation:

$$P_{\overline{\alpha},\overline{\beta}}(t_k, t_{k+1}) = \begin{cases} \tilde{P}_{\overline{\alpha},\overline{\beta}}(0, t_1) & \text{for } k = 0 \\ P_{\alpha,\beta}(t_{k-1}, t_k)\tilde{P}_{\overline{\alpha},\overline{\beta}}(t_k, t_{k+1}) & \text{for } k = 1, \ldots, M-1 \end{cases} \tag{1.14}$$

in which we define:

$$\tilde{P}_{\overline{\alpha},\overline{\beta}}(t_k, t_{k+1}) \equiv \frac{\Psi(t_k, t_{k+1})}{(1 - RR_\alpha)(1 - RR_\beta)} \qquad k = 0, \ldots, M-1 \tag{1.15}$$

where:

$$\Psi(t_k, t_{k+1}) \equiv |B_{\alpha,\beta}(t_k, t_{k+1})| \, e^{r(t_k,t_{k+1})(t_{k+1}-t_k)} \tag{1.16}$$

$B_{\alpha,\beta}(t_k, t_{k+1})$ is the basis expressed in forward terms (for further details see Appendix on p. 35). $\tilde{P}_{\overline{\alpha},\overline{\beta}}(t_k, t_{k+1})$ is the probability of joint default of α and β for the period $[t_k, t_{k+1}]$, conditional on their joint survivor till time t_k. $P_{\overline{\alpha},\overline{\beta}}$ denotes the unconditional joint default probability and $P_{\alpha,\beta}$ is the joint survival probability.

All the variables entering the definition of joint default probability stated in Eq. (1.14) are directly observable on the market, with the only exception of the recovery rates RR_α and RR_β. In order for Eq. (1.15) to assume a probability meaning, we seek a logistic transformation $\mathbb{L}(\cdot)$ of $\Psi(t_k, t_{k+1})$ of the type:

$$\mathbb{L}\Big(\Psi(t_k, t_{k+1})\Big) \equiv \frac{c_1}{1 + \exp\{-\Psi(t_k, t_{k+1})\}} + c_2 \tag{1.17}$$

where c_1 and c_2 are chosen such that:

$$\begin{cases} \mathbb{L}(0) = 0 \\ \lim\limits_{\Psi(t_k,t_{k+1})\to+\infty} \mathbb{L}\Big(\Psi(t_k, t_{k+1})\Big) = (1 - RR_\alpha)(1 - RR_\beta) \end{cases}$$

leading to $c_1 = 2(1-RR_\alpha)(1-RR_\beta)$ and $c_2 = -(1-RR_\alpha)(1-RR_\beta)$. If we substitute $\Psi(t_k, t_{k+1})$ with its logistic transformation in Eq. (1.15), we get:

$$\tilde{P}_{\overline{\alpha},\overline{\beta}}(t_k, t_{k+1}) = \frac{2}{1 + \exp\{-\Psi(t_k, t_{k+1})\}} - 1 \tag{1.18}$$

as the ultimate formula for the conditional probability of joint default for the period $[t_k, t_{k+1}]$. Recalling Eq. (1.14), we can state that the logistic transformation is sufficient to guarantee the consistency of the unconditional probability of joint default $P_{\overline{\alpha},\overline{\beta}}(t_k, t_{k+1})$, since, by construction, $0 \leq P_{\alpha,\beta}(t_k, t_{k+1}) \leq 1$, $\forall k = 0, \ldots, M-1$. Furthermore, the employment of the proposed logistic transformation leads to the dropping of the dependence of the formulae on arbitrary assumptions about the recovery rates, which appears to be a critical choice in other competing models (see inter alia Schönbucher, 2001).

The default correlation is estimated via the standard binomial correlation approach:

$$\rho_{\alpha,\beta}(t_k, t_{k+1}) = \frac{P_{\overline{\alpha},\overline{\beta}}(t_k, t_{k+1}) - P_{\overline{\alpha}}(t_k, t_{k+1})P_{\overline{\beta}}(t_k, t_{k+1})}{\sqrt{P_{\overline{\alpha}}(t_k, t_{k+1})\Big(1 - P_{\overline{\alpha}}(t_k, t_{k+1})\Big)P_{\overline{\beta}}(t_k, t_{k+1})\Big(1 - P_{\overline{\beta}}(t_k, t_{k+1})\Big)}} \tag{1.19}$$

where $P_{\overline{\alpha}}$ and $P_{\overline{\beta}}$ are the marginal probability of default for α and β, which are extracted from bond prices.

1.3.2 The Multivariate Case

In this section, we extend the methodology above to the case of multiple entities. The proposed multivariate generalization consists of two steps. First, the bivariate methodology presented above is used to estimate the default correlations of the single entities with a representative protection seller in the CDS market. Second, the single defaults are correlated through their common dependence on the protection seller, by means of a credit risk model with a factor model structure.

Let us consider N defaultable entities, say $\alpha_1, \dots, \alpha_N$. The goal is to estimate the joint default probability of such entities. Imagine that a protection seller β sells protection against the default of each of the N entities in the CDS market. Hence, we can apply the bivariate methodology above to estimate the pairwise default correlation between α_i and β, for $i = 1, \dots, N$ over the period $[t_k, t_{k+1}]$, which we denote as $\rho_{\alpha_i,\beta}(t_k, t_{k+1})$.

In what follows, we embrace the modelling set-up of credit risk models of the factor model type, by assuming that the dependence of the single defaults is triggered by common factors. Credit factor models offer analytical tractability while providing a realistic representation of the dependency structure of the single obligors (Schönbucher, 2001). In a standard one-factor model, the value of the assets of the i-th reference entity, say V_i, is driven by a common systematic component Y, and an idiosyncratic component, here denoted as Z_i, according to the model:

$$V_i = \varrho_i Y + \sqrt{1 - \varrho_i^2} Z_i \tag{1.20}$$

where ϱ_i is a parameter correlating the single obligor i with the systematic trigger Y. Assuming that $Y, Z_1, \ldots, Z_N$ are mutual independent with 0 mean and unit variance, the linear correlation between V_i and Y coincides with ϱ_i, whereas the correlation of reference entity i with $j \neq i$, is given by the product $\varrho_i \varrho_j$.

The systematic component Y in Eq. (1.20) is identified as being the protection seller β. From a financial and empirical point of view, this assumption leads to a realistic representation of the default correlation structure as long as:

1. the protection seller β is a representative institution for the considered reference entities (e.g. if the goal is to estimate the joint default probability for a given rating class, it is desirable that β itself is a representative institution of that rating class[6]) and/or

2. the protection seller β is an institution operating in a market/sector which arguably consists of the channel through which default propagation might occur (e.g. if the concern is the assessment of the likelihood of a joint default event which can possibly be triggered by a worsening in the macro-financial context, then β ought to be a representing institution operating in the financial sector and exposed to the considered entities).

In the light of the current debt sovereign crisis, the application proposed in Section 1.4 is referred to Euro Zone sovereign risk. In the empirical exercise, β is an EU

[6]Assuming homogeneity between reference entities and protection sellers is something not far from reality. Indeed, credit derivatives markets tend to be very concentrated among few players, both in terms of sellers and reference entities. This increases the interconnectedness of the system while posing a concrete threat for the global financial stability. The issue is well documented inter alia by ECB (2009).

bank exposed to the sovereign risk of the European area. The identification of the protection seller as the triggering factor for a joint default is justified from the point of view of both the extents listed above: β operates on the European markets and represents the financial sector, which was widely recognized as the channel through which the crisis evolved and spread out.

Therefore, the default correlation between α_i and α_j, with $i = 1, \ldots, N$, $j = 1, \ldots, N$ and $i \neq j$, is given by:

$$\rho_{\alpha_i,\alpha_j}(t_k, t_{k+1}) = \rho_{\alpha_i,\beta}(t_k, t_{k+1})\rho_{\alpha_j,\beta}(t_k, t_{k+1}) \tag{1.21}$$

Using Eq. (1.21), we can recover the full default correlation matrix for $(\alpha_1, \ldots, \alpha_N)$, which we denote as $R(t_k, t_{k+1})$, where:

$$R_{i,j}(t_k, t_{k+1}) \equiv \begin{cases} \rho_{\alpha_i,\beta}(t_k, t_{k+1})\rho_{\alpha_j,\beta}(t_k, t_{k+1}) & \text{if } i \neq j \\ 1 \quad \text{otherwise} \end{cases} \tag{1.22}$$

Joint default probabilities are estimated via simulation. We set up the simulation design as follows. Let $\mathbb{1}_i(t_k, t_{k+1})$ be a random variable taking the value 1 if α_i defaults in the time period $[t_k, t_{k+1}]$ and 0 otherwise. We assume that the system $\Big(\mathbb{1}_1(t_k, t_{k+1}), \ldots, \mathbb{1}_N(t_k, t_{k+1})\Big)$ follows a multivariate binomial distribution (see Davis and Lo, 2001, Cousin et al., 2012) with correlation equal to $R(t_k, t_{k+1})$:

$$\mathbb{1}_i(t_k, t_{k+1}) \sim \mathcal{B}\Big(P_{\overline{\alpha}_i}(t_k, t_{k+1})\Big) \tag{1.23}$$

$$corr\Big(\mathbb{1}_1(t_k, t_{k+1}), \ldots, \mathbb{1}_N(t_k, t_{k+1})\Big) = R(t_k, t_{k+1}) \tag{1.24}$$

We simulate the system $\Big(\mathbb{1}_1(t_k, t_{k+1}), \ldots, \mathbb{1}_N(t_k, t_{k+1})\Big)$ by means of dynamic copula functions. We adopt as a baseline a standard Gaussian copula approach and we contrast it with a Gumbel Archimedean copula, which is the only copula function allowing for positive tail dependence with the advantage of parameter parsimony (Cherubini et al., 2011). The generator function of the Gumbel copula is given by:

$$\phi(u) = [-\ln(u)]^{\theta} \tag{1.25}$$

where $\theta \in [1, +\infty)$ is the dependence parameter. The Gumbel N-dimensional copula is then given by:

$$C(u_1, \ldots, u_N) = \exp\left\{ - \left[\sum_{i=1}^{N} (-\ln(u_i))^{\theta} \right]^{\frac{1}{\theta}} \right\} \tag{1.26}$$

We denote the dependence parameter referred to the period $[t_k, t_{k+1}]$ as $\theta(t_k, t_{k+1})$ and estimate it as:

$$\theta(t_k, t_{k+1}) = \frac{1}{1 - \bar{R}(t_k, t_{k+1})} \tag{1.27}$$

where $\bar{R}$ is the average default correlation across the N countries:

$$\bar{R}(t_k, t_{k+1}) = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j>i}^{N} R_{i,j}(t_k, t_{k+1}) \tag{1.28}$$

The next section presents an application of this methodology to the sovereign risk in the Euro Area.

1.4 Empirical Application

The on-going EU sovereign debt crisis is causing great concern about the sustainability of national debt issued by the member states. This empirical application is devoted to the estimation of the likelihood of the default of one or more countries in the Euro Zone.

1.4.1 The Data

We consider bond and CDS data for the following countries: Austria, Belgium, Finland, Germany, France, Italy, Netherlands, Portugal, Slovakia, Slovenia and Spain[7]. This country selection is dictated by data availability. The data provider is Bloomberg^{TM}. The sample consists of daily observations form 01-Jan-2004 to 11-Oct-2012 (2291 observations). We choose 5 and 10 years as reference maturities and derive the 5- and 10-year equivalent of the annual market quotes. The goal is to estimate risk-neutral joint default probabilities for the periods $[0, 5]$ and $[5, 10]$. We then fix $t_0 = 0$, $t_1 = 5$, $t_2 = 10$. In Tab. 1.1 we report descriptive statistics for the variables employed in the estimation. Data series are plotted in Figs. 1.1-1.2.

[Tab. 1.1 and Figs. 1.1-1.2 about here.]

Sovereign bond spreads are estimated as the difference between the national bond yields and the German bond yields. Risk-free rates are the EU swap rates. We use 1, 5 and 10 year EU swap data series and we do interpolation for the intermediate maturities, when needed. In order to take into account the impact of funding issues on the basis, we consider the spread between the 6 month EU depo rates and the Euribor over the same maturity. We apply a Hodrick-Prescott filter to the rate series, in order to rule out excess volatility and get a trend measure of the funding asymmetry. We specify the Hodrick-Prescott smoothing parameter according to the rule proposed in Ravn and Uhlig (2002) applied at the daily frequency. We employ the same filtering procedure to the bid-ask quotes of bonds and CDS, in order to estimate a trend measure of the liquidity adjustment. We compute the basis and adjust it for liquidity and funding effects. The adjusted and the unadjusted bases are displayed in Figs. 1.3-1.4.

[7]The methodology requires an estimate of the probability of default of the protection seller β. For this sake, we consider CDS data for BNP Paribas, Deutsche Bank and Société Générale, which can be thought as the representative EU dealers for the over-the-counter CDS market (see ECB, 2009).

[Figs. 1.3-1.4 about here.]

The time series for the unadjusted bases fluctuate around the frictionless value of 0. For some of the countries analysed, the divergence from 0 is systematic, with Portugal, Slovenia and Slovakia showing a persistent negative basis, whereas a positive basis is typically observed for Austria and France in particular. This evidence is in accordance with the applied literature on the topic (see inter alia Fontana and Scheicher, 2010). After adjusting for the liquidity and the cost of funding asymmetries, most of the observations have a negative sign, which we attribute to the presence of counterparty risk, whereas the positive observations are considered as manifestation of market imperfections and then, they are averaged out.

The considered CDS quotes can be regarded as an average price for a CDS written by a top tier investment bank, which typically operates worldwide. From these quotes, we want to infer the fair price of a CDS offered by an EU bank exposed to the EU sovereign risk. The analytical derivation follows closely what has been done in Section 1.2.2 for partial collateralization. Let us define $q_{EU} \in (0, 1]$ as the relative importance within the investment banking sector of the EU investment banks. The market average quote of a CDS on α_i can be seen as the weighted average of a contract issued by an EU investment bank and a contract written by a non-EU institution. This leads to a multiplicative adjustment of the basis which is analogous to the one applied in the passage from Eq. (1.10) to Eq. (1.11). The resulting basis is denoted as $B^{EU}_{\alpha_i,\beta}$, and is given by:

$$B^{EU}_{\alpha_i,\beta}(t_k, t_{k+1}) = \frac{1}{q_{EU}} B_{\alpha_i,\beta}(t_k, t_{k+1}) \tag{1.29}$$

with $k = 1, \ldots, M$ and $i = 1, \ldots, N$.

1.4.2 The Simulation and Systemic Risk Measurement

We use Eq. (1.19) to estimate the pairwise default correlations between each of the countries in the sample and a representative EU investment bank, which we have denoted as β. The defaults are then correlated via the common dependence of the single states to the European financial sector, represented by β. We then estimate via simulation the joint probability of defaults of the considered EU countries.

The simulation engine requires the specifications of two parameters: the quota of collateralized trades on the OTC credit derivate market q_c and the relative size of the EU investment bank sector.

Regarding the specification of the first parameter, the ISDA Margin Survey (ISDA, 2012) states that 93% of the OTC transactions that took place in 2012 in the credit derivative markets have been assisted by collateralization. We fix q_c to the following set of values: 0.8, 0.9, 0.95. The consideration of values of q_c below the ISDA estimates are motivated as follows. A smaller value of q_c leads to a smaller estimate of the collateralization-adjusted basis (see Eq. 1.11) and thus to a more conservative estimate of the probability of default. Furthermore, collateralization is a practice become widespread only after the credit crunch crisis of late 2007, and thus we might consider the ISDA estimate for 2012 to be bigger than the estimate to be referred to the entire sample.

We provide an estimate of the parameter q_{EU} as follows. We assume that the global equity markets convey information on the exposures to local risk factors of a representative investment bank operating worldwide. In this perspective, q_{EU} represents the relative importance of the EU market within the global financial markets. Thus, for the sake of estimating q_{EU}, we consider MSCI data for benchmark stock indices for US, Europe, UK, Japan and Emerging markets, offering a wide coverage of the international stock markets. Using standard principal component analysis, we extract the first component of the weekly equity returns of the benchmark indices listed above, in order to estimate the global equity factor, common to the set of the considered financial markets. The estimate of q_{EU} is given by the contribution of the European index in the estimated global factor. The application of this procedure to weekly data from 2001 to 2012, leads to the extraction of a principal component accounting for more than 75% of the total variance and a point estimate for q_{EU} of 0.25. Along with this estimate, we consider the alternative values of 0.15 and 0.35 for robustness check.

The results of the simulation are reported in Figs. 1.5-1.6. We observe the 5-year and the 5-to-10-year probability having quite a similar dynamic evolution. In particular, they are negligible up to 2006. This situation is indicative of a well-functioning economic and financial system, with no tangible threat of sovereign risk. Afterwards, the estimated probabilities feature remarkable peaks in correspondence of some notable facts of the recent financial history. In particular, we observe a surge during the harshest period of the 2008-09 economic and financial crisis. Later, other peaks are recorded in conjunction with the first EU intervention for the Greece bailout in May-2010 and since mid-2011 onwards, to mark the spreading of the sovereign crisis throughout and outside Europe, a process which we are still witnessing. As expected the highest figures are recorded for the least conservative case $q_c = 0.95, q_{EU} = 0.15$.

For the 5-year case, the figures referred to the recent crisis exceeds the figure referred to the late 2000s crisis in 5 cases out of 9. On the contrary, for the case of the forward estimates in Fig. 1.6, much higher probabilities were recorded during 2008, as to anticipate the worsening of the crisis in Europe. The breakdown of the Euro caused by a joint default of the member states in the next 5 years is estimated to happen with a probability between 0.01% and 0.14%, a remote event, but with catastrophic impact. The magnitude of the estimates is in line with other applied contributions on the topic, such as Radev (2012) and Zhang et al. (2012).

[Figs. 1.5-1.6 about here.]

We adopt the 5-year joint default probability as our measure of systemic risk for the Euro Area. Our methodology is based on the hypothesis of absence of arbitrage, hence the estimates are produced under the risk-neutral probability measure. In the proposed set-up, risk-neutral probabilities offer a conservative indication on real-world probabilities and as such, can be used to identify periods of systemic risk and contagion.

In Fig. 1.7 and 1.8, we report the estimated probabilities of at least $1, 2, \ldots, N$ defaults to happen, contrasting the performance of the Gumbel copula with the Gaussian copula. The estimates of the probability of observing at least 1, 2, 3 and 4 default(s) for the 5-year case are plotted in the top panel of Fig. 1.7. The dynamics of these probabilities provides evidence of an increasing risk of default from early 2010 onwards, with the current estimate of observing at least another default after Greece in the next 5 years of the order of 35%, down from a peak recorded at the end of 2011 of about 60%. In this case, the estimation with the Gumbel copula and the Gaussian copula are quite similar. On the contrary, in the middle panel and, even more evidently, in the bottom panel, we document the inaccuracy of the Gaussian copula to capture the extreme event of a default of more than 7 countries. In this respect, similar conclusions can be drawn from the forward probabilities in Fig. 1.8, which however show a more marked trending behaviour than the 5-year estimate for the case of the default of a small number of countries (top panel).

[Figs. 1.7-1.8 about here.]

The simulated realizations of the multivariate default process $\left\{\mathbb{1}_i(t_k, t_{k+1})\right\}_{i=1,\ldots,N}$ defined in Section 1.3.2, offer an insight into conditional default probabilities, too. In particular, we look at the probability that at least one country defaults given that one default has been observed within a group of selected countries. We compute joint default probabilities conditional on the default of Italy, Portugal and Spain respectively for the period 2007-2012. Results are reported in Fig. 1.9. Overall, the conditional probability estimates for the period 2007-2009 exceed the 2011-2012 figures. This corresponds to the idea that the market impact of a default of any of the named countries would have been bigger during the late 2000s crisis than in the current sovereign crisis. A Spanish default in 2007 would have led to at least another default with a likelihood almost double than in the case of Italy and Portugal, whose default in more recent times would have had a smaller effect than a default of the other two (see top panel left of Fig. 1.9). In a similar way, Radev (2012) shows that the contribution of the default of Greece to systemic risk is limited, when compared to the impact of a German default.

[Fig. 1.9 about here.]

In Fig. 1.10, we compare the estimate of the 5-year joint default probability in the case $q_c = 0.9, q_{EU} = 0.25$ with the EuroStoxx50, which we consider to be a good indicator for the timing of the EU sovereign crisis. It is clearly specular behaviour of the joint default probability with respect to the dynamic of the stock index. In early 2007, the joint default probability started reacting, anticipating the subsequent fall in the stock index, and more remarkably, in mid-2011 the estimate surges sharply well before the index plummets amid concerns on the spreading of the crisis.

[Fig. 1.10 about here.]

To corroborate these claims with empirical evidence, the next section proposes a forecasting exercise.

1.4.3 The Forecast

The forecasting exercise is designed as follows. We consider the weekly returns of the EuroStoxx50, denoted with y_t, and the weekly changes in the 5-year estimate of the joint default probability, say ΔJDP_t, over the period 2007-2012, where most of the variability of ΔJDP_t is observed. We set up a simple regression model, which we use to forecast y_t by means of lagged values of ΔJDP_t. The model is as follows:

$$y_t = \omega + \sum_{l=1}^{L} \psi_l \Delta JDP_{t-l} + \epsilon_t \qquad (1.30)$$

where ω is the constant term, ψ_l is the coefficient referred to ΔJDP_{t-l}, L is the number of lags and ϵ_t is assumed to be a white noise normally distributed error term. In the application we consider different forecasting time horizons, setting $L = 1, 4, 12, 26, 52$, which corresponds to the case in which the forecasting power of the default probability is evaluated with a lag of one week, one month, one quarter, one semester and one year, respectively. The simple model in Eq. (1.30) cannot forecast equity markets: this small exercise is intended to show the capability of the default probability estimates to anticipate the most relevant episodes of stress during the EU sovereign crisis epitomized by extreme price movements in the stock markets.

Pre-2011 data are considered as in-sample. We perform an out-of-sample forecasting exercise over the period 2011-2012, which roughly corresponds to 30% of the period 2007-2012. We estimate Model (1.30) for every out-of-sample data point, following a standard walk-forward optimization procedure and perform a one step ahead forecast analysis. At every step, we compute $\mathbb{P}(y_{t+1} < 0)$, the probability of a negative equity return for the week ahead. The results are reported in Tab. 1.2.

[Tab. 1.2 about here.]

We focus on the biggest stock market drawdowns in the period 2011-2012, by reporting the results referred to the first decile of the out-of-sample equity return distribution. These observations span the second semester of 2011, when the EU sovereign debt crisis spread from the peripheral countries in Europe to the rest of the continent and ultimately affected the US, too. The biggest slump in the EU stock market was recorded in the last week of July 2011, with a weekly negative return of 13%. For this data point, on the basis of our simple regression model, we forecast a fall in the equity market, with a probability of 60 to 90%, when the forecasting time horizon is at least one-quarter long. Similar figures are recorded for the other observations in August-2011. Negative stock return probabilities above 50% are in general observed earlier in the same year (first two rows in Tab. 1.2), whereas more contrasted evidence emerges from the last three rows. The average drawdown probability across all the cases reported in Tab. 1.2 equates to more than 55%, providing evidence, albeit not strong, for the ability of the estimated default probabilities to forecast the materialization of a tail event on the equity market.

1.5 Final Remarks

In this chapter, we proposed a multivariate methodology for the estimation of the joint default probability of several entities. CDS and bond market data are used to assess the dependence of a defaultable entity's economic soundness on the financial cycle, considered as the trigger for default propagation. The application to the EU sovereign risk provided evidence of increasing systemic risk and danger of contagion from early 2007 and more significantly from late 2011 onwards. The estimates show to be very reactive to changes in market conditions and their magnitude is coherent with what found by Radev (2012) and Zhang et al. (2012). We documented the total inaccuracy of the Gaussian copula in capturing the extreme event of a joint default.

Marginal and conditional default probability estimates were also provided. We historically validated the forecasting capability of the proposed estimates through a comparison with the dynamics of a benchmark stock market index, which marked the timeline of the recent sovereign debt crisis. This forecasting power crucially depends on the fact that the estimation relies entirely on the information impounded in current market prices, which are observable at the daily frequency. This, however, comes with the disadvantage that the estimates can not embed any insight at the pure macroeconomic level, which is in fact considered only a-posteriori. In the following chapter, we develop a comprehensive indicator which blends the information coming from markets' dynamics with the current outlook on the real side of the economy.

Appendix - Derivation of Forward Spreads

The definition provided in Eqs. (1.15)-(1.16) requires the specification of $s_\alpha(t_k, t_{k+1})$ and $w_{\alpha,\beta}(t_k, t_{k+1})$. The former is given by the standard relation:

$$s_\alpha(t_k, t_{k+1}) = \frac{t_{k+1}}{t_{k+1} - t_k} s_\alpha(0, t_{k+1}) - \frac{t_k}{t_{k+1} - t_k} s_\alpha(0, t_k) \tag{1.31}$$

For the latter, consider that in an arbitrage-free world, the following relation can be stated:

$$w_{\alpha,\beta}(0, t_M)\left(1 + \sum_{k=1}^{M-1} P_{\alpha,\beta}(t_{k-1}, t_k) e^{-r(0,t_k)t_k}\right) = \sum_{k=1}^{M} w_{\alpha,\beta}(t_{k-1}, t_k) e^{-r(0,t_{k-1})t_{k-1}} \tag{1.32}$$

that is, the expected actual value of the payments in a contract with maturity t_M must equate the actual value of M forward CDS contracts referred to the time periods $[t_{k-1}, t_k]$ with $k = 1, \dots, M$. We use Eq. (1.32) to bootstrap the forward CDS quote as follows:

$$\begin{aligned} w_{\alpha,\beta}(t_k, t_{k+1}) = {} & w_{\alpha,\beta}(0, t_{k+1}) e^{r(0,t_k)t_k} + \\ & \sum_{\kappa=1}^{k} \Big[w_{\alpha,\beta}(0, t_{k+1}) P_{\alpha,\beta}(t_{\kappa-1}, t_\kappa) e^{-r(t_{\kappa-1},t_\kappa)(t_\kappa - t_{\kappa-1})} + \\ & - w_{\alpha,\beta}(t_{\kappa-1}, t_\kappa) e^{-r(0,t_{\kappa-1})t_{\kappa-1}} \Big] \end{aligned} \tag{1.33}$$

with $k = 0, \dots, M-1$.

Table 1.1: **Descriptive statistics for CDS spreads and bond yields.** We report summary statistics for the data used in the application. Data are referred to Austria, Belgium, Finland, France, Italy, Netherlands, Portugal, Slovakia, Slovenia and Spain. The four panels respectively refer to 5-year CDS, 10-year CDS, 5-year bond yields and 10-year bond yields. The sample spans from 01-Jan-2004 to 11-Oct-2012 and consists of daily observations, leading to 2291 data points.

CDS - 5 years

Country	*Mean*	*Standard deviation*	*Min*	*Max*
Austria	0.517%	0.616%	0.010%	2.690%
Belgium	0.689%	0.896%	0.021%	4.061%
Finland	0.228%	0.248%	0.030%	0.908%
France	0.461%	0.615%	0.015%	2.496%
Italy	1.157%	1.509%	0.056%	5.915%
Netherlands	0.634%	0.321%	0.105%	1.398%
Portugal	2.287%	3.624%	0.040%	15.269%
Slovakia	0.706%	0.786%	0.053%	3.282%
Slovenia	0.932%	1.278%	0.043%	5.111%
Spain	1.221%	1.585%	0.026%	6.410%

CDS - 10 years

Country	*Mean*	*Standard deviation*	*Min*	*Max*
Austria	0.591%	0.683%	0.018%	2.611%
Belgium	0.733%	0.912%	0.024%	3.975%
Finland	0.278%	0.293%	0.027%	1.103%
France	0.522%	0.680%	0.029%	2.581%
Italy	1.194%	1.435%	0.093%	5.696%
Netherlands	0.631%	0.405%	0.075%	1.574%
Portugal	2.089%	3.034%	0.061%	10.694%
Slovakia	0.814%	0.838%	0.071%	3.403%
Slovenia	1.242%	1.420%	0.073%	5.414%
Spain	1.181%	1.490%	0.031%	5.754%

BOND - 5 years

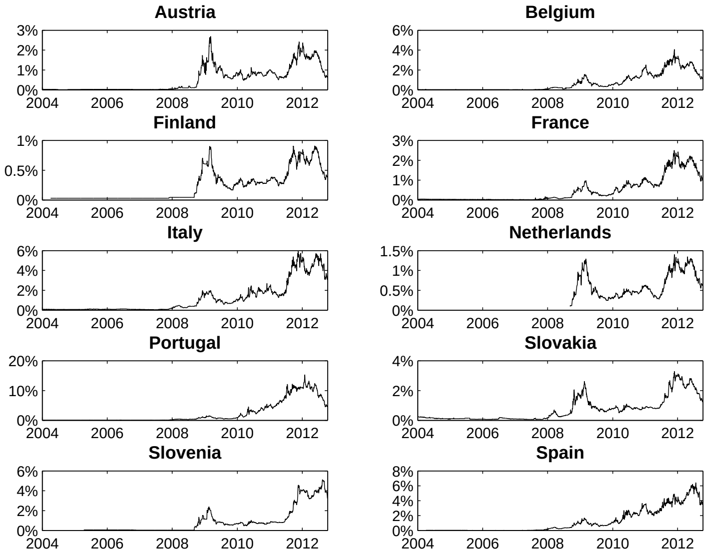
Country	*Mean*	*Standard deviation*	*Min*	*Max*
Austria	3.035%	0.873%	0.615%	4.897%
Belgium	3.280%	0.723%	1.065%	5.404%
Finland	2.442%	1.063%	0.526%	4.930%
France	2.960%	0.889%	0.734%	4.929%
Italy	3.745%	0.832%	2.562%	7.703%
Netherlands	2.869%	0.982%	0.558%	4.883%
Portugal	5.281%	3.609%	2.517%	21.748%
Slovakia	3.403%	0.734%	1.675%	4.973%
Slovenia	3.968%	1.051%	2.080%	5.671%
Spain	3.713%	0.790%	2.435%	7.498%

BOND - 10 years

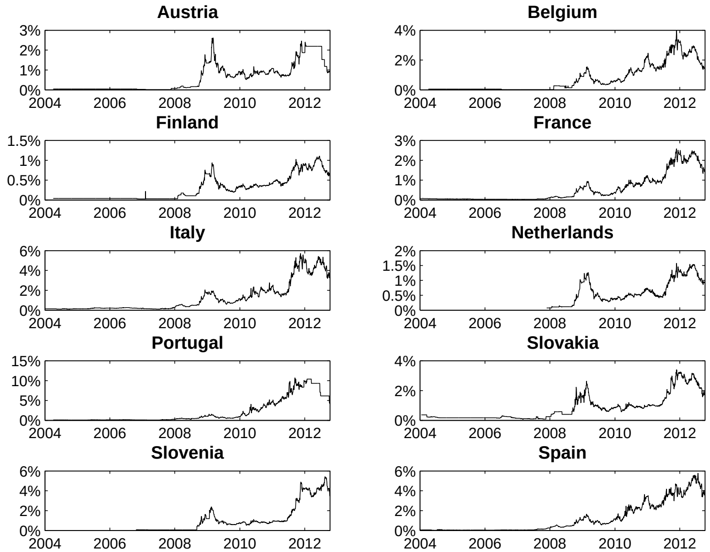
Country	*Mean*	*Standard deviation*	*Min*	*Max*
Austria	3.676%	0.623%	1.850%	4.921%
Belgium	3.895%	0.496%	2.394%	5.814%
Finland	3.283%	0.833%	1.322%	4.870%
France	3.637%	0.572%	2.046%	4.844%
Italy	4.453%	0.693%	3.217%	7.244%
Netherlands	3.542%	0.724%	1.521%	4.856%
Portugal	5.516%	2.686%	3.160%	16.605%
Slovakia	3.991%	0.464%	2.573%	5.062%
Slovenia	4.993%	0.975%	3.492%	6.123%
Spain	4.363%	0.790%	3.005%	7.566%

TABLE 1.2: **Results of the forecasting analysis.** In the first two columns, we report the observations in the first decile of the out-of-sample return distribution for the EuroStoxx50. The out-of-sample period spans from 01-Jan-2011 to 11-Oct-2012. For each of the reported observations, we present the probability of a negative return as forecast by the regression model in Eq. (1.30) when different number of lags L are considered.

		Probability of a drawdown				
Date	***Observed stock return***	$\boldsymbol{L = 1}$	$\boldsymbol{L = 4}$	$\boldsymbol{L = 12}$	$\boldsymbol{L = 26}$	$\boldsymbol{L = 52}$
04-Jul-2011	-5.029%	63.853%	57.623%	48.183%	59.151%	63.953%
25-Jul-2011	-5.526%	55.498%	51.980%	51.562%	57.924%	63.279%
01-Aug-2011	-12.967%	47.306%	42.771%	62.227%	81.906%	88.602%
15-Aug-2011	-6.596%	53.102%	59.478%	72.009%	79.830%	78.393%
29-Aug-2011	-4.980%	52.405%	39.249%	76.220%	80.351%	74.457%
05-Sep-2011	-4.209%	51.121%	49.762%	60.718%	70.487%	78.801%
14-Nov-2011	-6.270%	52.859%	52.443%	50.076%	27.601%	50.673%
05-Dec-2011	-4.385%	53.170%	51.698%	44.528%	24.973%	48.615%
02-Apr-2012	-4.163%	50.887%	48.717%	48.615%	23.189%	15.696%

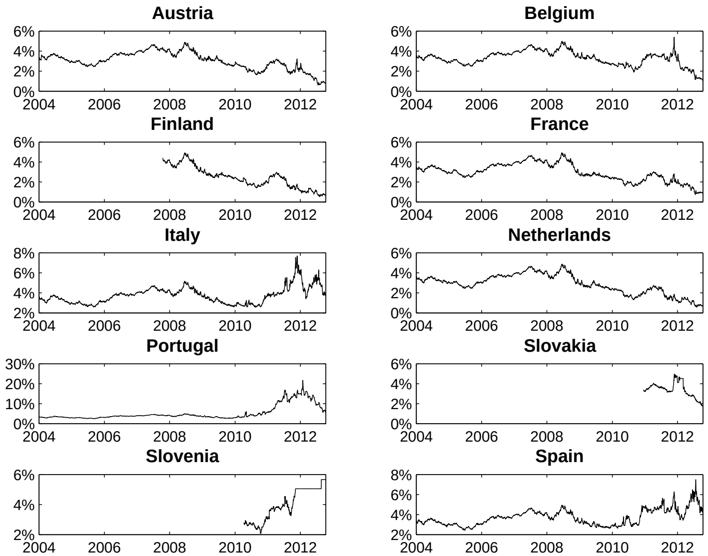


(A) CDS spreads - 5 years.

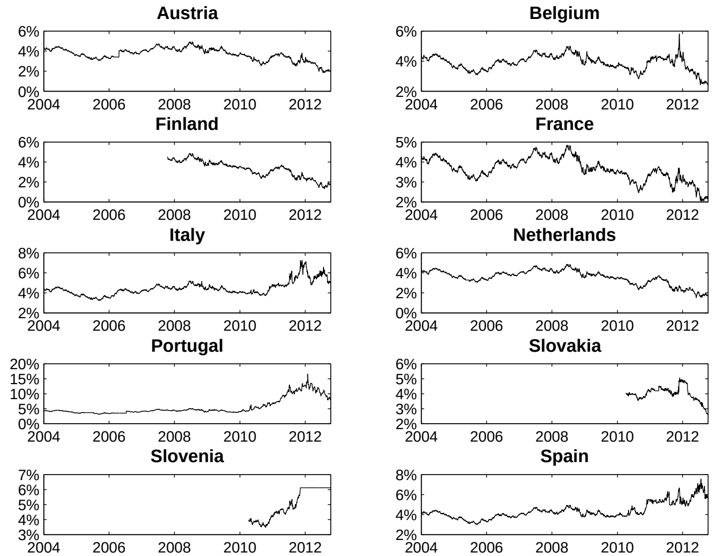


(B) CDS spreads - 10 years.

FIGURE 1.1: **Data plot: CDS spreads.** We plot the CDS spread data used in the application. The left panel shows the 5-year CDS quotes, whereas the right panel shows the 10-year CDS quotes. Data are referred to Austria, Belgium, Finland, France, Italy, Netherlands, Portugal, Slovakia, Slovenia and Spain. The sample consists of daily observations from 01-Jan-2004 to 11-Oct-2012.

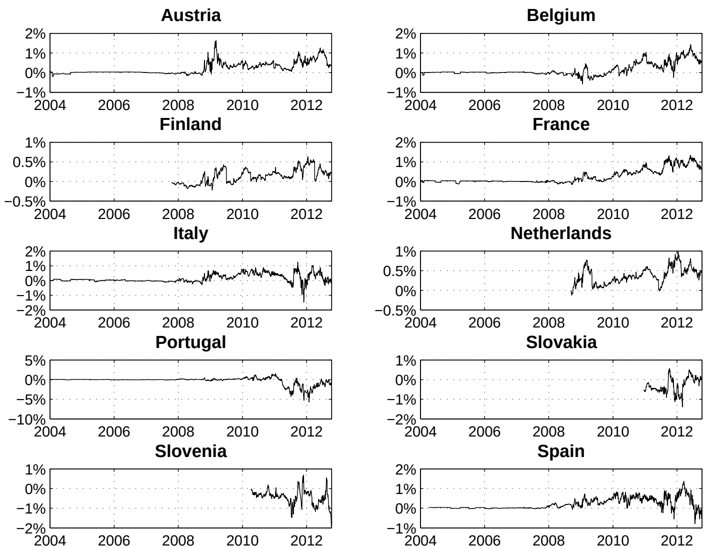


(A) Bond yields - 5 years.

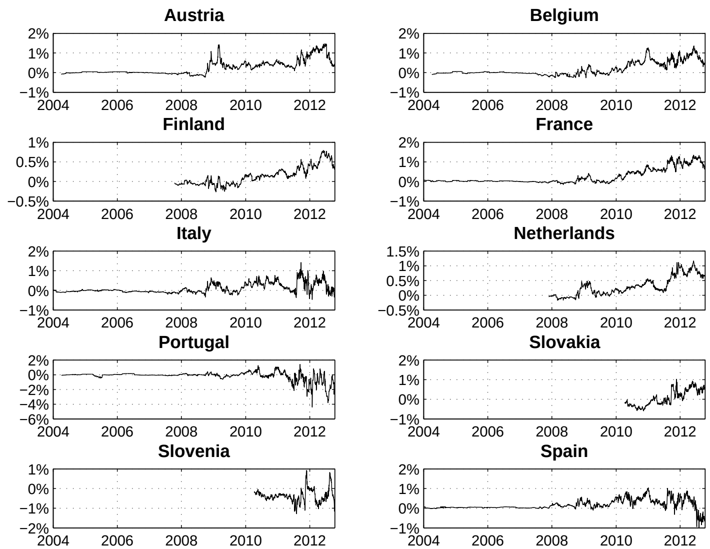


(B) Bond yields - 10 years.

FIGURE 1.2: **Data plot: Bond yields.** We plot the bond yield data used in the application. Panel (A) shows the 5-year bond yield data, whereas Panel (B) shows the 10-year bond yield data. Data are referred to Austria, Belgium, Finland, France, Italy, Netherlands, Portugal, Slovakia, Slovenia and Spain. The sample consists of daily observations from 01-Jan-2004 to 11-Oct-2012.

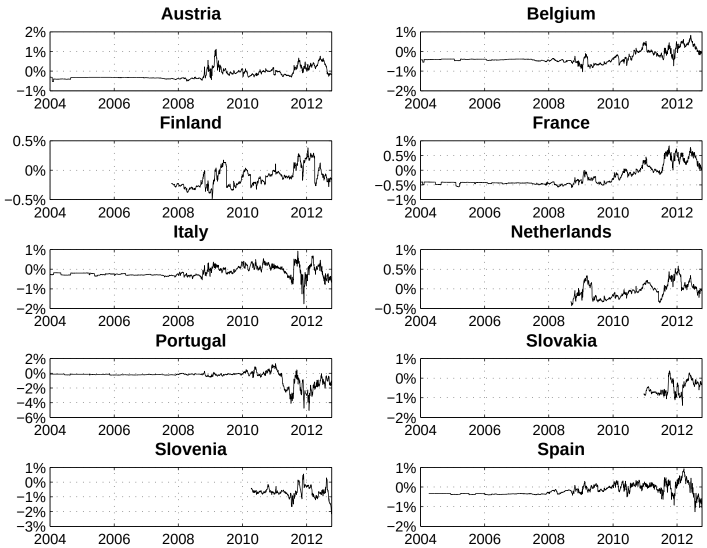


(A) The unadjusted bases - 5 years.

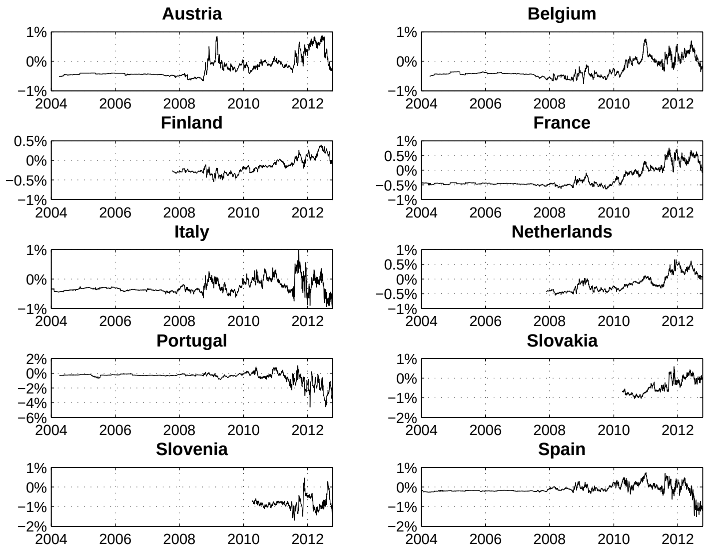


(B) The unadjusted bases - 10 years.

FIGURE 1.3: **The unadjusted bases.** We plot the unadjusted CDS-bond basis for Austria, Belgium, Finland, France, Italy, Netherlands, Portugal, Slovakia, Slovenia and Spain, from 01-Jan-2004 to 11-Oct-2012. The basis is computed as the difference between the CDS spread and the bond spread. Panel (A) shows the 5-year basis, whereas Panel (B) shows the 10-year basis.



(A) The liquidity- and funding-adjusted bases - 5 years.



(B) The liquidity- and funding-adjusted bases - 10 years.

FIGURE 1.4: **The liquidity- and funding-adjusted bases.** We plot the liquidity- and funding-adjusted CDS-bond basis for Austria, Belgium, Finland, France, Italy, Netherlands, Portugal, Slovakia, Slovenia and Spain, from 01-Jan-2004 to 11-Oct-2012. The liquidity- and funding-adjusted basis is computed according to Eq. (1.7). Panel (A) shows the 5-year basis, whereas Panel (B) shows the 10-year basis.

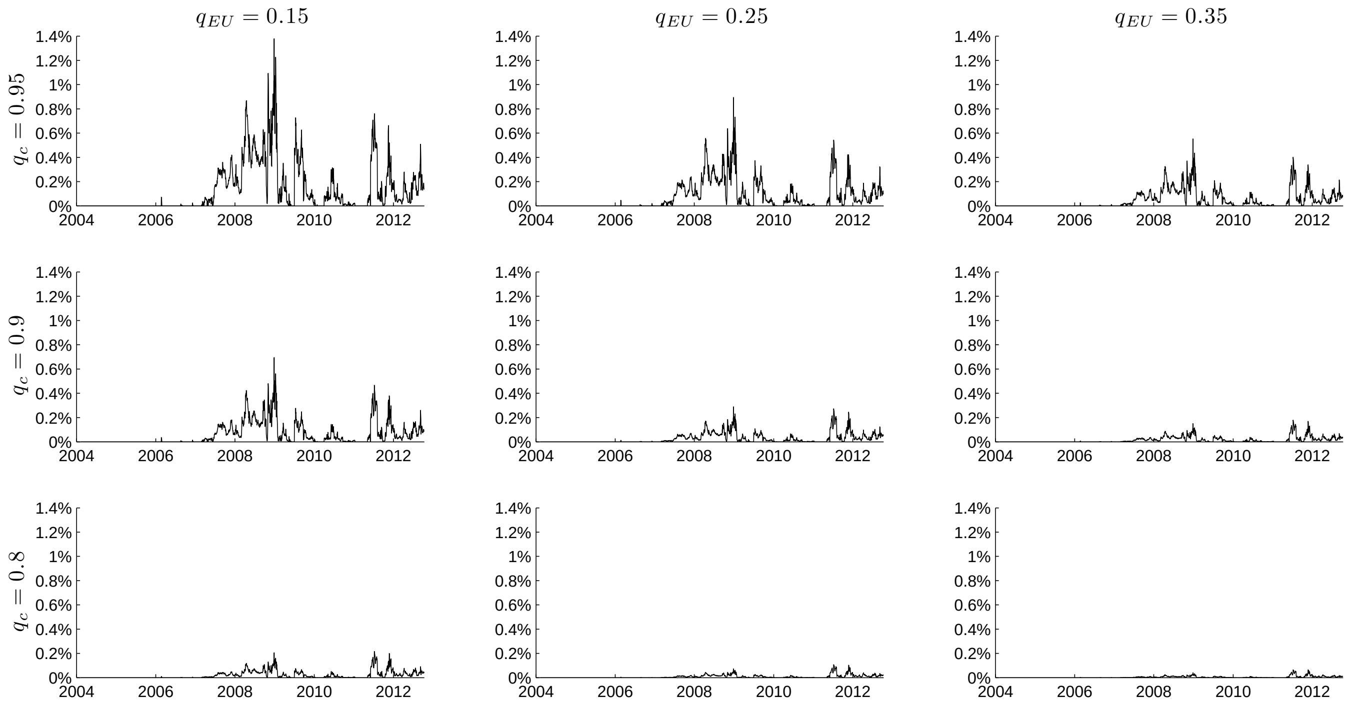


FIGURE 1.5: **Joint default probabilities (Gumbel copula) - 5 years.** We plot the estimates of the 5-year joint default probability for the considered EU countries. The probabilities are estimated via simulating the system presented in Eqs. (1.23)-(1.24) by means of the Gumbel copula in Eq. (1.26). Results are presented for different values of the parameters q_c and q_{EU}, which respectively are the quota of collateralized trades on the OTC credit derivate market, and the relative size of the EU investment bank sector.

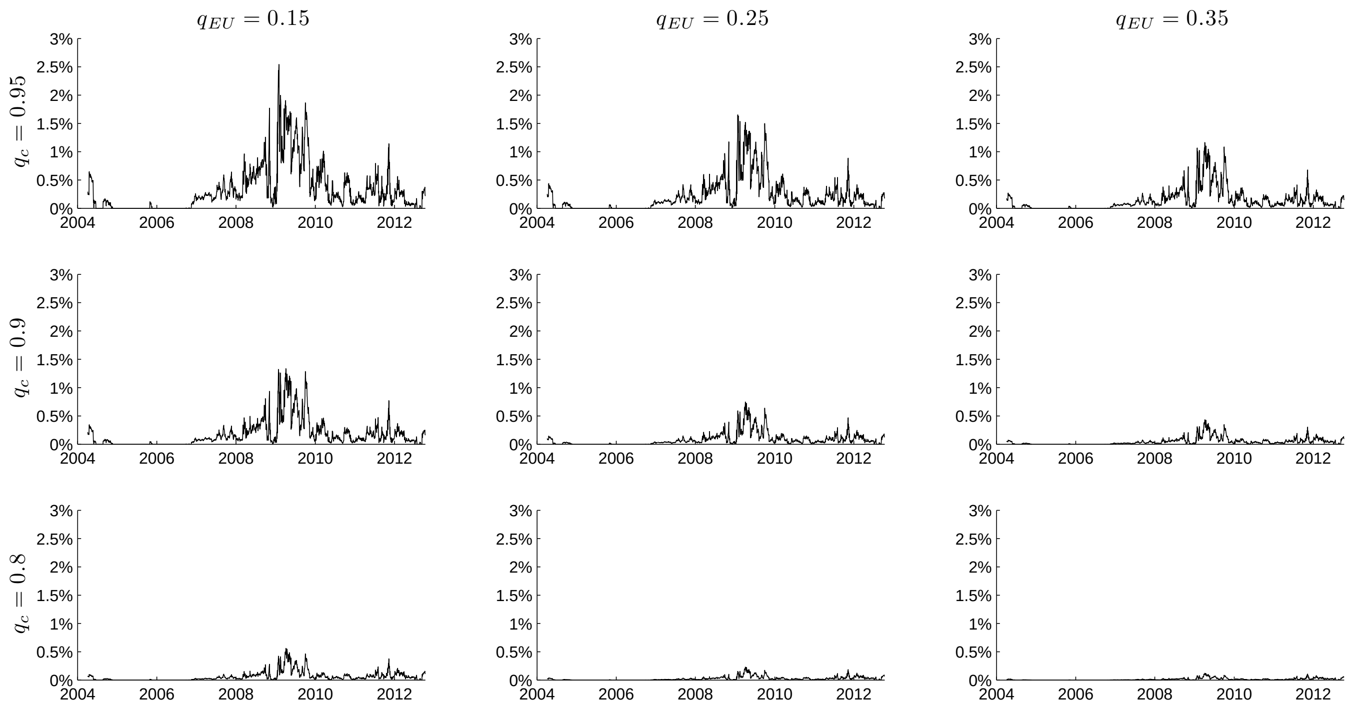


FIGURE 1.6: **Joint default probabilities (Gumbel copula) - 5 to 10 years.** We plot the estimates of the 5-to-10-year joint default probability for the considered EU countries. The probabilities are estimated via simulating the system presented in Eqs. (1.23)-(1.24) by means of the Gumbel copula in Eq. (1.26). Results are presented for different values of the parameters q_c and q_{EU}, which respectively are the quota of collateralized trades on the OTC credit derivate market, and the relative size of the EU investment bank sector.

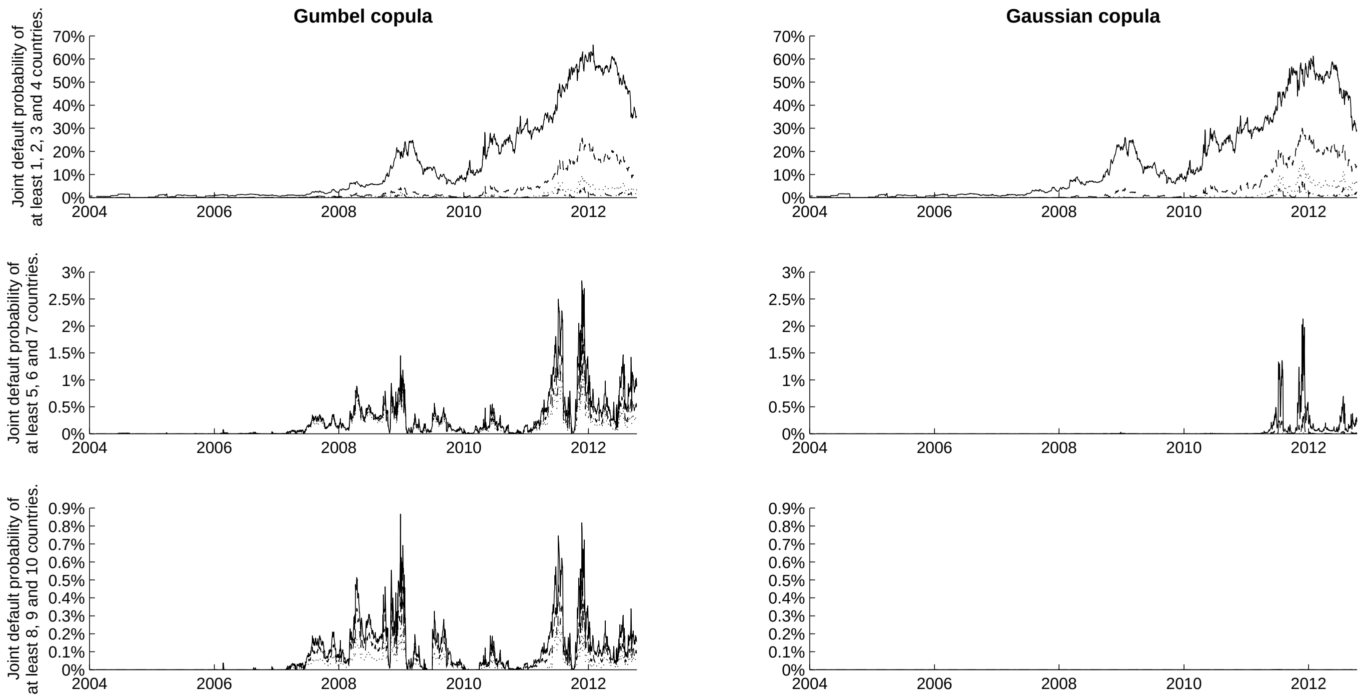


Figure 1.7: **Joint default probabilities for at least** $1, 2, \ldots, N$ **countries (Gumbel versus Gaussian copula) - 5 years.** We show a comparison between the Gumbel copula (left panel) and the Gaussian copula (right panel) at estimating the 5-year probability of default of at least 1 to 4 countries (top panel), 5 to 7 countries (middle panel) and 8 to 10 countries (bottom panel).

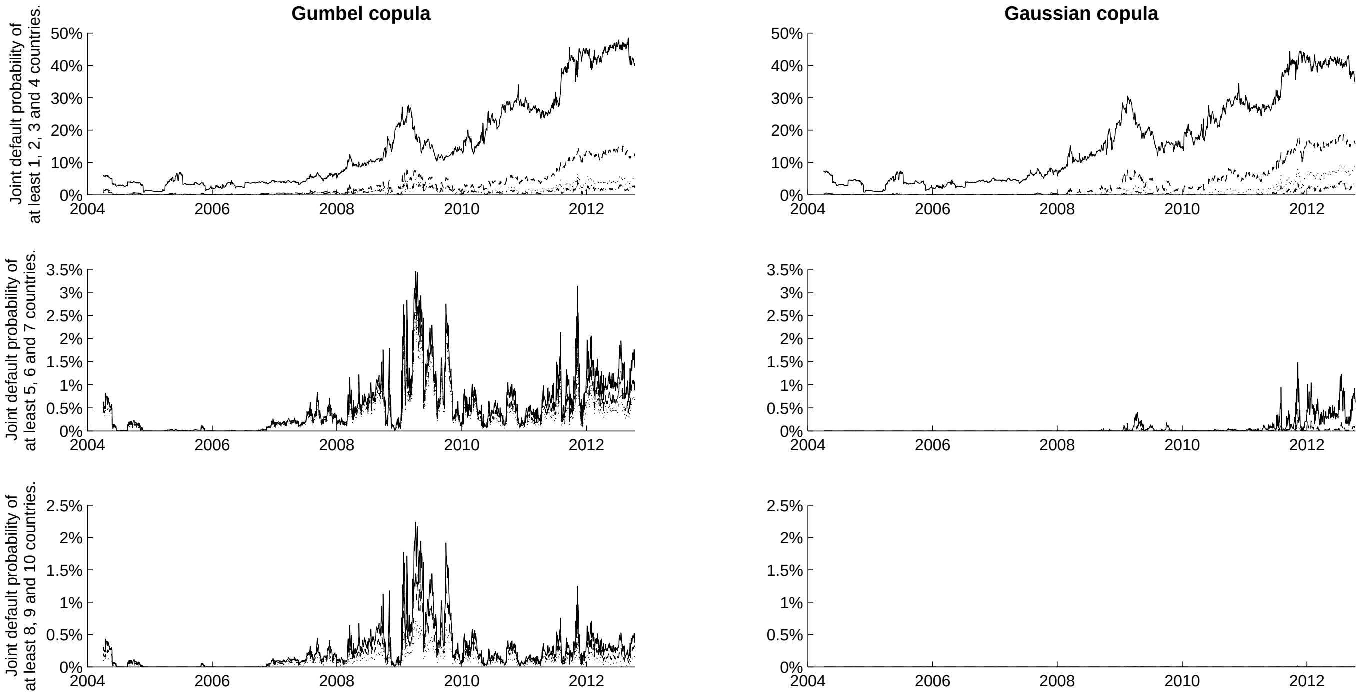


FIGURE 1.8: **Joint default probabilities for at least $1, 2, \ldots, N$ countries (Gumbel versus Gaussian copula) - 5 to 10 years.** We show a comparison between the Gumbel copula (left panel) and the Gaussian copula (right panel) at estimating the 5-to-10-year probability of default of at least 1 to 4 countries (top panel), 5 to 7 countries (middle panel) and 8 to 10 countries (bottom panel).

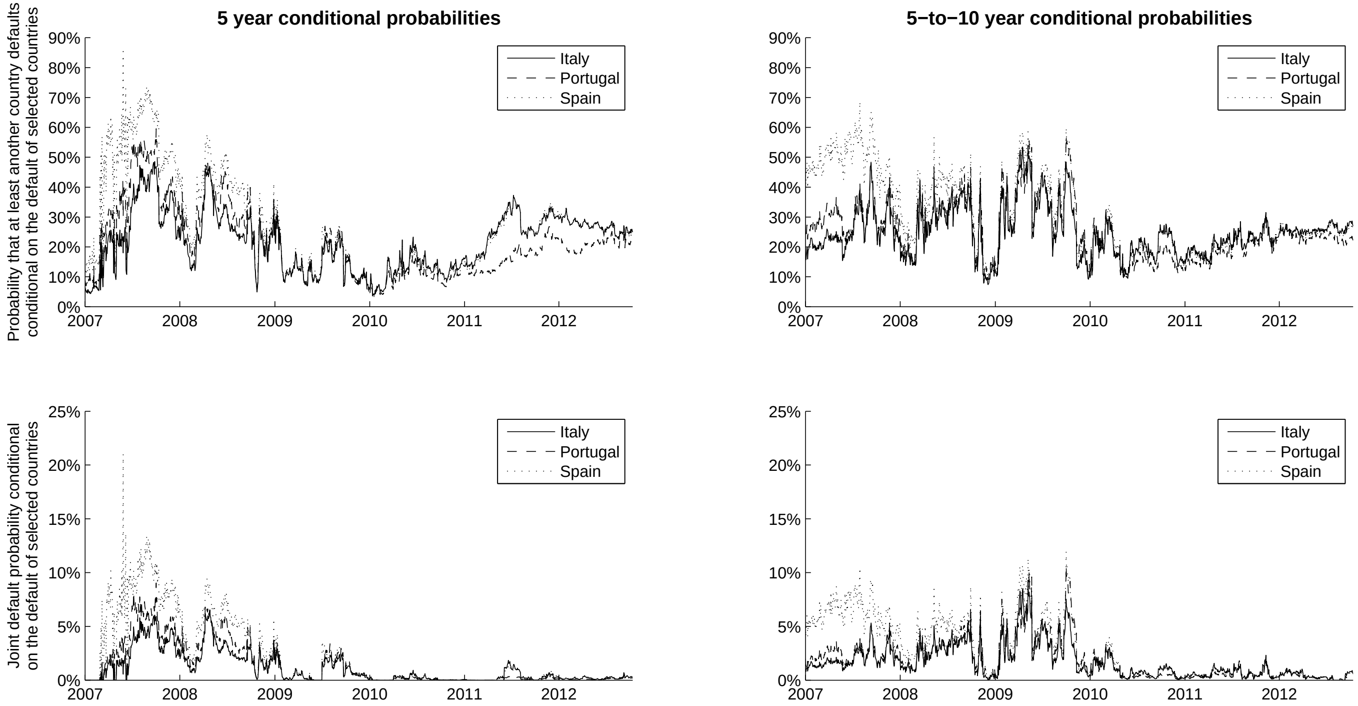


FIGURE 1.9: **Joint default probabilities conditional on the default of Italy, Portugal and Spain.** We plot default probabilities conditional on the default of Italy, Portugal and Spain. In the top panel we report the conditional probabilities of one or more additional default(s), whereas in the bottom panel we report the conditional joint probability of default. 5-year estimates are in the left panel, 5-to-10-year estimates are in the right panel.

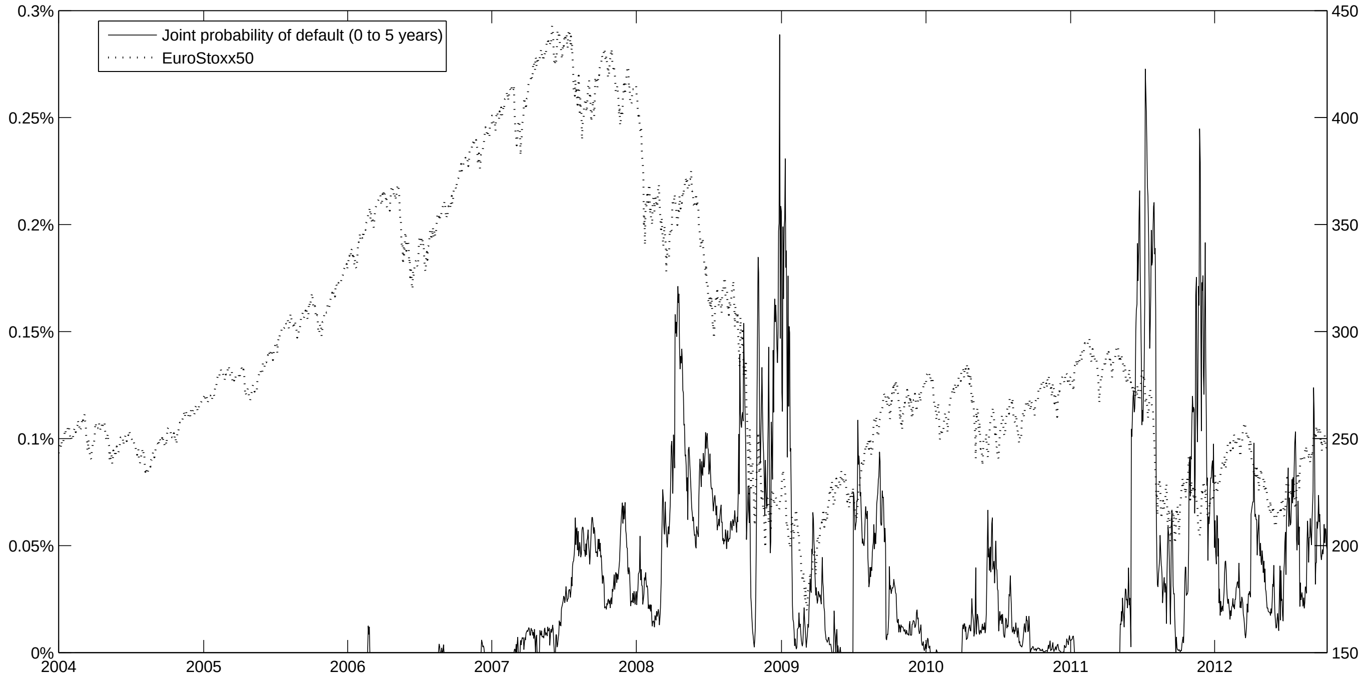


FIGURE 1.10: **Joint default probability and the EuroStoxx50 Index.** We compare the joint default probability estimates with the EuroStoxx50 Index. We report a plot of the daily time series of the index (dotted line, right axis), together with the estimate of the 5-year joint default probability for the EU countries, with $q_c = 0.9$ and $q_{EU} = 0.25$ (solid line, left axis).

List of Symbols

α	reference entity in the CDS contract
β	protection seller in the CDS contract
t	time index referred to the date of evaluation
T	time index referred to the maturity of the contracts
r	risk-free rate
y_α	yield on a ZCB issued by α
s_α	spread between the issuance cost of α and the risk-free rate
$w_{\alpha,\beta}$	quote of a CDS on α issued by β
$b_{\alpha,\beta}$	CDS-bond basis for α defined as the difference between $w_{\alpha,\beta}$ and s_α
λ_α	liquidity premium on a bond issued by α
s'_α	liquidity-adjusted counterpart of the bond spread s_α
l_α	proportionality factor linking the bond spread s_α with its liquidity-adjusted counterpart s'_α
s_α^{bid}	bond spread for the bid quote of a bond issued by α
s_α^{ask}	bond spread for the ask quote of a bond issued by α
$w_{\alpha,\beta}^{bid}$	bid quote of a CDS on α issued by β
$w_{\alpha,\beta}^{ask}$	ask quote of a CDS on α issued by β
$b'_{\alpha,\beta}$	liquidity-adjusted counterpart of $b_{\alpha,\beta}$
$\mathcal{L}$	Libor rate
d	depo rate
δ	spread between the Libor and the depo rate
$b''_{\alpha,\beta}$	funding-adjusted counterpart of $b'_{\alpha,\beta}$
q_c	average quota of collateralized nominal amount on CDS in the OTC market
$w''_{\alpha,\beta}$	quote of an uncollateralized CDS on α issued by β

$\tilde{w}''_{\alpha,\beta}$	quote of a fully collateralized CDS on α issued by β
$b'''_{\alpha,\beta}$	collateralization-adjusted counterpart of $b''_{\alpha,\beta}$
$B_{\alpha,\beta}$	component of $b'''_{\alpha,\beta}$ corresponding to counterparty risk
RR_α	recovery rate of α
RR_β	recovery rate of β
t_k	index referred to time period $k+1$ with $k = 0, \ldots, M-1$
$P_{\overline{\alpha},\overline{\beta}}$	joint default probability for α and β
$\tilde{P}_{\overline{\alpha},\overline{\beta}}(t,T)$	joint default probability for α and β over the period $[t,T]$ conditional on their joint survivor till time t
$P_{\alpha,\beta}$	joint survival probability for α and β
Ψ	numerator on the right-hand side of Eq. (1.15)
$\mathbb{L}(\cdot)$	logistic transformation
c_1	scale parameter in the logistic transformation $\mathbb{L}(\cdot)$
c_2	location parameter in the logistic transformation $\mathbb{L}(\cdot)$
$\rho_{\alpha,\beta}$	default correlation between α and β
$P_{\overline{\alpha}}$	marginal probability of default for α
$P_{\overline{\beta}}$	marginal probability of default for β
N	number of defaultable entities
i	index referred to the i-th defaultable entity with $i = 1, \ldots, N$
α_i	i-th defaultable entity
V_i	value of the assets of the i-th defaultable entity
Y	common systematic component in the credit risk factor model
Z_i	i-th idiosyncratic component in the credit risk factor model
ϱ_i	parameter linking the i-th defaultable entity with the systematic component Y
R	default correlation matrix for the defaultable entities $\alpha_1, \ldots, \alpha_N$
$\mathbb{1}_i$	random variable for the default process of the i-th defaultable entity
$\phi(\cdot)$	generator function for the Gumbel copula

θ	dependence parameter in the Gumbel copula
$C(\cdot,\dots,\cdot)$	Gumbel copula function
$\bar{R}$	average default correlation
q_{EU}	relative importance of the EU investment banks within the global investment bank sector
$B^{EU}_{\alpha_i,\beta}$	EU counterpart of $B_{\alpha,\beta}$ for the case in which the protection seller is an EU investment bank
y_t	weekly returns of the EuroStoxx50
JPD_t	weekly time series for the estimated 5-year joint default probability with $q_c = 0.9$ and $q_{EU} = 0.25$
ω	constant term in the forecasting model
ψ_l	coefficient referred to ΔJDP_{t-l} in the forecasting model
L	number of lags in the forecasting model
ϵ_t	error term in the forecasting model

Chapter 2

A Systemic Risk Indicator and Monetary Policy

2.1 Introduction

The chapter has two main objectives. First, we propose a comprehensive indicator to measure systemic risk at a global level. Second, we focus on the interaction of the indicator with policy decisions employed by the Federal Reserve (Fed), the European Central Bank (ECB) and the Bank of England (BoE) during the past two decades.

The 2007-2009 crisis originated in the market of mortgage-backed-securities and spread rapidly across the credit market and then to the overall capital market with a severe impact on the solidity of the international banking system. The effects of the crisis on the real economy are still to be fully understood. The current European sovereign debt crisis is just the last of a series of systemic events whose market depth and persistence have questioned the much celebrated markets' self-regulatory power as well as the overall ability of policy makers and regulators to adopt stability measures and stimulate economic growth. Just as in 2007-09, the current financial crisis demonstrates that systemic risk spreads globally across markets and institutions. Funding difficulties in one market/country can spill over to other markets/countries via internationally active institutions, and the tail risk in financial markets can be transmitted across the world.

As discussed in the Introduction, there are several methodological approaches to measure systemic risk at the global level. This chapter represents a novel contribution to the stream of literature on systemic risk which focuses on global (rather than limited to the financial sector) market dynamics as primary source of financial instability.

The joint treatment of financial markets' and economic cycle's information to assess systemic risk appears a requirement for policy makers and global institutions: the 2007-2009 crisis, just as more recent events, shows the limits of risk models for the financial crisis neglecting the economic cycle. Indeed the pro-cyclicality of international capital standards has been called upon (Allen and Saunders, 2002) to explain the crisis' depth. The link with the real economy is of paramount importance to assess systemic risk, and thus, here we propose a systemic risk indicator which includes macroeconomic variables so that the overall impact of systemic risk is captured at both the financial and economic level.

Notable contributions along the same line of research are the papers by Schwaab et al. (2011), De Nicoló and Lucchetta (2012) and Hollo et al. (2012).

Hollo et al. (2012) focus on the local European financial system to propose the Composite Indicator of Systemic Stress (CISS). The index is constructed by aggregating the information coming from market-specific subindices, referred to the sector of bank and non-bank financial intermediaries as well as to security (equity and bond) markets and foreign exchange markets. The aggregation is done in a dynamic correlation framework, so that the resulting indicator highlights the periods in which market stress prevails at the same time on all the subindices. The application to the

Euro Area shows the capability of the indicator of picking up the instability periods in the recent financial history. The CISS however fails to incorporate the relevant information stemming from the economic sector, as the extent to which financial stress tends to depress real economic activity is analysed only a-posteriori.

The paper by De Nicoló and Lucchetta (2012) proposes a modelling framework leading to distinct forecasts for a financial and a real systemic indicator. Starting from the G10 systemic risk definition, the authors propose a real measure of systemic risk such as the GDP-at-risk defined as "the worst predicted realization of quarterly growth in real GDP at 5% probability", while a financial risk measure is proposed through the financial system-at-risk (FSaR), defined as "the 5% worst predicted realization of market-adjusted returns for a large portfolio". Though inspired by the same systemic risk definition, rather than proposing two separate indicators, in this chapter, we propose a global measure of systemic risk.

Schwaab et al. (2011) adopt a dynamic state-space model which takes macro-financial and credit risk variables as an input to determine forward crises indicators. Macroeconomic variables are introduced to explain the time dynamics of expected default frequencies in US and Europe. The information structure is very rich and the authors propose a financial distress indicator based on early-warning signals, thus also partially forward-looking. More importantly, the authors focus on joint global economic and financial movements to qualify their systemic assessment and translate such information into a risk indicator defined in the $[0, 1]$ set, thus interpretable as a probability measure. Similarly, in this work, an extended information basis is maintained, capturing systemic events at an international level and a risk indicator with similar statistical properties is derived. The definition of systemic risk adopted by Schwaab et al. (2011) is based on a simultaneous failure of a large number of financial intermediaries, and the estimation procedure identifies multiple systemic risk indicators, directly referred to the financial sector only. On the contrary, the indicator we propose is more comprehensive as it can be considered a global financial and economic risk factor. It is constructed by mapping an extended set of market risk premia, estimated ex-post on a quarterly basis and the current economic cycle into a normalized 0-1 measure.

The other main aim that inspired our work in proposing a global risk indicator is the possibility to evaluate the reactions of monetary policy makers during crises. The definition of a global risk indicator allows us to test, through an extension of the Taylor rule (Taylor, 1993), the relationship between systemic risk and monetary interventions by the Federal Reserve, the Bank of England and the European Central Bank since 1995, 1997 and 1999, respectively. Notwithstanding the general dependence of monetary policy interventions on market and economic forward signals, we are interested in investigating to what extent systemic risk might have induced a departure of policy interventions from classical anti-inflationary and output stabilization measures.

We follow up from an early work by Hayford and Malliaris (2005), who, by means of an extension of the Taylor rule to include a measure of overvaluation of the American stock market, found evidence of a significant reaction of the Fed to the late 1990s stock market bubble. In the same spirit is the paper by Gnan and Cuaresma (2008), which provides an estimate for the 4 major Central Banks (the ECB, the Fed, the BoE and the Bank of Japan) of the Taylor rule augmented by a financial instability variable, namely the equity return volatility for each of the considered areas. The empirical estimates allow authors to conclude for the presence of relevant differences in the elasticity of interest rates to financial instability. In this chapter, we aim to understand how Central Bankers react to a shift in the riskiness of the system and, to this purpose, we extend the relation proposed in Gnan and Cuaresma (2008) by including the proposed systemic risk indicator as well as by considering in the sample the period of the recent financial crisis. Thus, the application developed in this study adds to previous works the analysis of monetary responses to a common systemic risk threat, during a prolonged period of financial stress.

The main findings of the chapter can be summarized as follows. Based upon the 1995-2011 crisis events, we validate the capability of the indicator of signalling the relevant episodes of financial tension in the recent history. Further, the empirical investigation on the interaction of the indicator with monetary policy clarifies under which stressed economic and financial conditions and to which extent expansionary decisions adopted by the Fed and the BoE in recent years were also led by riskiness of the system. On the contrary, there is evidence that ECB showed some reluctance to give up its role in maintaining price stability, except during the recent period of economic and financial instability. Finally, we compare the proposed indicator with alternative coincident measures of systemic risk and show its ability in capturing the materialization of systemic risk instabilities which triggered the reaction of the Fed, the ECB and the BoE.

The remainder of the chapter is organized as follows. In Section 2.2, we describe the methodology behind the construction of the systemic risk indicator, and we report an empirical application to show the capability of the proposed indicator to capture the crisis events over the period 1995-2011. Section 2.3 reports an empirical investigation on the interaction of the indicator with monetary policy decisions at the Fed, the ECB and the BoE. Section 2.4 draws the main conclusions of the chapter.

2.2 A Systemic Risk Indicator

In this section, we introduce a risk indicator, which provides a quarterly measure of the global riskiness in the economic and financial system. The indicator can be regarded as a mapping from a set of exogenous economic and financial variables to a risk measure in the $(0, 1)$ space, with 0 indicating absence of systemic risk and 1 maximum systemic risk. The indicator is calibrated over the period 1995-2011 thus exploiting the rich history of events thereby observed. By introducing a filtered average systemic risk fluctuation, time-varying positive and negative deviations from such average are considered and monetary interventions are related to those deviations.

The proposed indicator is based on a wide data coverage, in respect of the different asset classes and geographical areas considered (for details see Section 2.2.3). A logistic model is adopted to link the indicator to a set of explanatory variables selected on the basis of the definition of systemic risk provided by the official documentation of the G10 Report on Consolidation in the Financial Sector (G10, 2001, p.126):

Definition 2.1. (*Systemic Financial Risk*). Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy.

To measure the "loss of economic value" that might materialize in the financial system, a *risk appetite index* is constructed following the methodology used by Credit Suisse First Boston (CSFB), as described in Wilmot et al. (2004). There is a stream of the literature that shows that risk appetite measures have a very high ability in explaining financial market movements, including systemic instabilities (Kumar and Persaud, 2002, Bandopadhyaya and Jones, 2006). Financial turmoil is related to a homogeneous fall of market risk premia, going hand-in-hand with a substantial outflow of financial resources from the markets. On the contrary, low systemic risk is characterized by the presence of positive risk premia and diversification among markets, with inflows and outflows from a market to another.

As for the measure of uncertainty in financial markets, the average discrepancy of the volatilities from their long-term value is considered, so that positive and negative deviations from long-term benchmarks are taken into account. The risk indicator is an increasing function of positive deviations from the market-specific long-term volatility. Finally, in order to keep track of the real side of the economy, we consider the *output gap* of a set of countries, covering a wide geographic area.

From a methodological viewpoint, the introduction of several time-varying macro-financial gap measures for capital market dynamics and the economic cycle inform a systemic risk indicator with cyclical features. Such property allows an endogenous and normalized characterization of systemic risk relevant for economic agents and policy makers alike. As a robustness check of our conclusions on the relationship between monetary policy and systemic risk, several alternative models are tested, taking into account the presence of structural breaks (Doornik, 2009, Castle et al., 2011).

Let $\xi \in (0,1)$ denote the systemic risk indicator, where $\xi \to 0^+$ indicates vanishing systemic risk, while $\xi \to 1^-$ corresponds to systemic risk approaching its maximum. The indicator is defined as a logistic transform:

$$\xi \equiv \left[1 + \exp\left(-\beta_0 - \beta_1 \sum_{k=1}^{K} \gamma_k \tilde{X}_{\cdot,k}\right)\right]^{-1} \tag{2.1}$$

where $\tilde{X} \in \mathbb{R}^{T \times K}$ is the normalized version of the matrix $X \in \mathbb{R}^{T \times K}$ of explanatory variables, such that:

$$\tilde{X} \equiv \left\{ \tilde{X}_{t,k} \middle| \mathbb{E}\left(\tilde{X}_{t,k}\right) = 0, \mathbb{E}\left(\tilde{X}_{t,k}\right)^2 = 1, \forall k \right\} \tag{2.2}$$

with $t = 1, ..., T$ and $k = 1, ..., K$, where T is the sample size and K is the number of the explanatory variables. The coefficient vectors $\beta \equiv [\beta_0 \ \beta_1]'$ and $\gamma \equiv [\gamma_1 \dots \gamma_K]'$ are unknown and have to be estimated.

There are two main issues to cover: the choice of the variables in X and the estimation procedure to get estimates of β and γ.

2.2.1 The Choice of the Relevant Variables

In this section, we provide a description of the variables in X as defined in Eq. (2.2). The presentation develops as if the data set used is at the quarterly frequency.

Let us first focus on the *risk appetite index*. Consider $n = 1, ..., N$ markets for quarters $t = 1, \ldots, T$ and a benchmark index for each of them. Let $\mu_{n,t}$ and $\sigma_{n,t}$ be the average and the standard deviation of the returns for index n during quarter t, respectively. Then, for each quarter, the following regression is estimated:

$$\mu_{n,t} = \alpha_t \sigma_{n,t} + \varepsilon_{n,t} \tag{2.3}$$

The slope α_t and the determination coefficient R_t^2 of the regression above are inputs to the systemic risk index.

According to Eq. (2.3), increasing systemic risk over time is captured by a decreasing and negative estimate for α_t, corresponding to negative risk premia and an outflow of financial resources from the markets at time t. The higher R_t^2, the stronger the markets' investments outflow. On the other hand, a situation of low systemic risk is characterized by the presence of positive risk premia and diversification among markets, with inflows and outflows. This situation is likely to correspond to a positive estimate of α_t and a very low R_t^2. Hence, the systemic risk indicator is a *decreasing* function of α_t and an *increasing* function of R_t^2.

To measure "the uncertainty in the financial system", we define the average percentage deviation of the volatilities from their long-term value σ_n^{LT}:

$$s_t \equiv \frac{1}{N}\sum_{n=1}^{N}\frac{\sigma_{n,t}-\sigma_n^{LT}}{\sigma_n^{LT}} \tag{2.4}$$

where σ_n^{LT} with $n = 1, \ldots, N$ are the full-sample standard deviations of the returns on the n-th index. The systemic risk indicator is an *increasing* function of s_t, as increasing volatilities over their long-term values are directly associated with financial instability.

In order to monitor conditions on the real side of the economy, the time series of the output gap for several countries are considered, so that a wide geographic coverage is provided. The output gap $y_{\cdot,j}$ for country j with $j = 1, \ldots, J$ is estimated as the percentage logarithmic deviation of the actual GDP from the potential GDP:

$$y_{t,j} \equiv 100(g_{t,j} - g^*_{t,j}) \tag{2.5}$$

where $g_{t,j}$ is the logarithm of the actual GDP for the j-th country, while $g^*_{t,j}$ is the logarithm of the potential GDP. The potential GDP is computed applying a univariate Hodrick and Prescott (1997, HP henceforth) filter to the logarithm of the original series of the GDP with smoothing parameter λ_{HP} set to 1600, consistently with both the rule proposed in Ravn and Uhlig (2002) and the relevant literature on the topic. This method is less accurate than the production function approach (Arnold, 2004), but it is less costly from a computational point of view and it is still reliable for our purposes. The systemic risk indicator is expected to be a *decreasing* function of $y_{\cdot,j}$ with $j = 1, \ldots, J$.

To summarize, the relevant variables in the matrix X and the expected sign of the relation between each of them and ξ are:

$$X \equiv \begin{bmatrix} \underset{(-)}{\alpha} & \underset{(+)}{R^2} & \underset{(+)}{s} & \underset{(-)}{y_{\cdot,1}} & \dots & \underset{(-)}{y_{\cdot,J}} \end{bmatrix} \tag{2.6}$$

2.2.2 Parameters Estimation

Once that the variables of interest are identified, the systemic risk indicator defined in Eq. (2.1) can be obtained by estimating the vector parameters β and γ. In Eq. (2.1), we first get γ, estimated via discriminant analysis, then β is derived.

We discriminate between high and low systemic risk regimes within the sample, by identifying explanatory variables' extreme observations and then splitting them into two subsets, one for high systemic risk conditions and the other for low risk. Let $v \in \mathbb{R}^K$ be a threshold vector defined by:

$$v \equiv \begin{bmatrix} 0 & \bar{R}^2 & \bar{s} & 0 & \dots & 0 \end{bmatrix}' \tag{2.7}$$

where $\bar{R}^2$ and $\bar{s}$ are the 50-th constant percentiles of R_t^2 and s_t respectively. A natural choice of the threshold for α_t and $y_{t,j}$ is 0, having these variables an immediate financial and economic interpretation. Now, let τ^+ and τ^- identify the extreme high and low systemic risk observation sets, defined as:

$$\tau^+ \equiv \{t | X_{t,k} > v_k, \forall k\} \tag{2.8}$$

$$\tau^- \equiv \{t | X_{t,k} < v_k, \forall k\} \tag{2.9}$$

leading to the subsets of normalized explanatory variables:

$$\tilde{X}^+ \equiv \left\{ \tilde{X}_{t,\cdot} | t \in \tau^+ \right\} \tag{2.10}$$

$$\tilde{X}^{-} \equiv \left\{ \tilde{X}_{t,\cdot} | t \in \tau^{-} \right\} \tag{2.11}$$

In a multidimensional space, intra-group distances are measured with respect to the centroids of the sets $\tilde{X}^{+}$ and $\tilde{X}^{-}$:

$${}_{c}\tilde{X}^{+}_{k} \equiv \frac{1}{|\tau^{+}|} \sum_{t \in \tau_{+}} \tilde{X}_{t,k} \tag{2.12}$$

$${}_{c}\tilde{X}^{-}_{k} \equiv \frac{1}{|\tau^{-}|} \sum_{t \in \tau_{-}} \tilde{X}_{t,k} \tag{2.13}$$

with ${}_{c}\tilde{X}^{+\prime}$ and ${}_{c}\tilde{X}^{-\prime}$ being column vectors, elements of $\mathbb{R}^{K}$. $\gamma \in \mathbb{R}^{K}$ is estimated by solving the following optimization problem:

$$\begin{aligned} \min_{\gamma \in \mathbb{R}^{K}} \quad & \left[\sum_{t \in \tau^{+}} \left| {}_{c}\tilde{X}^{+}\gamma - \tilde{X}_{t,\cdot}\gamma \right| + \sum_{t \in \tau^{-}} \left| {}_{c}\tilde{X}^{-}\gamma - \tilde{X}_{t,\cdot}\gamma \right| \right] \\ \text{s.t.} \quad & \mathbf{1}'\gamma = 1 \\ & \gamma_{k} \geq \bar{\gamma}_{k} \quad \forall k = 1, \ldots, K \end{aligned} \tag{2.14}$$

where $\bar{\gamma}_{k}$ is a lower bound on γ_{k} and $\mathbf{1}$ is a unit K-dimensional column vector. Problem (2.14) can be rewritten as a linear programming problem by introducing a set of auxiliary variables, one for each observation in the sets τ^{+} and τ^{-}:

$$\begin{aligned} \min_{\gamma \in \mathbb{R}^{K}} \quad & \left[\sum_{t \in \tau^{+}} z^{+}_{t} + \sum_{t \in \tau^{-}} z^{-}_{t} \right] \\ \text{s.t.} \quad & \mathbf{1}'\gamma = 1 \\ & -z^{+}_{t} < {}_{c}\tilde{X}^{+}\gamma - \tilde{X}_{t,\cdot}\gamma < z^{+}_{t} \quad \forall t \in \tau^{+} \\ & -z^{-}_{t} < {}_{c}\tilde{X}^{-}\gamma - \tilde{X}_{t,\cdot}\gamma < z^{-}_{t} \quad \forall t \in \tau^{-} \\ & \gamma_{k} \geq \bar{\gamma}_{k} \quad \forall k = 1, \ldots, K \\ & z^{+}_{t} \geq 0 \quad \forall t \in \tau^{+} \\ & z^{-}_{t} \geq 0 \quad \forall t \in \tau^{-} \end{aligned} \tag{2.15}$$

The implementation of this procedure provides us with $\hat{\gamma}$, an estimate of γ.

The estimates of β_0 and β_1 are derived as follows. Let $\tilde{X}^-_{\hat{\gamma}}$ and $\tilde{X}^+_{\hat{\gamma}}$ be two representative percentiles of the linear combination $\tilde{X}\hat{\gamma}$, say the $100p^+$-th and the $100p^-$-th percentiles. A natural choice for p^+ and p^- is:

$$p^- \equiv \frac{|\tau^-|/T}{2} \tag{2.16}$$

$$p^+ \equiv 1 - \frac{|\tau^+|/T}{2} \tag{2.17}$$

Then the estimates of β_0 and β_1 are obtained by solving the following system of equations:

$$\begin{cases} \xi\left(\beta|\tilde{X}^-_{\hat{\gamma}}\right) = p^- \\ \xi\left(\beta|\tilde{X}^+_{\hat{\gamma}}\right) = p^+ \end{cases} \tag{2.18}$$

which can be linearized as:

$$\begin{cases} \beta_0 + \beta_1 \tilde{X}^-_{\hat{\gamma}} = -\ln\left[(p^-)^{-1} - 1\right] \\ \beta_0 + \beta_1 \tilde{X}^+_{\hat{\gamma}} = -\ln\left[(p^+)^{-1} - 1\right] \end{cases} \tag{2.19}$$

Since $\tilde{X}^-_{\hat{\gamma}} \neq \tilde{X}^+_{\hat{\gamma}}$ by construction, the system has always a unique solution $\hat{\beta}$.

We have now $\tilde{X}$, $\hat{\gamma}$ and $\hat{\beta}$, and thus the in-sample time series for ξ can be constructed according to Eq. (2.1).

The procedure has several interesting features. Firstly, it is based on the probability space partition of the historical distribution of the explanatory variables. As such, the assessment accuracy of the systemic risk indicator increases with time. Secondly, a high systemic risk measure can only be achieved if financial markets are jointly falling, the average historic volatility is high and the economic cycle of the major world economic areas is negative. Any deviation from the worst case percentiles of either underlying variables decreases the value of the risk indicator. Thirdly, financial instability phenomena originating within the financial sector and thus resulting into heavy market losses of financial securities impacts the overall systemic risk assessment only if they determine broader market turmoil and an economic downturn. Fourthly, high and low systemic risk conditions are discriminated with respect to endogenous time-varying average values which lead to a mean-reverting behaviour of the relevant explanatory variables and the risk indicator. Finally, no causality effect is considered *a-priori* from financial markets into the real economy, nor vice-versa.

2.2.3 Evaluating the Capability of the Indicator to Capture the Crisis Events over 1995-2011

In this section, we describe the procedure to estimate the indicator proposed above relying on 17 years of data spanning from 1995:1 to 2011:4 ($T = 68$). The systemic risk indicator is estimated using daily quotes of 21 benchmark indices for the following asset classes: equity, bond (government, corporate and money market instruments) and commodity, covering the following geographical areas: United States, Euro Area, United Kingdom, Japan, Emerging Market Countries. Furthermore, the GDP of these geographical areas is considered. Details about these two data-sets are reported in Tabs. 2.1 and 2.2.

[Tabs. 2.1-2.2 about here.]

The estimates for α, R^2 and s are plotted in Fig. 2.1, while the normalized output gap indices are reported in Fig. 2.2.

[Figs. 2.1-2.2 about here.]

In Fig. 2.1, one can see α (top panel of the figure) falls during instability periods of the recent financial history, such as the Asian Crisis, the period around September

2001 and the 2007-2009 economic and financial crisis. It is worth noticing that for the last two cases a peaking R^2 can be also observed, witnessing a homogeneous outflow from financial markets. s has a remarkable peak between the end of 2008 and the beginning of 2009, revealing that in that period, in a context of high degree of uncertainty, the volatilities in financial markets were on average 50% higher than the historical ones.

Fig. 2.2 shows the high correlation between the economic cycles especially during 2008. One can clearly notice the jump of the Japanese economy just before the Asian Crisis and the expansionary trace followed by the United States in the late '90s.

In order to estimate the parameters according to the methodology in Section 2.2.2, the set τ^+ and τ^- have to be populated. Not surprisingly the observations in τ^+ are 2008:4, 2009:1 and 2009:2, while those in τ^- are 2006:3, 2006:4 and 2007:4. The period between 2008 and 2009 can be thought as the most relevant in terms of systemic risk out of the previous 15 years.

The second half of 2006 has been detected as a period of very low systemic risk: that period was characterized by a positive macroeconomic status as well as by the presence of a positive risk premium in the markets. In the last quarter of 2007, the first effects of the subprime crisis hit the North American market inducing, still in a positive macroeconomic context, an outflow towards fixed income securities. The subprime crisis was at the time a US phenomenon, not yet affecting the overall system and the systemic risk indicator.

The derivation of the systemic risk indicator requires as inputs the estimated β and γ coefficients. Problem (2.15) is first solved, setting the lower bounds for the parameters as follows:

$$\bar{\gamma} \equiv \frac{1}{2}\begin{bmatrix}\frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{18} & \frac{1}{18} & \frac{1}{18}\end{bmatrix}' \tag{2.20}$$

This choice corresponds to the case of one half of an equal weighting of the variables, in which the lower bounds on the coefficients referred to the UK, Japan and Emerging Market cyclical indicators are constrained to be one third of the Euro Area and US coefficients.

By solving Problem (2.15) and the linear system in Eq. (2.19), we get the estimates:

$$\hat{\gamma} = [.478 \quad .083 \quad .189 \quad .083 \quad .083 \quad .028 \quad .028 \quad .028]' \tag{2.21}$$

$$\hat{\beta} = [-1.415 \quad 2.637]' \tag{2.22}$$

The solution of the optimization problem to estimate γ assigns a higher weight to the financial explanatory variables, and in particular to α and s. Fig. 2.3 reports the in-sample estimation of the systemic risk indicator.

[Fig. 2.3 about here.]

Alternative specifications of the bounds $\bar{\gamma}$ are also considered for robustness check. In particular, we also re-estimate the model by specifying either $\bar{\gamma} = \mathbf{0}$ or, without imposing any bounds, $\bar{\gamma}_k = -\infty$, $\forall k$. For both cases, the predominance of the financial variables, especially of α and s, is preserved; however, the estimates of the parameters for the cyclical indicators show some degree of variability mainly due to the high collinearity of the cyclical indicators, as can be seen in Fig. 2.2. The robustness check showed that the systemic risk indicator is not affected by the alternative bounds adopted, just as unaffected are the dates corresponding to τ^+ and τ^-.

We provide a measure of uncertainty related to parameters via bootstrap. The parameters associated to α and s are statistically significant at the usual 1% significance level; the same applies to the parameters associated to R^2 and $y_{\cdot,j}$ $(j = 1, .., 5)$ though they appear more sensitive to the bounds.

2.2.4 A Dynamic Equilibrium Value and the Recent Financial History

Given the estimated systemic risk indicator ξ_t, we want to determine a smooth and time-varying *fundamental* equilibrium value for it. This allows us to discriminate between positive and negative deviations of the time-t estimate ξ_t from its long-term trend, which will be denoted as ξ_t^*. Such deviations will be used as an input to the empirical analysis of the monetary response to systemic risk in Section 2.3.

Consider the following exponential weighted moving average with decay factor λ:

$$\xi_t^* \equiv \ddot{\xi}_t^* + \lambda^{T-t+1}(\bar{\xi}^* - \ddot{\xi}_t^*) \tag{2.23}$$

where $\ddot{\xi}_t^*$ is the trend component of the systemic risk indicator time series, detected using the HP filter (with smoothing parameter set equal to 1600), while $\bar{\xi}^*$ is defined as the value of ξ_t conditional on $X_{t,\cdot} = \tilde{v}$, the normalized threshold vector v. λ is chosen in the interval $[0, 1]$ so that $\lambda^T = \zeta$, with ζ small positive value, set here equal to 10^{-6}. According to Eq. (2.23), ξ_t^* can be thought as an application of the HP filter to the indicator original series, with an end-of-sample-problem correction given by the term $(\bar{\xi}^* - \ddot{\xi}_t^*)$, that receives an increasing weight as the end of the sample is approached. For more details on this aspect, see Arnold (2004).

In Fig. 2.3, we plot the systemic risk indicator and its equilibrium value ξ^*, shadowing the periods in which the indicator lies above its equilibrium value and highlighting the relevant facts in the recent financial history.

The indicator peaks during the financial-economic instability periods of the last 17 years. Neglecting the first part of the sample, corresponding to a recovery period for which a historically moderate level for the indicator is observed, there are 3 periods in which ξ is over its equilibrium value, which are: 1998:2 - 1999:2, 2001:1 - 2003:2 and 2008:3 - 2009:3. In this respect, the indicator proposed in this chapter may be interpreted as a coincident index of systemic stress, as it captures the materialization of systemic tensions.

The identification of each period listed above has an immediate economic interpretation. The first is associated to the panic that spreads out immediately after the default on the Russian debt in August 1998; the second corresponds to the economic and financial slowdown of the early 2000, further deteriorated by the events of 9/11. The third identified period corresponds to the recent economic and financial downturn[1]. The indicator crosses from below ξ_t^* during the third quarter of 2008 (corresponding to the default of Lehman Brothers in September 2008) and stayed over it till 2009:3, being the end of 2008 characterized by high market volatility and the begin of 2009 by a fragile macroeconomic context and uncertainty about the recovery. By the end of 2009, the indicator falls below its equilibrium value as a consequence of the temporary recovery of the financial markets and the improvement of macroeconomic fundamentals, especially in the US. However, in the first semester of 2010 and more markedly towards the end of 2011, the indicator shows a tendency to approach again its equilibrium value: this corresponds to when difficulties on the sovereign debt crisis experienced by peripheral European countries become apparent, spreading throughout the Euro Area and ultimately affecting the whole system.

[1]The dynamics of the indicator described so far follows closely the dynamics of the 1-year VaR of the distribution of the defaults for the overall economy, as proposed by IMF (2009).

Chapter 3 proposes a thorough dissection and comparison of the detected periods of financial turmoil.

2.3 Monetary Policy and Systemic Risk

In this section, we report an empirical analysis on the interactions between systemic events and monetary policy decisions by the Fed, the ECB and the Bank of England.

We expand the Taylor rule to assess the sensitivity of the target interest rate to a systemic factor to be added to the canonical inflation rate and output gap variables. In principle, under severe systemic instability, an easing of monetary policy is expected, coherently with the mission statements of the named Institutions. Indeed, the Fed mission (Fed, 1917) points out, among its macro-areas of intervention, the aim of "*maintaining the stability of the financial system and containing systemic risk that may arise in financial markets*". On the other hand, the main objective of the ECB is to maintain price stability and, "*acting also as a leading financial authority, [it] aims to safeguard financial stability and promote European financial integration*" (ECB, 2011). Similarly to the mandate of the Fed and the ECB, the Bank of England Act (BoE, 2009) states, alongside the standard goals of price stability and output stabilization, the statutory objective of "*protecting and enhancing the stability of the financial systems of the United Kingdom*".

In this chapter, we evaluate the impact of systemic risk as an exogenous risk factor to both Fed, the ECB and the Bank of England. It is widely recognized that the 2007-2009 crisis originated in the US and affected the Euro Area at a later stage, primarily through the financial system. The current sovereign debt crisis, albeit localized, also highlights the need of cooperative monetary effort to ensure global stability. Relying on the filtered systemic risk behaviour displayed in Fig. 2.3, periods of high and low systemic risk are defined and monetary interventions under the two regimes are tested.

2.3.1 Model Formulation

To empirically test the previous arguments, let us consider the model:

$$i = f(\pi, y, \xi) \tag{2.24}$$

where i is the target interest rate, π is the inflation rate, y is the output gap and ξ is the systemic risk indicator. We estimate both a cointegrated relationship and an Error Correction Model (ECM) respectively of the form:

$$i_t = \phi + \eta t + \psi' Z_t + \epsilon_t \tag{2.25}$$

$$\Delta i_t = \omega + \sum_{l=1}^{L} \rho_l \Delta i_{t-l} + \sum_{l=0}^{L} \theta_l' \Delta Z_{t-l} + \delta \epsilon_{t-1} + u_t \tag{2.26}$$

where $Z_t \equiv [\pi_t \;\; y_t \;\; \xi_t]$ is a vector of explanatory variables, t represents a deterministic trend, while ϵ_t and u_t are white noise processes. We evaluate three alternative model specifications. The first model, which we label as Model Specification 1 (MS1), is estimated considering just inflation and output gap as explanatory variables, that is $Z_t \equiv [\pi_t \;\; y_t]$. The second model (MS2) is estimated considering also the systemic risk indicator as explanatory variable, that is $Z_t \equiv [\pi_t \;\; y_t \;\; \xi_t]$. The final model (MS3) is estimated distinguishing between the case in which the systemic risk indicator is above its equilibrium value from the case in which it is not, that is $Z_t \equiv [\pi_t \;\; y_t \;\; \xi_t^+ \;\; \xi_t^-]$, where:

$$\xi_t^+ \equiv \begin{cases} \xi_t & \text{if } \xi_t \geq \xi_t^* \\ 0 & \text{otherwise} \end{cases} \tag{2.27}$$

$$\xi_t^- \equiv \begin{cases} \xi_t & \text{if } \xi_t < \xi_t^* \\ 0 & \text{otherwise} \end{cases} \tag{2.28}$$

MS1 allows us to check whether the systemic indicator is indeed relevant for monetary policy. MS2 is the benchmark. MS3 enables us to verify whether the Central Banks react differently to systemic risk, depending on the extent that ξ is above or below its equilibrium value.

In the empirical application, the system in Eqs. (2.25)-(2.26) is estimated starting from Generalized Unrestricted Models (GUM), choosing $L = 5$ consistently with the empirical macroeconomic literature. The GUMs are then reduced to parsimonious correctly specified representations by controlling for the presence of structural breaks, by means of Autometrics^{TM} (Doornik, 2009, Castle et al., 2011), an automatic procedure for model selection available in PcGive^{TM}.

We test for the presence of structural breaks by including in the model the following dummies:

$$B_{d,t}^M \equiv \mathbb{1}_{\{t \geq d\}} \tag{2.29}$$

$$B_{d,t}^T \equiv (t - d + 1)\mathbb{1}_{\{t \geq d\}} \tag{2.30}$$

with $d = 1, \ldots, T$, date of the break, and where $\mathbb{1}_{\{\cdot\}}$ is the indicatrix function. $B_{d,t}^M$ and $B_{d,t}^T$ are designed to capture breaks in the mean and in the trend, respectively. The estimation using Autometrics^{TM} is run fixing a restrictive target size of 1% for the model selection procedure. The final selected model is then chosen using the Schwarz (SC), the Hannan-Queen (HQ) and the Akaike (AIC) Information Criteria.

2.3.2 Data Description

The sample period for the Fed model spans over 1995:1-2011:4, while for ECB over 1999:1-2011:4 and for the BoE over 1997:1-2011:4. As for the target interest rate, the quarterly average of the Fed Funds Rates, the Euro Overnight Index Average (EONIA) and the Sterling Overnight Interbank Average rate (SONIA) are considered for the Fed, the EBC and the BoE, respectively.

In the Fed model, following Taylor (1993), Judd and Rudebusch (1998) and Hayford and Malliaris (2005), we specify the inflation rate as annualized 4-th order moving average of the percentage rate of change of the GDP deflator:

$$\pi_t \equiv 100 \left\{ \left[1 + \frac{1}{4} \sum_{i=1}^{4} \left(\frac{P_{t-i+1}}{P_{t-i}} - 1 \right) \right]^4 - 1 \right\} \tag{2.31}$$

where P_t is the quarterly series of the GDP deflator.

Inflation in the Euro Area is measured by the quarterly average of the one-year growth rate of the Consumer Price Index (CPI), as in Gerlach-Kristen (2003).

In line with BoE (2012), we measure inflation using the Retail Price Index excluding mortgage interest payments (RPIX) until December 2003 and the CPI from January 2004 onwards. We consider the quarterly average of the one-year growth rate of the above indices.

Following Hayford and Malliaris (2005), the Congressional Budget Office (CBO) estimate of the potential GDP is used in the construction of the output gap for United States, while for the Euro Area the estimate provided by the HP filter is employed (see Section 2.2.1). The OECD estimates of the output gap in UK is used as cyclical indicator for the UK economy.

Refer to Tab. 2.3 for the details on the data series. Descriptive statistics for the time series employed in the estimations are reported in Tab. 2.4, while the plot of the series is in Figs. 2.4-2.6.

[Tabs. 2.3-2.4 and Figs. 2.4-2.6 about here.]

From the graphical inspection of the series, there is evidence of different regimes affecting the interest rate series. In the case of the Fed Funds rates, the most notable turning points in the monetary conditions were in early 2000, in mid-2004 and in the second part of 2007. Similarly, for the ECB, we can distinguish phases of accommodating monetary policy, as in the period 2001-2005 and since late 2008 on, from periods characterized by restrictive decisions. The BoE figure is characterized by a similar monetary policy conduct. For the three Institutions, the reaction to the early 2000s slowdown and to the global financial crisis 2007-2009 are immediately apparent.

In the following two sections we focus on the behaviour of the Fed, the ECB and the BoE, exploring the differences in the timing, the magnitude and the reasoning of their policy interventions.

2.3.3 Empirical Results

We begin the analysis by estimating the long-run relation as defined in Eq. (2.25). The final parsimonious specifications for the three models (Fed, ECB and BoE) are reported in Tab. 2.5.

[Tab. 2.5 about here.]

The estimated parameters are statistically significant and consistent with the economic theory. Namely, the coefficients of π_t and y_t are positive, implying a restrictive reaction in case of rising inflation and/or overheated economic growth. However, the coefficient associated to the inflation term is never greater than 1 and thus it does not confirm what expected from the original formulation of the Taylor rule. This may depend on the choice of the inflation measure as highlighted by Hayford and

Malliaris (2005). In the ECB model, the magnitude of the inflation elasticity is coherent with what estimated in Gerlach and Lewis (2011).

The estimates are stable to the change at the head of the Board of the Fed in early 2006. This has been tested by substituting in Eq. (2.25) ψ with $\psi + \psi_{gr} B^{M}_{2006:1,\cdot}$, where ψ_{gr}, referring to the Greenspan period, is not significant.

The long-term decreasing trend is correctly detected by the trend component included in the model. Notice how the detected breaks are consistent with the features outlined in the Fig. 2.4 and how they capture the turning points in the monetary conditions. Note also that the systemic risk indicator does not appear in the long-run relationship. A comparison between the long-run component and the actual data is proposed in Fig. 2.7.

[Fig. 2.7 about here.]

To test for the stability of the cointegration vector, we employ a KPSS residual-based test suitable for the presence of structural breaks, that takes the form:

$$T^{-2}\hat{w}^{-2}\sum_{t=1}^{T}\left(\sum_{j=1}^{t}\hat{\epsilon}_j\right)^2 \tag{2.32}$$

where $\hat{w}^2$ is a consistent estimate of the long-run variance of $\{\epsilon_t\}_{t=1,\dots,T}$. Following Mogliani (2010), four alternatives are proposed for the kernel function employed in the estimation of the long-run variance. The results are reported in Tab. 2.6. Bootstrap and fast double bootstrap p-values (Davidson and MacKinnon, 2007) are provided. The four tests confirm the stability of the cointegrating vector.

[Tab. 2.6 about here.]

In a second stage, the ECM formulation in Eq. (2.26) is estimated, including the first difference of the detected breaks in Eq. (2.25). In the case of the Fed model, the inclusion of dummy variables on large residuals avoid misspecification problems for 2 model specifications out of the 3 considered. Namely, running the standard misspecification tests to check for the presence of autocorrelation, heteroscedasticity and normality of the residuals, there is evidence of no misspecification in MS2 and MS3, while the estimates for MS1 shows hetoroscedasticity in the residuals. On the contrary, in the case of the ECB and the BoE models, we observe correct specification for all the proposed alternative models. We thus employ the SC, the HQ and the AIC jointly to choose between the correctly specified alternative formulations. There is clear evidence of the superiority of the model specification MS3 for each of the Central Banks, as it can be seen in Tab. 2.7.

[Tab. 2.7 about here.]

The final selected models are reported in Tab. 2.8.

[Tab. 2.8 about here.]

All coefficients but the constants in the Fed and in the BoE models are significant at a 1% significance level. The models are correctly specified and provide a good fitting of the data. Fig. 2.8 reports a comparison between actual and fitted values.

[Fig. 2.8 about here.]

The error correction term $\hat{\epsilon}_{t-1}$ is statistically significant and negative in all the models. The changes in the target interest rates are driven by an autoregressive component, changes in the cyclical indicator and the inflation rates, and the first difference of the systemic indicator. In this setting, the breaks detection captures the monetary regime shifting, while the indicator captures short term reactions to increasing systemic risk.

Thus, there is evidence that the considered Institutions react to changes in systemic risk conditions. The coefficients of the lagged $\Delta\xi_t$ terms, as expected, have negative sign since an increase in the riskiness of the system is likely to induce an expansionary decision by the monetary authorities. In the case of the Fed, the reaction is different depending on whether the systemic risk is above or below its equilibrium value. This is supported by both the dominance of MS3 on MS2 and by the magnitude of the coefficients referred to $\Delta\xi^+_{t-1}$ and $\Delta\xi^-_{t-1}$. Systemic instabilities influence monetary decisions at the Fed and the BoE up to lag 5.

In the next section, we evaluate when and in which systemic risk conditions the Fed, the ECB and the BoE reacted to shifts in the riskiness of the system.

2.3.4 Reactions to Systemic Instability

The aim of this section is to compare the reactions of the Fed, the ECB and the BoE to systemic risk events. Relying on the estimated models in Section 2.3.3, we quantify the magnitude and analyse the timing of the policy decisions of the three Central Banks.

Let $Z^\xi_{t,b}$ with $b = Fed, ECB, BoE$ be the regressors referred to ξ in the Fed, the ECB and the BoE model, respectively, so that:

$$\Delta Z^\xi_{t,Fed} \equiv \left[\Delta\xi^+_{t-1} \quad \Delta\xi^+_{t-5} \quad \Delta\xi^-_{t-1}\right] \tag{2.33}$$

$$\Delta Z^\xi_{t,ECB} \equiv \Delta\xi^+_{t-1} \tag{2.34}$$

$$\Delta Z^\xi_{t,BoE} \equiv \left[\Delta\xi^+_{t-1} \quad \Delta\xi^+_{t-5}\right] \tag{2.35}$$

and let θ_b^ξ with $b = Fed, ECB, BoE$ be the corresponding coefficients.

In each of the models, the null hypothesis that the residuals are normally distributed can not be rejected, that is $u_{t,b} \sim \mathcal{N}(0, \sigma_b^2 I)$, where σ_b is the standard deviation of $u_{t,b}$, defined as the error term in model for Central Bank b, and I is the identity matrix. Hence, the estimated parameters are also normally distributed:

$$\hat{\theta}_b^\xi \sim \mathcal{N}\left(\theta_b^\xi, \Sigma_{\theta_b^\xi}\right) \tag{2.36}$$

where $\Sigma_{\theta_b^\xi}$ is the variance-covariance matrix of θ_b^ξ, which, in absence of misspecification, is consistently estimated as:

$$\hat{\Sigma}_{\theta_b^\xi} = \hat{\sigma}_b^2 \left(\Delta Z_{\cdot,b}^{\xi}{}' \Delta Z_{\cdot,b}^\xi\right)^{-1} \tag{2.37}$$

The estimated reactions to systemic risk are defined as:

$$\Delta \hat{i}_{t,b}^\xi \equiv \hat{\theta}_b^{\xi\prime} \Delta Z_{t,b}^\xi \tag{2.38}$$

Combining the previous results:

$$\Delta \hat{i}_{t,b}^\xi \Big| \Delta Z_{t,b}^\xi \sim \mathcal{N}\left(\theta_b^{\xi\prime} \Delta Z_{t,b}^\xi, \Delta Z_{t,b}^{\xi}{}' \Sigma_{\theta_b^\xi} \Delta Z_{t,b}^\xi\right) \tag{2.39}$$

Thus, under the null hypothesis $H_0 : \Delta i_{t,b}^\xi = 0$:

$$\Delta \hat{i}_{t,b}^\xi \left(\Delta Z_{t,b}^{\xi}{}' \hat{\Sigma}_{\theta_b^\xi} \Delta Z_{t,b}^\xi\right)^{-1/2} \Big| \Delta Z_{t,b}^\xi \sim \mathcal{T}(\nu) \tag{2.40}$$

where $\mathcal{T}(\nu)$ is the t-Student distribution with ν degrees of freedom, where $\nu = T - p$, with T the number of observations and p is the number of parameters estimated in the model.

The significant reactions to systemic risk are plotted in Fig. 2.9. Significance is evaluated with the usual 1% significance level.

[Fig. 2.9 about here.]

The sharper reactivity by the Fed with respect to the BoE and, in particular, to the ECB is immediately apparent. Accommodative responses were given to the Russian crisis in late 1998, during the early 2000s slowdown and in coincidence with the recent financial crisis. A cyclical re-stabilizing behaviour is evident, too. Note the case of 2009:4, where systemic risk have triggered an accommodative reaction, which was offset by a reaction of opposite sign to rising inflation.

Instabilities have overall prompted less interventions by the ECB rather than by the Fed and the BoE. There is, however, evidence that the European Central Bank reacted to the early 2000s financial and economic slowdown, and, more evidently, it responded to the recent financial crisis.

The Bank of England was more active than the ECB in addressing systemic risk, although its reactions were not as sharp as in the case of the Fed. During 2010, we can see that pressure was put on the Bank of England towards a restrictive move, suggested by both a temporary improvements of the systemic risk conditions and the rising inflation. This is part of a debate which is still very timely.

The most remarkable episode however, coincides with the 2008-09 financial crisis, when, in the most harsh period of the crisis, the Fed, the ECB and the BoE, together with other 4 industrialized countries' Central Banks (Canada, Switzerland, Sweden and Japan) reacted with a joint intervention to the worsening of the global macroeconomic situation. For all the Central Banks, we record flat rates since mid-2010 onwards, and correspondingly we observe no substantial reactions throughout the 2011. This coincides with the shift of monetary policy towards the adoption of unconventional monetary measures, such as the Quantitative Easing (QE) programmes deployed at the Fed and the BoE, and the Securities Markets Programme (SMP), the Long-Term Refinancing Operations (LTROs) and the Covered Bond Purchase Programme (CBPP) promoted by the ECB in recent years.

2.3.5 Robustness Checks using Alternative Tension Indicators and Local Cyclical Indicators

In this section, we report a sensitivity analysis by comparing the performance of the global systemic risk indicator with respect to alternative indicators of market nervousness. We also evaluate Central Banks reaction when only local cyclical indicators are considered in the definition of systemic risk.

2.3.5.1 Alternative Indicators of Market Tension

We consider alternative indicators of market nervousness and in particular the VIX, the TED spread for the US, the Libor-OIS spread and the CISS in Hollo et al. (2012) for the EU.

The VIX provides a 30-day forward-looking volatility measure for the US stock market, being its value derived by S&P500 option contracts with 30 days to maturity. It is a popular measure of stock market uncertainty, capable to provide an accurate forecast of future volatility (see Blair et al., 2001).

The TED spread is defined as the spread between the rates on short term Eurodollar future contracts and the rates on the short term US government debt. It is considered by market participants as an indicator of the credit risk in the overall economy, as the rates on the T-bills is perceived as "risk-free", whereas the rates on the Eurodollar deposit convey information on the counterparty risk embedded in interbank loans. Similarly, the Libor-OIS spread is considered by many as an indicator of the health of the banking sector. Indeed, on the one hand, the Libor rate is the rate at which highly rated banks are willing to lend money to other such banks, thus carrying information about the risk of banking defaults. On the other hand, the Overnight Indexed Swap (OIS) rate is the fixed rate in a swap contract where the floating leg is the average of the overnight rates over the term of the contract. No exchange of principal is required, thus little default risk is reflected in the OIS rate, which then expresses the market expectations on overnight rates over the maturity of the swap contract.

Finally, in the robustness check, we consider the Composite Indicator of Systemic Stress (CISS) proposed by Hollo et al. (2012). The index is constructed by aggregating the information coming from market-specific subindices, referred to the sector of bank and non-bank financial intermediaries as well as to security (equity and bond) markets and foreign exchange markets. The aggregation is done in a dynamic correlation framework, so that the resulting indicator highlights the periods in which market stress prevails at the same time on all the subindices. The application to the Euro Area shows the capability of the indicator of picking up the instability periods in the recent financial history.

We look at the listed alternative indicators in the period in which the systemic risk indicator has been evaluated. The quarterly average of the indicators is considered and the corresponding trend component estimated via the HP filter. Fig. 2.10 provides a comparison between our indicator and the quarterly average of the VIX, the TED spread, the Libor-OIS and the CISS, together with the respective long-run values.

[Fig. 2.10 about here.]

From a graphical comparison of the VIX with our indicator, we can see that the two have the same long-run dynamic behaviour. However, from a closer inspection, a few important discrepancies can be highlighted. There are two notable periods when the VIX peaked over its trend, while on the contrary the indicator stays below it: they are the second half of 1997 and of 2007, associated to the Asian crisis and the US subprime crisis respectively[2]. As argued in Section 2.2.3, these two periods are associated with country or sector specific crises, which are not relevant in systemic terms. Furthermore, this emphasizes the fact that high volatile markets are a necessary, but not sufficient, condition for systemic risk to increase. On the other hand, sluggish volatility on the markets does not imply an immediate contraction in systemic risk, as the period 2008-2009 shows.

The TED spread and the Libor-OIS have a common remarkable peak in correspondence of the 2008-09 financial crisis. With this respect, they characterize as good indicators for the different phases of the 2008-09 financial crisis. However, they do not convey any other strong signals in the data span considered, not being very informative before 2007.

The CISS is a local indicator, referred in particular to the European economy. When we compare it with our indicator, we can see the latter signalling with more strength the shocks which are common to the whole system. As an example of this, see for instance the case of the early 2000s slowdown.

We formulate a methodology to perform a robustness check for the final models reported in Tab. 2.8, comparing the explicative power of our indicator and of the considered alternative indicators.

Let $Z^{\xi}_{t,b}$, with $b = Fed, ECB, BoE$, be the regressors referred to ξ in the Fed, the ECB and the BoE model, respectively (see Eqs. 2.33-2.35). Let θ^{ξ}_{b} denote the corresponding estimated parameters, I_t be the quarterly average of the alternative indicator at time t and I^*_t the corresponding trend component extracted via the HP

[2] A similar discrepancy can be noticed for the last quarter of 2011. For further details, see the postscript of this chapter on p. 84.

filter. As in the case of ξ_t, define:

$$I_t^+ \equiv \begin{cases} I_t & \text{if } I_t \geq I_t^* \\ 0 & \text{otherwise} \end{cases} \tag{2.41}$$

$$I_t^- \equiv \begin{cases} I_t & \text{if } I_t < I_t^* \\ 0 & \text{otherwise} \end{cases} \tag{2.42}$$

The robustness check consists in the inclusion of the term $\left(\Delta Z_{t,b}^I - \Delta Z_{t,b}^\xi\right)$ in each of the two models, where:

$$\Delta Z_{t,Fed}^I \equiv \left[\Delta I_{t-1}^+ \quad \Delta I_{t-5}^+ \quad \Delta I_{t-1}^-\right] \tag{2.43}$$

$$\Delta Z_{t,ECB}^I \equiv \Delta I_{t-1}^+ \tag{2.44}$$

$$\Delta Z_{t,BoE}^I \equiv \left[\Delta I_{t-1}^+ \quad \Delta I_{t-5}^+\right] \tag{2.45}$$

Denote as δ_b^I the coefficients corresponding to the extra-term $\left(\Delta Z_{t,b}^I - \Delta Z_{t,b}^\xi\right)$.

Under the null hypothesis $H_0 : \theta_b^\xi = \delta_b^I$, there is superiority of the alternative indicator I to the systemic risk indicator in explaining interest rates dynamics.

Tab. 2.9 reports the p-value associated with this null hypothesis, as well as the p-value associated with the hypothesis that the coefficients of $\left(\Delta Z_{t,b}^\xi, \Delta Z_{t,b}^I\right)$ are jointly insignificant, and the partial adjusted R^2 associated with the couple $\left(\Delta Z_{t,b}^\xi, \Delta Z_{t,b}^I\right)$.

[Tab. 2.9 about here.]

The null hypothesis H_0 is rejected in all the cases with a high confidence level. Furthermore, there is clear evidence that the coefficients associated with $\Delta Z_{t,b}^I$ are jointly insignificant, whereas the variables referred to ξ are always significant. Thus, the numbers in Tab. 2.9 all confirm in favour of the evidence of the superiority of the risk indicator with respect to the considered alternative indicators.

2.3.5.2 Local Cyclical Indicators

A further robustness analysis was performed to check whether the Central Banks reacted differently to systemic risk, when in addition to financial variables, only local cyclical indicators were considered as components of the systemic risk indicator. The resulting indicators together with a comparison with the original series of the indicator is reported in Fig. 2.11.

[Fig. 2.11 about here.]

A robustness check was carried out in the same way as described above for the alternative tension indicators. The main finding is that the pattern of the reaction functions of the institutions does not change, though there is evidence of higher reaction to local macroeconomic factors.

2.4 Final Remarks

In this chapter, we proposed a comprehensive indicator able to measure systemic risk at a global level. The indicator is constructed by integrating the dynamics of international financial and commodity markets with signals emerging from the economic cycle. Based upon the 1995-2011 crisis events, the indicator interpreted quite accurately recent financial history. We also showed that financial markets severe downturns and increasing volatility are not sufficient to explain the overall systemic risk in the economy, but an insight on the current outlook on the macroeconomic situation is also crucial for detecting instabilities at the global level.

We then evaluated the interaction of the indicator with monetary policy decisions undertaken by the Fed, the ECB and the Bank of England. We identified important differences between Central Banks' monetary conducts during a prolonged period of economic and financial crisis. There is evidence that expansionary decisions adopted by the Fed and the Bank of England were led by riskiness of the system, while the ECB showed some reluctance to give up its role in maintaining price stability, except during the recent period of economic and financial instability. The response of the monetary authority is not prompted by the conditions in the global financial markets alone, but also by the global outlook on the real side of the economy, with the two factors being captured by the systemic risk indicator we proposed. Finally, we compared the proposed indicator with alternative coincident measures of systemic risk and showed its ability in capturing the materialization of systemic risk instabilities which triggered the reaction of the Fed, the ECB and the BoE.

Postscript of the Chapter

The aim of this postscript is the updating of the proposed systemic risk indicator, using out-of-sample data for the year 2012, which consist of the latest data available at the time of writing (April, 2013). An updated version of Fig. 2.3 is reported in Fig. 2.12.

[Fig. 2.12 about here.]

The evaluation of the indicator up to the end of 2012 highlights a new period of instability, corresponding to the spreading of the European sovereign debt crisis. The indicator goes beyond the equilibrium level in Q3:2011 and Q4:2011, and stays just below it during the first half of 2012. The last part of 2011 has been identified in Chapter 1 as the moment in which the crisis spread from the peripheral countries in Europe to the rest of the continent and ultimately to the US. However, when looking at the magnitude of the late 2011 figure, the EU crisis does not show up as vigorously as the 2007-09 financial crisis, which was characterized by a value of the indicator approaching 1. This extent is further investigated in the next chapter, where a dissection of the features of the two crises is proposed by means of a novel modelling set-up to test for contagion versus excess interdependence during periods of financial instability.

Table 2.1: **Market data for the systemic risk indicator.** We report a description of the market data employed for the construction of the systemic risk indicator. ID Index is a sequential identification index for the i-th market, with $i = 1, \dots, N$. We report the asset class and the geographical area (columns 2 and 3) which the index belongs to. Columns 4 and 5 report the name and the ticker under the data provider system (Datastream^{TM}). The last column contains the date of the first available observation.

ID Index	***Asset Class***	***Area***	***Name***	***Ticker***	***Base date***
1	Equity	United States	MSCI US	MSUSAML	31-Dec-69
2	"	Euro Area	MSCI EMU	MSEMUIL	31-Dec-87
3	"	United Kingdom	MSCI UK	MSUTDKL	31-Dec-69
4	"	Japan	MSCI JAPAN	MSJPANL	31-Dec-69
5	"	EM Countries	MSCI EM	MSEMKFL	31-Dec-87
6	Government Bond	United States	JPM GBI US	JGUSAU$	01-Sep-03
7	"	Euro Area	JPM GBI EUR	JGEUAEE	01-Sep-03
8	"	United Kingdom	JPM GBI UK	JGUKAU£	01-Sep-03
9	"	Japan	JPM GBI JAP	JGJPAJY	01-Sep-03
10	"	EM Countries	JPM EMBI+ COMP	JPMPTOT	31-Dec-93
11	Corporate Bond	United States	ML US CORP	MLCORPM	30-Mar-73
12	"	Euro Area	ML EMU CORP	MLCPLCE	31-Dec-96
13	"	United Kingdom	ML CORP ALL UK	ML£CAUL	07-May-04
14	"	Japan	ML JAP CORP	MLJPCPY	15-Sep-05
15	"	EM Countries	ML EMRG CORP	MLICD0$	31-Dec-04
16	Money Market Instruments	United States	JPM US CASH 3M	JPUS3ML	31-Dec-85
17	"	Euro Area	JPM EURO CASH 3M	JPEC3ML	22-Oct-86
18	"	United Kingdom	JPM UK CASH 3M	JPUK3ML	31-Dec-85
19	"	Japan	JPM JAP CASH 3M	JPJP3ML	31-Dec-85
20	"	EM Countries	ML USD EMRG SOV	MLIGD0$	31-Dec-04
21	Commodity	*none*	S&P GSCI	CGSYSPT	31-Dec-69

Table 2.2: **Data for the cyclical indicators.** We report a description of the data employed for the estimation of the cyclical indicator used in the construction of the systemic risk indicator. Columns 1 and 2 report the name and the ticker under the data provider system (Datastream^{TM}). Column 3 reports the frequency of the data. The last column contains the date of the first available observation.

Name	***Ticker***	***Frequency***	***Base date***
GDP US	USGDP...D	Quarterly	1950:1
GDP Euro Area	EKGDP...D	Quarterly	1995:1
GDP UK	UKGDP...D	Quarterly	1955:1
GDP Japan	JPGDP...D	Quarterly	1980:1
Citigroup Economic Surprise Indices	TBCESIR	Daily	01-Jan-03

TABLE 2.3: **Data employed in the empirical application for the Fed, ECB and BoE.** Reported is a description of the data employed in the empirical application in Section 2.3. We report the name and the ticker under the data provider system (Datastream^{TM}), as well as the frequency of the series used to build the target interest rate series, the inflation rate and the cyclical indicator in the model for the Fed, the ECB and the BoE (top, middle and bottom panel, respectively).

Variable	***Name***	***Ticker***	***Frequency***
Target rate	US Federal Funds	FRFEDFD	Daily
Inflation Index	US GDP DEFLATOR	USONA001E	Quarterly
GDP	US GDP	USGDP...D	Quarterly
Potential GDP	US CBO Forecast - Potential GDP	USFCGDPPD	Quarterly

Variable	***Name***	***Ticker***	***Frequency***
Target rate	Euro OverNight Index Average (EONIA)	EUEONIA	Daily
Inflation Index	CPI (no energy and unprocessed food)	EKESCPXUF	Monthly
GDP	EK GDP	EKGDP...D	Quarterly

Variable	***Name***	***Ticker***	***Frequency***
Target rate	Sterling Overnight Interbank Average Rate (SONIA)	BOESONI	Daily
Inflation Index	UK Retail Price Index (RPIX)	UKRPAXMIF	Monthly
	UK Consumer Price Index (RPI)	UKCPCOREF	Monthly
Cyclical indicator	UK Output Gap - OECD	UKOCFOGPQ	Quarterly

Table 2.4: **Descriptive statistics for the Fed, the ECB and the BoE model.** Reported are the summary statistics for the empirical application in Section 2.3. i is the target interest rate, π is the inflation rate, y is the cyclical indicator and ξ is the systemic risk indicator. The normality test is the JarqueBera test. The top panel is referred to the Fed model, the middle panel to the ECB model and the bottom panel to the BoE. The sample size respectively starts from 1995:1, 1999:1 and 1997:1 for the Fed, ECB and BoE, and ends in 2011:4. The frequency is quarterly.

	i	π	y	ξ
Mean	3.347	2.085	-0.875	0.259
Standard deviation	2.235	0.723	2.830	0.266
Skewness	-0.243	0.124	-0.993	1.337
Kurtosis	1.433	2.747	2.960	3.764
Min	0.075	0.458	-7.429	0.025
Max	6.520	3.522	3.537	0.989
Normality test	23.699 [0.0000]**	0.20576 [0.9022]	31.017 [0.0000]**	56.387 [0.0000]**

	i	π	y	ξ
Mean	2.585	1.713	0.076	0.285
Standard deviation	1.325	0.521	1.408	0.286
Skewness	-0.182	0.056	0.173	1.133
Kurtosis	2.040	1.815	2.603	3.094
Min	0.345	0.856	-2.850	0.025
Max	4.844	2.637	3.144	0.989
Normality test	3.0474 [0.2179]	4.8367 [0.0891]	0.35648 [0.8367]	34.894 [0.0000]**

	i	π	y	ξ
Mean	4.186	2.285	-0.030	0.275
Standard deviation	2.086	0.669	2.224	0.276
Skewness	-0.720	0.265	-0.677	1.203
Kurtosis	2.491	2.800	2.618	3.320
Min	0.409	1.054	-4.549	0.025
Max	7.364	3.902	3.886	0.989
Normality test	15.240 [0.0005]**	0.82703 [0.6613]	10.616 [0.0050]**	43.340 [0.0000]**

TABLE 2.5: **Long-run relation estimates.** We report the estimation of the long-run relation in Eq. (2.25) for the Fed, the ECB and the BoE, after the reduction by Autometrics^{TM}. Standard errors are reported in parenthesis.

	Fed model	***ECB model***	***BoE model***
const.	4.738 (0.280)	3.191 (0.325)	5.0135 (0.462)
trend	−0.073 (0.013)	−0.393 (0.122)	
π_t	0.825 (0.106)	0.411 (0.087)	0.7039 (0.164)
y_t	0.365 (0.044)	0.466 (0.026)	0.5456 (0.0367)
$B^M_{1999:1}$			−1.3414 (0.192)
$B^M_{2001:3}$	−1.155 (0.305)		
$B^M_{2001:4}$		−1.259 (0.162)	−1.3227 (0.197)
$B^M_{2003:1}$			−1.2632 (0.254)
$B^M_{2003:3}$		−0.618 (0.132)	
$B^M_{2009:2}$	2.240 (0.354)		
$B^T_{1999:4}$		0.685 (0.146)	
$B^T_{2001:1}$		−0.279 (0.037)	
$B^T_{2001:2}$	−0.140 (0.030)		
$B^T_{2003:4}$			0.4030 (0.0733)
$B^T_{2004:4}$	0.602 (0.044)		
$B^T_{2005:1}$			−0.4625 (0.0911)
$B^T_{2007:2}$	−0.650 (0.044)		
$B^T_{2008:4}$		−0.192 (0.016)	−0.1545 (0.0333)

TABLE 2.6: **Test for the stability of the cointegration vector.** We report the results of the test for the stability of the cointegration vector for different choices of the kernel function employed for the estimation of the long-run variance of the residuals (for details see Mogliani, 2010). Bootstrap p-values and fast double bootstrap p-values are provided (Davidson and MacKinnon, 2007). The Fed model is in the top panel, the ECB model in the middle panel and the BoE model in the bottom panel.

LR variance kernel	***Stat***	***Bootstrap p-value***	***Fast Double Bootstrap p-value***
Bartlett	0.02181	0.53745	0.53895
Quadratic Spectral	0.01974	0.65157	0.65297
Parzen (Andrews and Monahan, 1992)	0.02228	0.53845	0.53835
Kurozumi (2002)	0.02227	0.58536	0.58816

LR variance kernel	***Stat***	***Bootstrap p-value***	***Fast Double Bootstrap p-value***
Bartlett	0.03616	0.21772	0.21582
Quadratic Spectral	0.03694	0.14071	0.13681
Parzen (Andrews and Monahan, 1992)	0.04497	0.05911	0.05601
Kurozumi (2002)	0.03963	0.20352	0.20182

LR variance kernel	***Stat***	***Bootstrap p-value***	***Fast Double Bootstrap p-value***
Bartlett	0.03277	0.20472	0.20732
Quadratic Spectral	0.03077	0.22652	0.23252
Parzen (Andrews and Monahan, 1992)	0.03650	0.10731	0.11421
Kurozumi (2002)	0.03298	0.26753	0.26743

Table 2.7: **Information criteria for the alternative model specifications.** MS1, MS2 and MS3 are three alternative model specifications for Eqs. (2.25)-(2.26). We report information criteria for these alternative specifications. SC is the Schwarz Criterion, HQ is the Hannan-Quinn Criterion and AIC the Akaike Information Criterion (Fed model in the top panel, ECB model in the middle panel and the BoE model in the bottom panel).

	SC	***HQ***	***AIC***
MS1	-	-	-
MS2	0.527	0.403	0.323
MS3	0.145	-0.152	-0.343

	SC	***HQ***	***AIC***
MS1	-0.639	-0.920	-1.085
MS2	-0.683	-0.989	-1.170
MS3	-0.771	-1.077	-1.258

	SC	***HQ***	***AIC***
MS1	0.651	0.380	0.209
MS2	0.347	0.121	-0.0212
MS3	0.184	-0.0419	-0.184

TABLE 2.8: **Error correction specifications.** We report the estimation of the error correction model in Eq. (2.26) for the Fed, the ECB and the BoE, after the reduction by Autometrics^{TM}. Standard errors are reported in parenthesis. AR is the Breusch-Godfrey test for residual serial correlation, ARCH is the Engle test for the presence of ARCH effects, NORM is the Doornik-Hansen test for normality of residuals and HT is the White test for heteroscedasticity. P-values are reported.

	Fed model	***ECB model***	***BoE model***
const.	0.014 (0.045)	0.263 (0.098)	0.012 (0.030)
Δi_{t-1}	0.701 (0.086)	0.374 (0.098)	0.348 (0.062)
Δi_{t-4}	−0.337 (0.068)		
$\Delta \pi_t$	0.316 (0.093)	0.295 (0.103)	0.246 (0.092)
$\Delta \pi_{t-1}$		−0.518 (0.121)	
$\Delta \pi_{t-2}$			−0.392 (0.096)
$\Delta \pi_{t-3}$		0.230 (0.112)	
Δy_t	0.126 (0.054)	0.301 (0.054)	0.305 (0.052)
Δy_{t-1}	−0.197 (0.057)		
Δy_{t-5}		0.101 (0.035)	
$\Delta \xi^+_{t-1}$	−0.827 (0.257)	−0.685 (0.239)	−0.730 (0.280)
$\Delta \xi^+_{t-5}$	−1.192 (0.247)		−0.874 (0.215)
$\Delta \xi^-_{t-1}$	−0.711 (0.278)		
$\hat{\epsilon}_{t-1}$	−0.480 (0.082)	−0.616 (0.124)	−0.325 (0.100)
$\Delta B^M_{1999:1}$			−1.2741 (0.226)
$\Delta B^M_{2001:4}$		−0.546 (0.149)	
$\Delta B^M_{2003:1}$			−0.4492 (0.213)
$\Delta B^M_{2003:3}$		−0.466 (0.138)	
$\Delta B^T_{2001:1}$		−0.283 (0.103)	
$\Delta B^T_{2001:2}$	−0.204 (0.077)		
$\Delta B^T_{2004:4}$	0.440 (0.110)		
$\Delta B^T_{2007:2}$	−0.329 (0.095)		
$D_{2008:4}$	−1.127 (0.264)		
T	62	46	54
R^2	87.4%	93.5%	85.4%
AR	0.237	0.908	0.752
$ARCH$	0.129	0.586	0.870
$NORM$	0.902	0.030	0.096
HT	0.040	0.960	0.036

Table 2.9: **Robustness check with alternative indicators.** Top panel: p-values associated with the null hypothesis of superiority of the alternative indicators in explaining interest rate dynamics. Middle panel: p-value associated with the hypothesis that the two groups of coefficients of $\left(\Delta Z^{\xi}_{t,b}, \Delta Z^{I}_{t,b}\right)$ are jointly insignificant. Bottom panel: partial adjusted R^2 associated with the couple $\left(\Delta Z^{\xi}_{t,b}, \Delta Z^{I}_{t,b}\right)$. $Z^{\xi}_{t,b}$ denotes the regressors referred to ξ in the model for bank b, with $b = Fed, ECB, BoE$. $Z^{I}_{t,b}$ denotes the same regressors, constructed using the alternative indicator I, with I denoting the VIX, the TED spread, the Libor-OIS spread and the CISS indicator by Hollo et al. (2012).

	Fed model	***ECB model***	***BoE model***
VIX	0.0001	0.0061	0.0018
TED spread	0.0005		
Libor-OIS		0.0058	
CISS		0.0071	

	Fed model	***ECB model***	***BoE model***
VIX	(0.0001, 0.6187)	(0.0062, 0.7048)	(0.0018, 0.9025)
TED spread	(0.0005, 0.4237)		
Libor-OIS		(0.0128, 0.6427)	
CISS		(0.0071, 0.6385)	

	Fed model	***ECB model***	***BoE model***
VIX	(60.44%, 4.59%)	(21.78%, 0.47%)	(35.44%, 0.46%)
TED spread	(55.43%, 6.18%)		
Libor-OIS		(17.37%, 0.66%)	
CISS		(19.98%, 0.68%)	

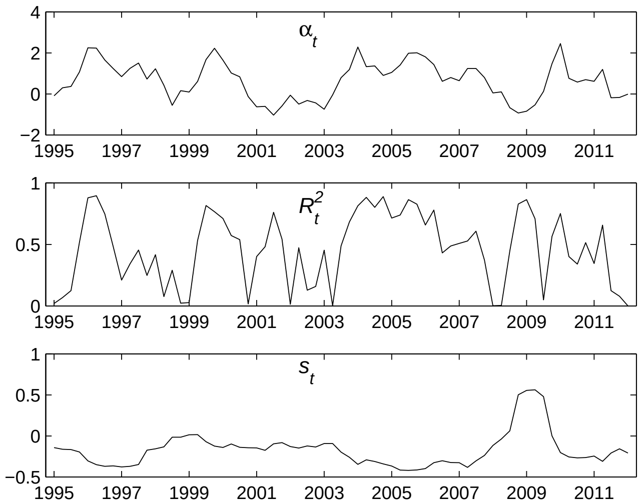


FIGURE 2.1: **The estimated financial variables α, R^2 and s.** We plot the estimated financial variables α, R^2 and s entering in the systemic risk indicator (quarterly data from 1995:1 to 2011:4). α and R^2 are the slope and the determination coefficient of the regression in Eq. (2.3), whereas s is the cross-sectional average percentage deviation of the market volatilities from their long-term value, as defined in Eq. (2.4).

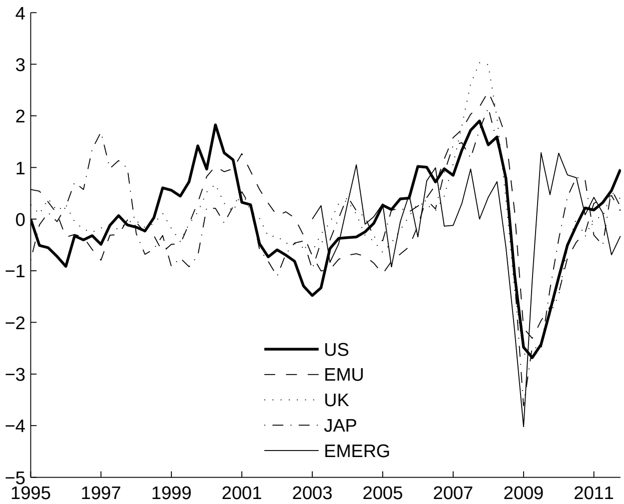


FIGURE 2.2: **Cyclical indicators.** We plot the normalized value of the cyclical indicators entering in the systemic risk indicator, as defined in Eq. (2.5) (quarterly data from 1995:1 to 2011:4).

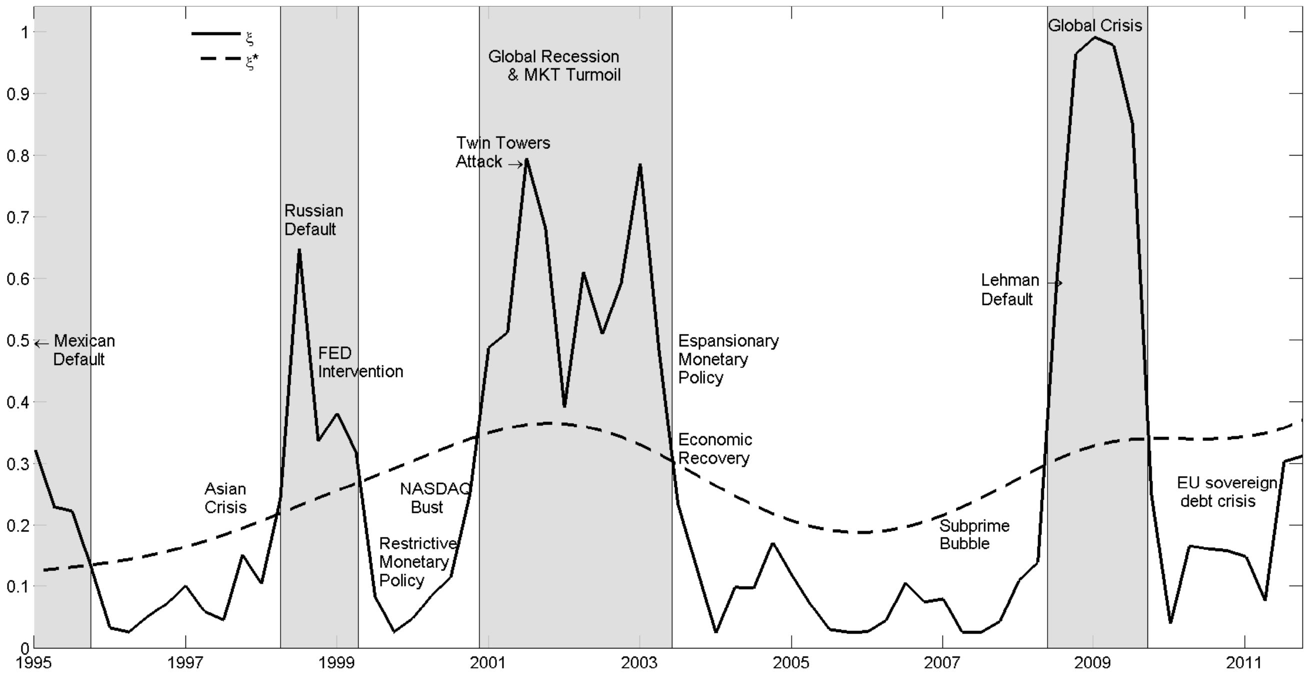


FIGURE 2.3: **The systemic risk indicator and the recent financial history.** We plot the systemic risk indicator, highlighting the most notable facts in the recent financial history (1995:1-2011:4). Shaded areas mark the periods in which the indicator (solid line) is above its equilibrium value (dashed line).

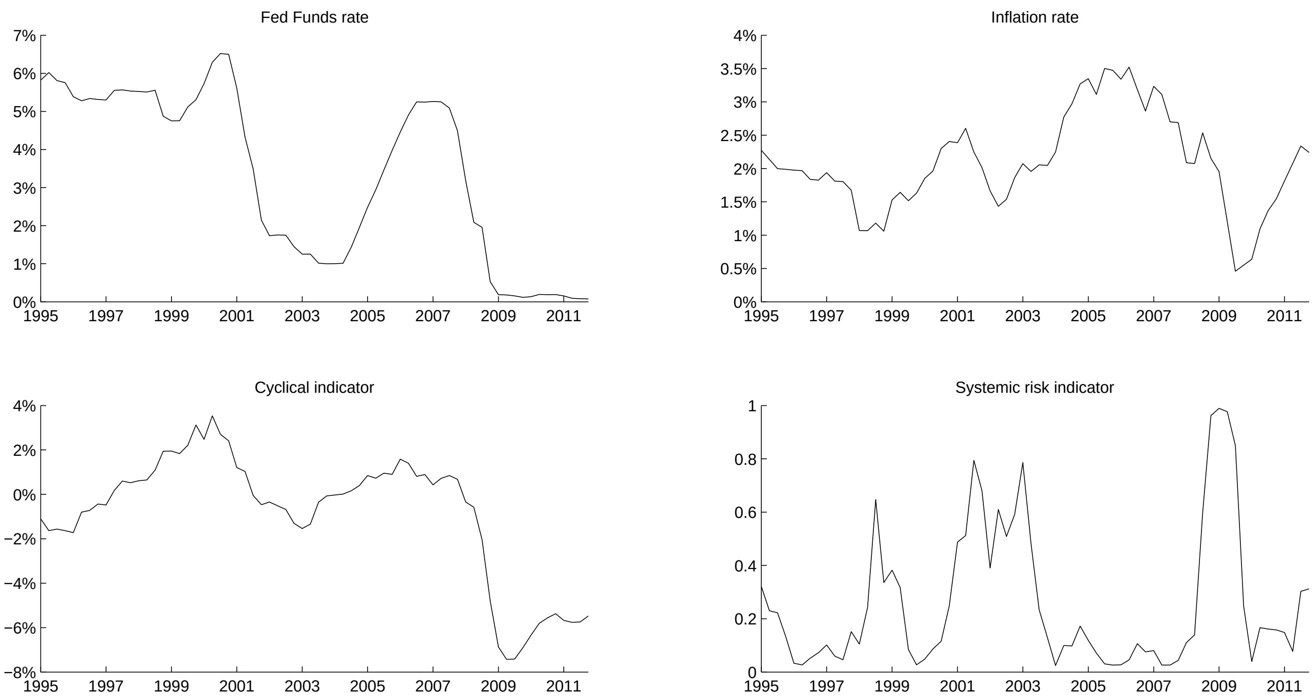


FIGURE 2.4: **Data for the Fed model.** We plot the data used in the Fed model (quarterly data from 1995:1 to 2011:4). Top-left panel: quarterly average of the Fed Funds rates. Top-right panel: annualized 4-th order moving average of the percentage rate of change of the US GDP deflator. Bottom-left panel: US cyclical indicator constructed using the CBO estimate for the potential output (refer to Eq. 2.5). Bottom-right panel: systemic risk indicator.

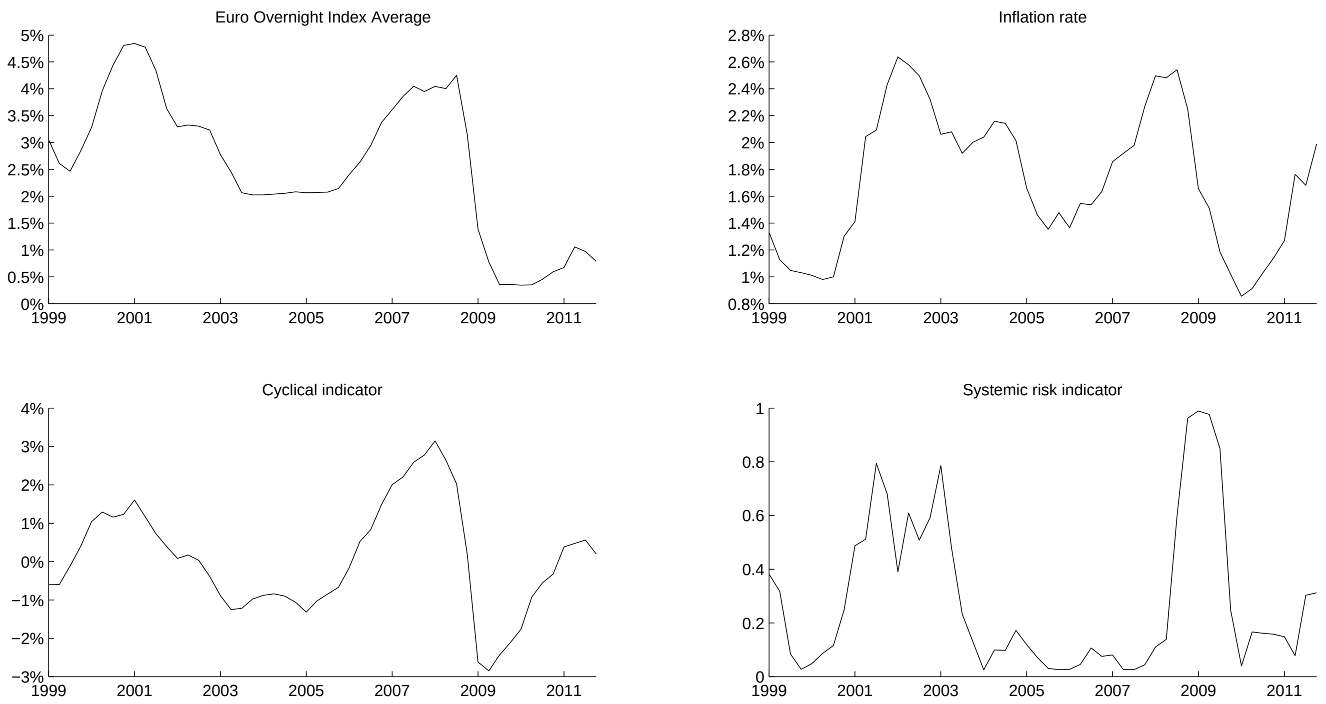


FIGURE 2.5: **Data for the ECB model.** We plot the data used in the ECB model (quarterly data from 1999:1 to 2011:4). Top-left panel: quarterly average of the EONIA rates. Top-right panel: quarterly average of the one-year growth rate of the Consumer Price Index (CPI) for the Euro Area. Bottom-left panel: EU cyclical indicator, constructed using the HP estimator of the potential output. Bottom-right panel: systemic risk indicator.

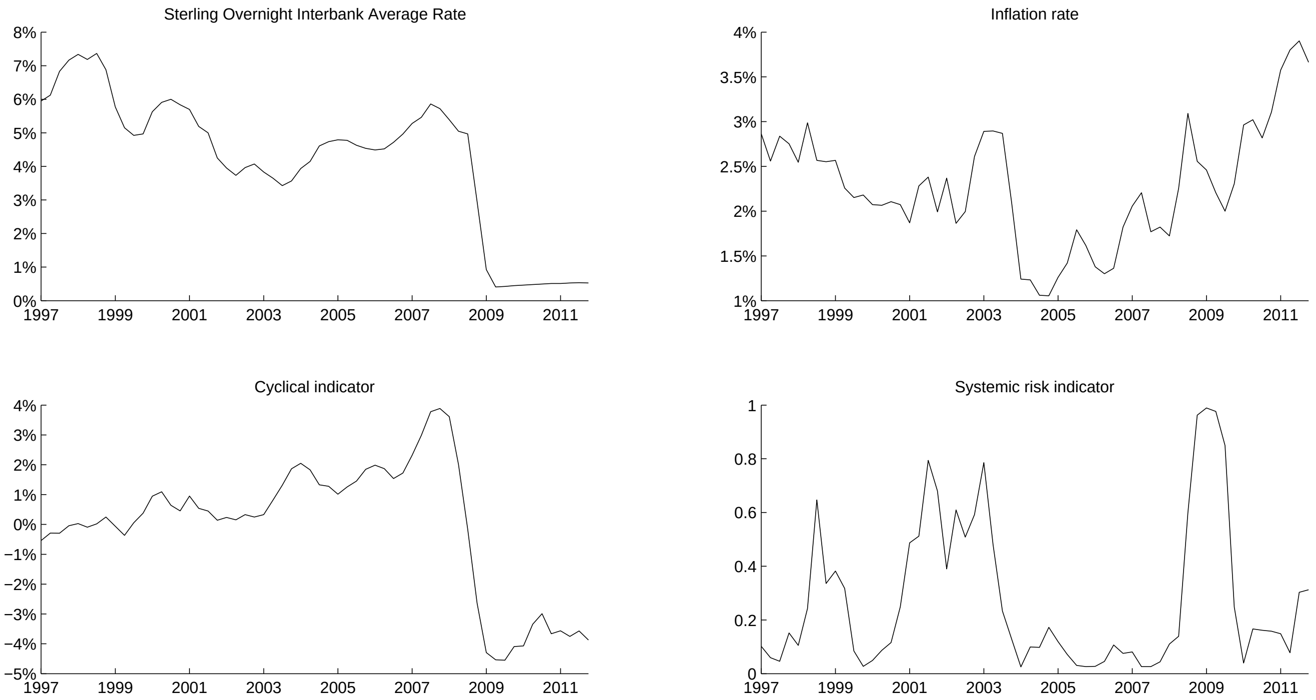
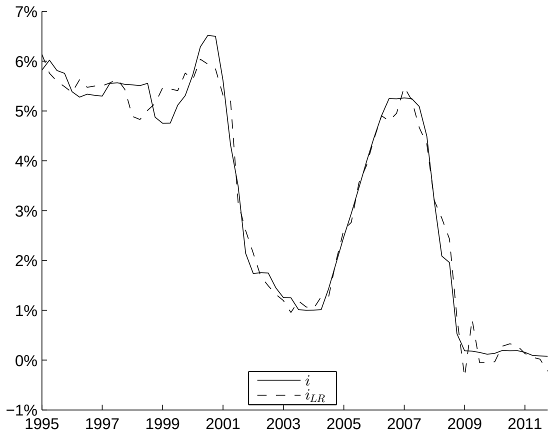
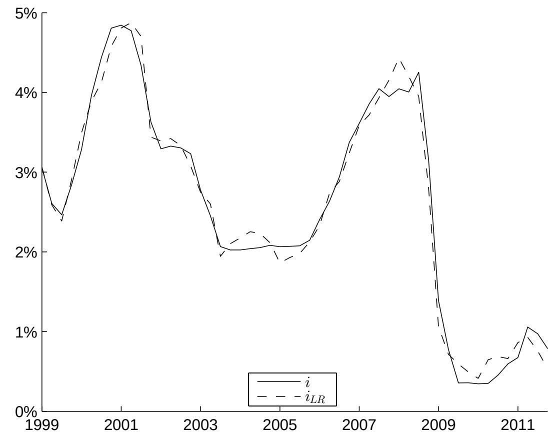


Figure 2.6: **Data for the BoE model.** We plot the data used in the BoE model (quarterly data from 1997:1 to 2011:4). Top-left panel: quarterly average of the SONIA rates. Top-right panel: quarterly average of the one-year growth rate of the Retail Price Index excluding mortgage interest payments (RPIX) until December 2003 and of the Consumer Price Index (CPI) from January 2004 onwards. Bottom-left panel: UK cyclical indicator, constructed using the HP estimator of the potential output. Bottom-right panel: systemic risk indicator.





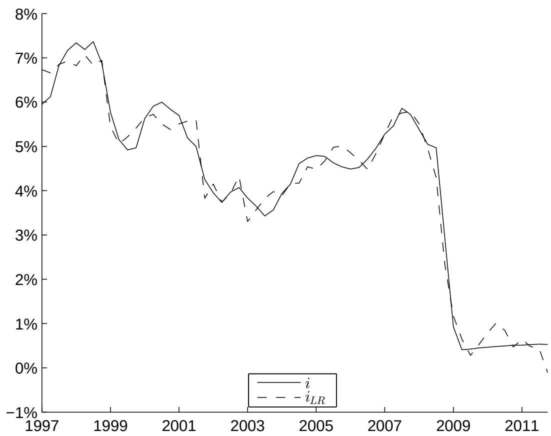


FIGURE 2.7: **Cointegrating regression.** Actual (solid line) vs. fitted (dashed line) values in the estimation of the long run relation in Eq. (2.25) (Fed model in the top panel, ECB model in the middle panel and the BoE model in the bottom panel).

FIGURE 2.8: **Error correction specification.** Actual (solid line) vs. fitted (dashed line) values in the estimation of the error correction model in Eq. (2.26) (Fed model in the top panel, ECB model in the middle panel and the BoE model in the bottom panel).

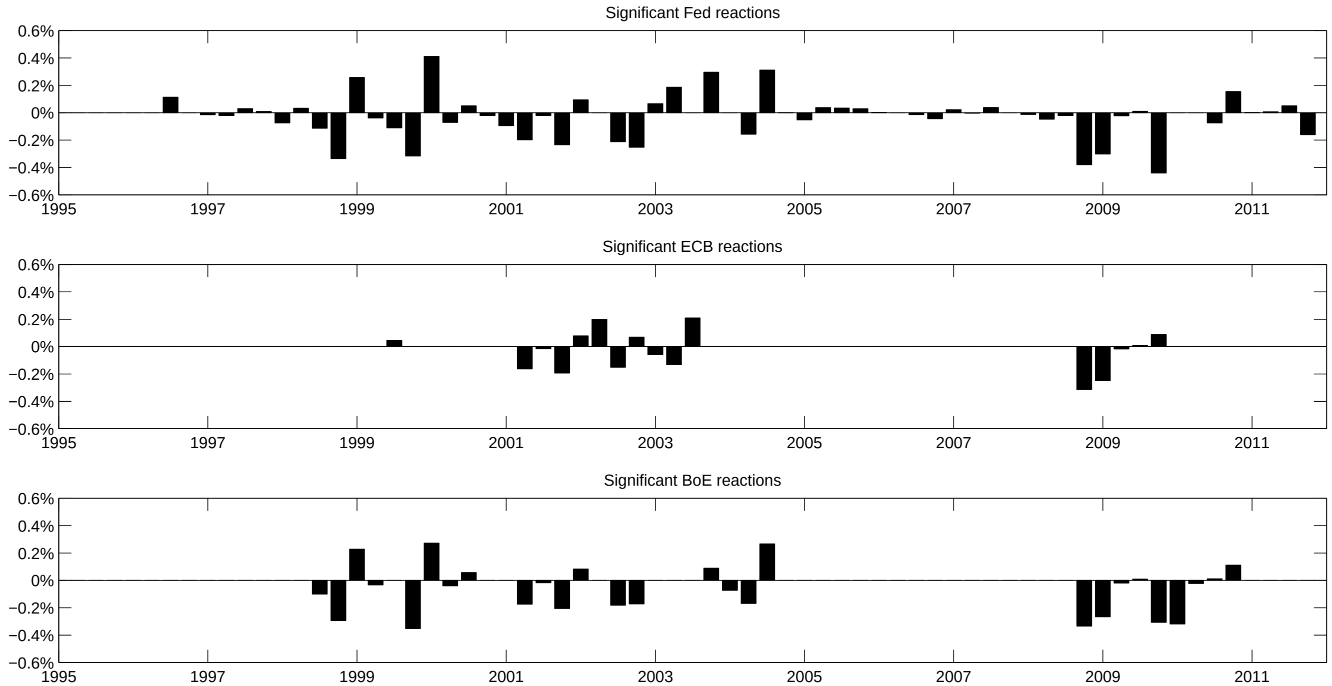


FIGURE 2.9: **Fed, ECB and BoE reactions to systemic risk.** We compute Central Banks' reactions to the riskiness of the system by stressing the estimated models with the observed variations of the systemic risk indicator. The estimated reactions to systemic risk are defined as $\Delta\hat{i}^{\xi}_{t,b} \equiv \hat{\theta}^{\xi\prime}_{b}\Delta Z^{\xi}_{t,b}$, where $Z^{\xi}_{t,b}$ with $b = Fed, ECB, BoE$ are the regressors referred to ξ in the Fed, the ECB and the BoE model, respectively (see Eqs. 2.33-2.35) and θ^{ξ}_{b} are the corresponding coefficients. We plot only the significant reactions at the 1% significance level. Significance is evaluated using the result in Eq. (2.40).

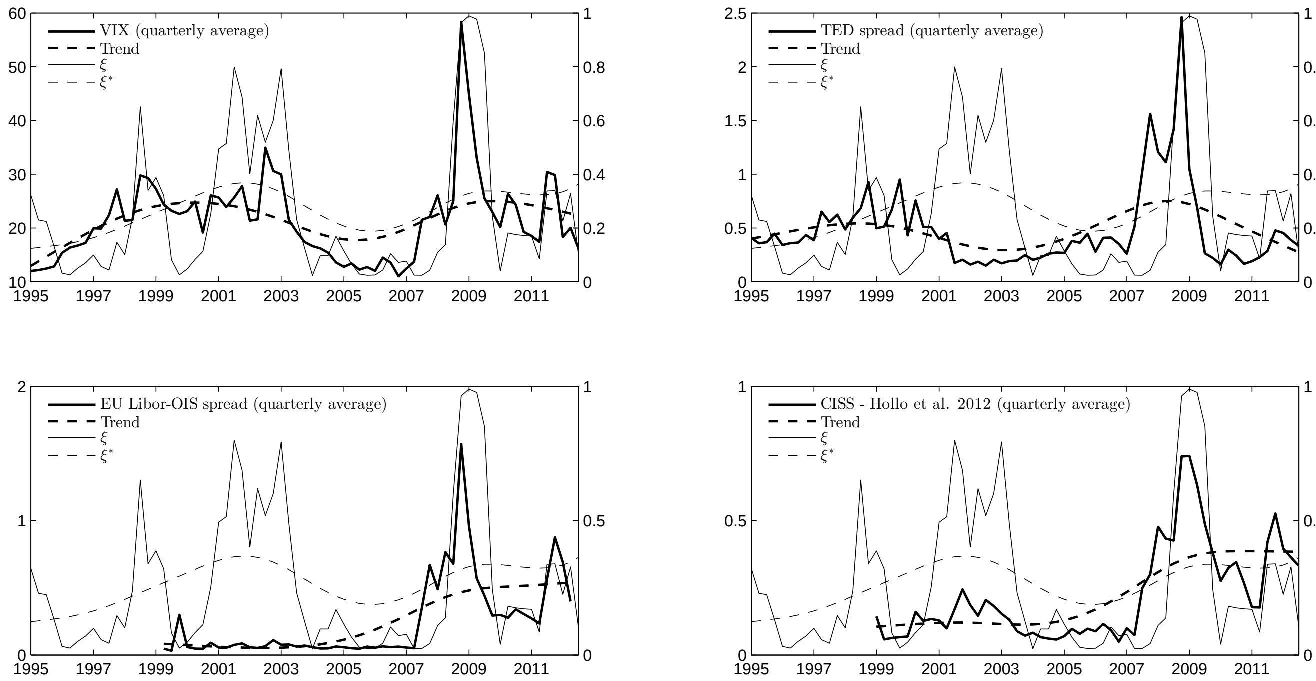


FIGURE 2.10: **Comparison with alternative systemic risk indicators.** We report a graphical comparison between our indicator and alternative financial tension indicators, namely the VIX, the TED spread, the CISS by Hollo et al. (2012) and the EU Libor-OIS spread (clockwise order from top-left panel). The bold lines are the quarterly average of the alternative indicators and the bold dashed lines are the corresponding trend components estimated via the HP filter.

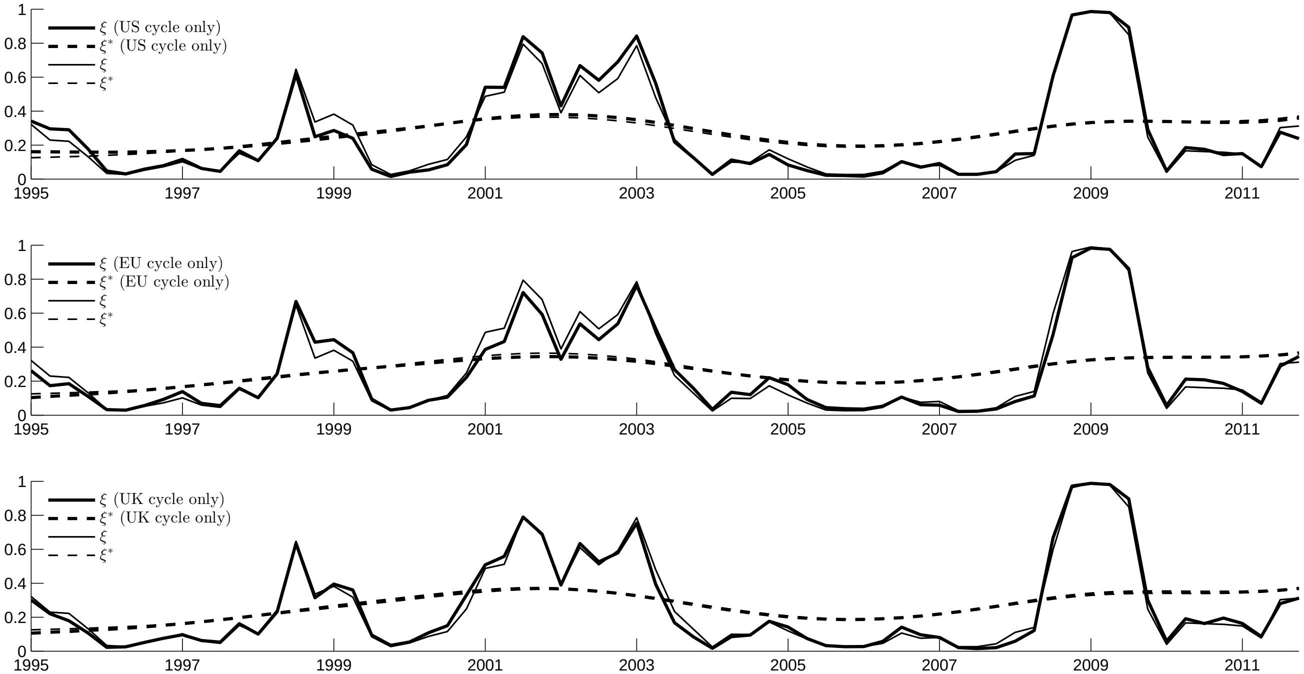


FIGURE 2.11: **The systemic risk indicator with local cyclical indicators.** We report a graphical comparison between the proposed indicator and the indicator constructed using local cyclical indicators only for the US (top panel), the Euro Area (middle panel) and the UK (bottom panel).

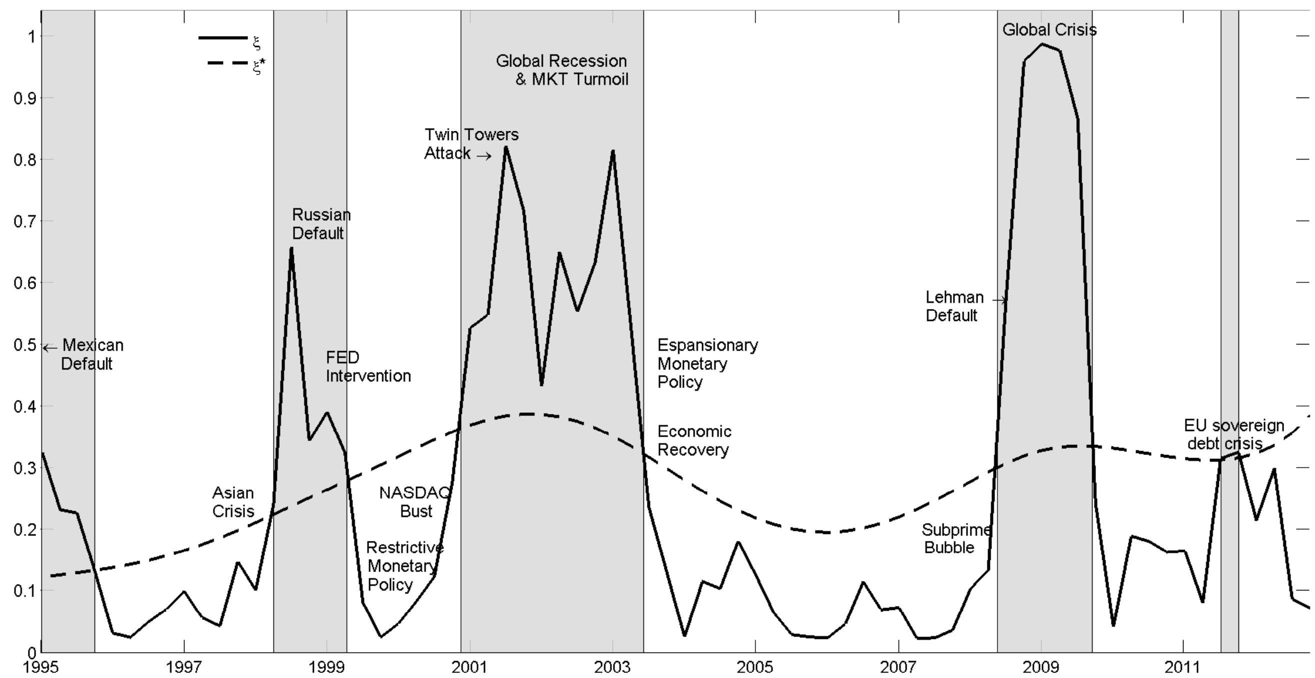


FIGURE 2.12: **Update of Fig. 2.3 to 2012:4.** We update the indicator using out-of-sample data referred to 2012:1 to 2012:4.

List of Symbols[3]

t	time index
ξ_t	systemic risk indicator
K	number of variables entering in the systemic risk indicator
T	sample size in the systemic risk indicator estimation
N	number of the markets considered in the systemic risk indicator estimation
J	number of considered geographical areas
β	two-dimensional column vector of parameters in the logistic mapping for the systemic risk indicator specification
γ	K-dimensional column vector of parameters referred to X in the systemic risk indicator specification
X	$T \times K$ matrix of exogenous variables for the systemic risk indicator
$\tilde{X}$	standardized version of the matrix X
$\mu_{n,t}$	mean return of index n in quarter t
$\sigma_{n,t}$	standard deviation of returns on index n in quarter t
α_t	slope in the regression of $\mu_{n,t}$ over $\sigma_{n,t}$ for quarter t
$\varepsilon_{n,t}$	error term in the regression of $\mu_{n,t}$ over $\sigma_{n,t}$ for quarter t
R_t^2	determination coefficient in the regression of $\mu_{n,t}$ over $\sigma_{n,t}$ for quarter t
σ_n^{LT}	long-term standard deviation of index n
s_t	cross-sectional average percentage deviation of the market volatilities from their long-term value
$y_{t,j}$	output gap for the j-th geographical area at time t

[3] Variables denoted by a lowercase letter not appearing in this list are intended to be an index varying from 1 to the integer represented by the corresponding uppercase letter, whose definition can be found in this legend.

$g_{t,j}$	logarithm of the actual GDP of the j-th geographical area at time t
$g^*_{t,j}$	logarithm of the potential GDP of the j-th geographical area at time t
λ_{HP}	smoothing parameter in the HP filter
v	K-dimensional vector of threshold values for the variables in X
$\bar{R}^2$	50-th constant percentiles of R^2_t
$\bar{s}$	50-th constant percentiles of s_t
τ^+	set of time indices corresponding to dates characterized by extreme high systemic risk
τ^-	set of time indices corresponding to dates characterized by extreme low systemic risk
$\tilde{X}^+$	observations of $\tilde{X}$ corresponding to dates characterized by extreme high systemic risk
$\tilde{X}^-$	observations of $\tilde{X}$ corresponding to dates characterized by extreme low systemic risk
${}_c\tilde{X}^+$	K-dimensional row vector representing the centroid of $\tilde{X}^+$
${}_c\tilde{X}^-$	K-dimensional row vector representing the centroid of $\tilde{X}^-$
$\bar{\gamma}$	lower bound for the γ parameters
(z^+_t, z^-_t)	auxiliary variables used in the estimation of γ
p^+	quota of the extreme high systemic risk observations
p^-	quota of the extreme low systemic risk observations
$\tilde{X}^+_{\hat{\gamma}}$	$100p^+$-th percentile of the linear combination $\tilde{X}\hat{\gamma}$
$\tilde{X}^-_{\hat{\gamma}}$	$100p^-$-th percentile of the linear combination $\tilde{X}\hat{\gamma}$
ξ^*_t	trend component of the systemic risk indicator
$\ddot{\xi}^*_t$	trend component of the systemic risk indicator detected using the HP filter
$\tilde{v}$	normalized version of the threshold vector v

$\bar{\xi}^*$	value of ξ computed in correspondence of $\tilde{\upsilon}$
λ	decay factor in the specification of ξ_t^*
ζ	numerical tolerance for the estimation of the decay factor λ
i_t	target interest rate
π_t	inflation rate
ϕ	constant term in the long-run relation
η	trend coefficient in the long-run relation
ψ	cointegrating vector
Z_t	regressors in the cointegration model
ϵ_t	error correction term
i_{LR}	fitted values in the long-run relation
L	lag order of the ECM
ω	constant term in the ECM
ρ_l	autoregressive coefficient associated to lag order l in the ECM
θ_l	vector of coefficients referred to the l-th lag of the regressors Z in the ECM
δ	coefficient referred to the error correction term
u_t	error term in the ECM
ξ_t^+	systemic risk indicator when above its trend component ξ_t^*
ξ_t^-	systemic risk indicator when below its trend component ξ_t^*
d	date of a break with $d = 1, \ldots, T$
$B_{d,t}^M$	time t value of the dummy variable capturing a break in the mean occurred on date d
$B_{d,t}^T$	time t value of the dummy variable capturing a break in the trend occurred on date d
P_t	GDP deflator
ψ_{gr}	change in the cointegrating vector associated to the Greenspan era
w^2	long-run variance of the error correction term

D_t	spike dummy variable for time t
b	index for the Central Bank with $b = Fed, ECB, BoE$
$Z_{t,b}^{\xi}$	time t observation of the regressors referred to ξ in the model for bank b
θ_b^{ξ}	coefficient referred to $\Delta Z_{t,b}^{\xi}$
$u_{t,b}$	error term in the ECM for Central Bank b
σ_b	standard deviation of $u_{t,b}$
$\Sigma_{\theta_b^{\xi}}$	variance-covariance matrix of θ_b^{ξ}
$\Delta i_{t,b}^{\xi}$	reaction of institution b to systemic risk at time t
ν	degrees of freedom in the ECM
p	number of estimated parameters in the ECM
I_t	quarterly average of the competing tension indicator index for quarter t
I_t^*	trend component of I_t extracted via the HP filter
I_t^+	quarterly average of I_t when above its trend component I_t^*
I_t^-	quarterly average of I_t when below its trend component I_t^*
$Z_{t,b}^I$	time t observation of the regressors $Z_{\cdot,b}^{\xi}$ constructed using the competing indicator I
δ_b^I	coefficients corresponding to the extra-term $\left(\Delta Z_{t,b}^I - \Delta Z_{t,b}^{\xi}\right)$ in the ECM for robustness check

Chapter 3

Modelling Financial Markets Comovements: A Dynamic Multi-Factor Approach

3.1 Introduction

In this chapter, we propose an in-depth study of the two major crisis episodes of recent times, the big recession of 2007-2009 and the on-going European sovereign debt crisis. The scope of the study is to provide an insight on the features of the two crises, measuring the extent to which financial markets tend to comove during periods of financial distress.

In broader terms, the study of financial market comovements is of paramount importance for its implications in both theoretical and applied finance. The practical relevance of a thorough understanding of the mechanisms governing market correlations lies in the benefits that this induces in the processes of asset allocation and risk management. Recent crisis episodes have shifted the focus of the literature on the characterization of financial market comovements during periods of financial turmoil. Most of the crises that have hit the financial markets in the past decades are the result of the propagation of a shock which originally broke out in a specific market. This phenomenon has been extensively explored in the literature and has led to the use of the term "contagion" to denote the situation in which a crisis originated in a specific market infects other interconnected markets. For a review of the contributions at the heart of the literature on contagion see the papers by Karolyi (2003), Dungey et al. (2005) and Billio and Caporin (2010).

A well-documented phenomenon linked to a situation of contagion is an increase of the observed correlations amongst the affected markets. The origins of this empirical evidence trace back to the contributions of King and Wadhwani (1990), Engle et al. (1990) and Bekaert and Hodrick (1992). Longin and Solnik (2001) and, in particular, the influential paper by Forbes and Rigobon (2002), criticize the common practice to identify periods of contagion using testing procedures based on market correlations. Forbes and Rigobon (2002) show that the presence of heteroscedasticity biases this type of testing procedure, leading to over-acceptance of the hypothesis of the presence of contagion. Bae et al. (2003), Pesaran and Pick (2007) and Fry et al. (2010) propose testing procedures robust to the presence of heteroscedasticity.

In this chapter we take a different stand. We propose a modelling framework which allows to contrast a situation of *contagion*, in the Forbes and Rigobon's (2002) sense, as opposed to the case in which *excess interdependence* on financial markets is triggered by spiking market volatility. Contagion is no longer thought as correlation in excess of what implied by an economic model (as in Bekaert et al., 2005, 2012), it instead corresponds to a specific market situation which our modelling set-up can capture. A situation of contagion entails a persistent change in financial linkages between markets. On the contrary, conditional heteroscedasticy of financial time series does not display trending behaviour (Schwert, 1989, Brandt et al., 2010), thus a rise in correlations caused by excess volatility has only a temporary effect. This feature is in line with the literature on market integration (Bekaert et al., 2009), which explores the degree of interconnectedness of markets through time, borrowing from Forbes and Rigobon's (2002) analysis the fact that excess interdependence, triggered by volatility, might lead to spurious identification of cases of market integration. In this chapter, we bring together the literature on contagion with the literature on market integration in that we associate a situation of contagion to a prolonged episode of market distress altering the functioning of the financial system. On the contrary, a situation of excess interdependence is a short lasting phenomenon. Being able to distinguish between contagion and excess interdependence has a crucial information content as to how a crisis develops and spreads out.

We study comovements amongst financial markets during crises, both in a multi-country and a multi-asset class perspective, contributing to the extant empirical literature on international and intra asset class shock spillovers. We analyse stock, bond and FX comovements in US, Euro Area, UK, Japan and Emerging Countries, providing an extensive coverage of the global financial markets. Most of the contributions to the literature on comovements entail single asset classes, with the vast majority focusing on stock and bond markets (see inter alia Driessen et al., 2003, Bekaert et al., 2009, Baele et al., 2010). There is a strand of literature embracing a genuine multi-country and multi-asset-class approach in the study of shock spillovers. Dungey and Martin (2007) propose an empirical model to measure spillovers from FX to equity markets to investigate the breakdown in correlations observed during the 1997 Asian financial crisis. Ehrmann et al. (2011) analyse the financial transmission mechanism across different asset classes (FX, equities and bonds) in the US and the Euro Area, using a simultaneous structural model.

The main contribution of the chapter is threefold. First, we propose a dynamic factor model which allows to test for the presence of excess interdependence versus contagion in a multi-asset and multi-country framework. Second, we disentangle the different sources of comovements between financial markets, and analyse their dynamics during financial crisis periods. Third, we report an empirical application using a sample period which encompasses both the 2007-09 crisis as well as the current sovereign debt crisis: this is an interesting laboratory to use the proposed framework to explore financial market comovements during crisis periods.

The empirical analysis suggests interesting findings. In our multi-factor framework, the global factor is the most pervasive of the considered factors, while the asset class factor is the most persistent and the country factor is negligible. We find evidence of contagion stemming from the US stock market during the 2007-09 financial crisis and presence of excess interdependence during the spreading of the European debt crisis from mid-2010 onwards. Any contagion or excess interdependence effect disappears at the overall average level, because of that some of the considered assets display diverging repricing dynamics during crisis periods.

The remainder of the chapter is organized as follows. In Section 3.2, a description of the dataset is provided. In Section 3.3, we specify the model. Section 3.4 presents the empirical results. Section 3.5 concludes.

3.2 Data

We analyse comovements of equity indices, foreign exchange rates, money market instruments, corporate and government bonds in US, Euro Area, UK, Japan and Emerging Countries. To minimise the impact of nonsynchronous trading across different markets, we base the study on weekly data from 1^{st} January 1999 to 14^{th} March 2012, yielding to 690 weekly observations. The starting date coincides with the adoption of the Euro, being the Euro Area one of the key geographical areas considered in the analysis. The sample offers the possibility to explore a variety of different market scenarios. The most notable facts are the speculation driven market growth of late 1990s, the financial and economic slowdown of early 2000s, the burst of the markets during the mid-2000, the financial turmoil of the period 2007-2009 and the following slow recovery, still pervaded by a big deal of uncertainty, prompted by the sovereign debt crisis in Europe and US between 2010 and 2012. This allows us to pick up from an in-sample analysis which are the distinctive features of market comovements during crisis periods.

Details on the time series used are in Tab. 3.1. The data sources are Datastream^{TM} and Bloomberg^{TM}. We embrace the MSCI definition of Emerging Markets and we select the 5 most relevant countries in term of size of their economy, according to the ranking based on the real annual GDP provided by the World Bank. Thus we select Brazil, India, China, Russia and Turkey as Emerging Countries. We exclude from the analysis money and government bond markets for Japan and Emerging Market, as the series were affected by excess noise caused by measurement errors. We consider the US dollar as the numeraire: all the series are US dollar denominated and the US dollar is the base rate for the FX pairs in the dataset.

[Tab. 3.1 about here.]

In what follows, each of the variable is considered in the form of simple percentage weekly returns. In Tab. 3.2, we report the list of the modelled variables together with descriptive statistics.

[Tab. 3.2 about here.]

The most remarkable facts are the extreme values which were recorded in correspondence of the 2008-2009 crisis period. This was particularly evident for stock markets and for short term rates, whereas along the country spectrum, the most hit were Emerging Markets. All of the series exhibit the typical characteristic of non-normality with high asymmetry and kurtosis. The price series are plotted in Fig. 3.1. The downturn at the end of the year 2008 is immediately apparent and common to all the considered series.

[Fig. 3.1 about here.]

We propose a dynamic factor model with multiple sources of shocks, at global, asset class and country level. In order to validate this approach, a first preliminary in-sample correlation analysis is undertaken. We observe high correlation intra asset class groups. Particularly remarkable are the cases of equity and government bond yields, with correlations in the 70-80% range. We observe substantial correlation even within countries, in particular there is evidence of high interconnection between corporate bonds and FX markets at country level: Euro Area (91.3%), Japan (83.6%) and UK (83.3%). Hence, there is evidence for the presence of both an asset class and a country effect. However, the asset class effect seems to be systematically more pervasive than the country one.

3.3 A Dynamic Multi-Factor Model

In this section, we set up the modelling framework. We present the general formulation, explore the issues related to the estimation methods implemented and use the proposed model to dynamically analyse market comovements.

The novelty of the work is the formulation and the estimation of a dynamic factor model which allows to test for the presence of contagion in the Forbes and Rigobon's (2002) sense versus the presence of volatility triggered episodes of excess interdependence.

Since the seminal works of Ross (1976) and Fama and French (1993), multifactor models for asset returns have been the main tool for studying and characterizing comovements. Building on this standard latent factor financial literature, let $R_t^{i,j}$ represent the weekly return for the asset belonging to asset class $i = 1, \dots, I$ and county $j = 1, \dots, J$ at time t. The general representation of the model is as follows:

$$R_t^{i,j} = \mathbb{E}[R_t^{i,j}] + F_t^{i,j} \beta_t^{i,j} + \epsilon_t^{i,j} \tag{3.1}$$

$$\beta_t^{i,j} = diag(\mathbf{1} - \phi^{i,j})\beta^{i,j} + diag(\phi^{i,j})\beta_{t-1}^{i,j} + \psi^{i,j} Z_{t-1} + u_t^{i,j} \tag{3.2}$$

where $\mathbb{E}[R_t^{i,j}]$ is the expected return for asset class i in country j at time t, $\beta_t^{i,j}$ is a vector of dynamic factor loadings, mapping from the zero-mean factors $F_t^{i,j}$ to the single asset returns. $F_t^{i,j}$ is a 3-dimensional row vector of factors at the global, asset class and country level. We entertain the possibility that the factors $F_t^{i,j}$ are heteroscedastic, that is $\mathbb{E}[F_t^{i,j\prime} F_t^{i,j}] = \Sigma_{F,t}^{i,j}$, where $\Sigma_{F,t}^{i,j}$ is the time-varying covariance matrix of the factors. $\epsilon_t^{i,j}$ is assumed to be white noise and independent of $F_t^{i,j}$. $\beta^{i,j}$ is the long-run value of $\beta_t^{i,j}$, $\phi^{i,j}$ and $\psi^{i,j}$ are 3-dimensional vectors of parameters to be estimated, $\{u_t^{i,j}\}_{t=1,\dots,T}$ are independent and normally distributed. We assume $u_t^{i,j}$ to be independent of $\epsilon_t^{i,j}$. $diag(\cdot)$ is the diagonal operator, transforming a vector into a diagonal matrix. Z_t is a conditional variable controlling for period of market distress.

Following Dungey and Martin (2007), different sources of shocks are considered, at global, asset class and country level, in a latent factor framework. A first factor, denoted as G_t, is designed to capture the shocks which are common to all financial assets modelled, whereas A_t^i is the asset class specific factor for asset class $i = 1, \dots, I$ and the country factor C_t^j is the country specific factor for county $j = 1, \dots, J$ at time t. We denote $F_t^{i,j} \equiv [G_t \ A_t^i \ C_t^j]$ and, correspondingly, for the factor loading we specify $\beta_t^{i,j} \equiv [\gamma_t^{i,j} \ \delta_t^{i,j} \ \lambda_t^{i,j}]'$.

The full model is a multi-factor model with dynamic factor loadings and heteroscedastic factors. This model setting allows us to explore and characterize dynamically the comovements among the considered assets. Time-dependent exposures to different shocks let us disentangle dynamically the different sources of comovement between financial markets, namely distinguishing among shocks spreading at a global level, at the asset class or rather at the country level. On the other hand, the presence of time-varying exposures to common factors enables us to test for the presence of contagion, controlling at the same time for excess interdependence induced by heteroscedasticity in the factors. In the following sections, we explore the features of the model and use it to characterize financial market comovements during crises.

3.3.1 Factor Estimation

Model (3.1)-(3.2) is estimated in the following form:

$$R_t^{i,j} = \mathbb{E}[R_t^{i,j}] + \hat{F}_t^{i,j}\beta_t^{i,j} + \epsilon_t^{i,j} \tag{3.3}$$

$$\beta_t^{i,j} = diag(\mathbf{1} - \phi^{i,j})\beta^{i,j} + diag(\phi^{i,j})\beta_{t-1}^{i,j} + \psi^{i,j}\hat{Z}_{t-1} + u_t^{i,j} \tag{3.4}$$

where $\hat{F}_t^{i,j}$ and $\hat{Z}_t$ are an estimate of the factors $F_t^{i,j}$ and Z_t. In this section, we concentrate on the estimation of $F_t^{i,j}$, whereas the estimation of Z_t is presented in Section 3.3.2. The factors $F_t^{i,j}$ are estimated by means of principal component analysis (PCA). The choice of PCA is dictated by model simplicity and interpretability, yet providing consistent estimates of the latent factors[1].

[1] In the factor model literature, consistency of the factor estimation is a well established result for the case in which the factor loadings are stable. In this chapter, we make use of the limiting theory developed by Stock and Watson (1998, 2002, 2009) and Bates et al. (2012), which suggests that PCA remains a consistent method for factor estimation even for the case of unstable factor loadings.

The global factor G is extracted using the entire set of variables considered, whereas A and C are by construction asset class and country specific, being extracted from the different asset class and country groups, respectively. In this setting, the number of variables from which the factors are extracted, say K, is fixed and small, whilst the number of observations T tends to infinity ($T \to +\infty$). Let us first consider the case of the global factor G. To estimate it, we define the series of the demeaned returns as $r_t^{i,j} \equiv R_t^{i,j} - \mathbb{E}[R_t^{i,j}]$ and we stack them into the matrix $\mathbf{r}$. We then consistently estimate the variance-covariance matrix of $\mathbf{r}$, say $\Sigma_\mathbf{r}$, via maximum likelihood, as:

$$\hat{\Sigma}_\mathbf{r} \equiv \frac{1}{(T-1)}\mathbf{r}'\mathbf{r} \tag{3.5}$$

Let $(l_k, \mathbf{w_k})$ be the eigencouples referred to the covariance matrix $\Sigma_\mathbf{r}$, with $k = 1, \ldots, K$, such that $l_1 > l_2 > \ldots > l_K$. We estimate $(l_k, \mathbf{w_k})$ by extracting the eigenvalue-eigenvector couples from the estimated covariance matrix of the returns $\hat{\Sigma}_\mathbf{r}$, denoted as $(\hat{l}_k, \hat{\mathbf{w}}_\mathbf{k})$.

The estimate $\hat{G}$ of the common factor G is given by the principal component extracted using the matrix $\hat{\Sigma}_\mathbf{r}$, that is:

$$\hat{G} = \mathbf{r}\hat{\mathbf{w}}_\mathbf{1} \tag{3.6}$$

$\hat{G}$ is a consistent estimator of the factor G. Indeed, from the standpoint that $\hat{\Sigma}_\mathbf{r}$ is a consistent estimator of $\Sigma_\mathbf{r}$, we claim that, as a direct consequence of the invariance property for maximum likelihood estimators, the estimated eigencouples $(\hat{l}_k, \hat{\mathbf{w}}_\mathbf{k})$ consistently estimate $(l_k, \mathbf{w_k})$ (Anderson, 2003).

Analogously, to estimate the asset class and the country specific factors A^i and C^j (with $i = 1, \ldots, I$ and $j = 1, \ldots, J$), we define $\mathbf{r^i} \equiv [r_t^{i,j}]_{j=1,\ldots,J}$ and $\mathbf{r^j} \equiv [r_t^{i,j}]_{i=1,\ldots,I}$ as the matrices of returns referred to asset class i and country j, respectively. Denote as $\Sigma_{\mathbf{r^i}}$ and $\Sigma_{\mathbf{r^j}}$ the corresponding covariance matrix and let $\hat{\mathbf{w}}_{\mathbf{1}}^{\mathbf{i}}$ and $\hat{\mathbf{w}}_{\mathbf{1}}^{\mathbf{j}}$ be the eigenvectors corresponding to the largest eigenvalues of the estimates $\hat{\Sigma}_{\mathbf{r^i}}$ and $\hat{\Sigma}_{\mathbf{r^j}}$. The estimates of the asset class and the country specific factors $\hat{A}^i$ and $\hat{C}^j$ are then given by:

$$\hat{A}^i = \mathbf{r^i}\hat{\mathbf{w}}_{\mathbf{1}}^{\mathbf{i}} \tag{3.7}$$

$$\hat{C}^j = \mathbf{r^j}\hat{\mathbf{w}}_{\mathbf{1}}^{\mathbf{j}} \tag{3.8}$$

As we use demeaned return, the extracted factors will have zero mean by construction.

When the number K of variables from which factors are extracted is fixed and small, no criteria is available regarding how to establish the number of factors to be extracted (see inter alia Bai and Ng, 2002). Then, following Dungey and Martin (2007), and from the standpoint of the descriptive analysis in Section 3.2, we assume that the relevant factors are three: the first at a global level, and the other two at an asset class and country levels, respectively.

For the sake of model interpretability, we orthogonalize the factors, so that the three groups of factors are mutually uncorrelated. The preliminary correlation analysis presented in Section 3.2 suggests that the asset class factors are more pervasive than the country ones. So, we first orthogonalize the asset class factors with respect to the global factor. Then, we orthogonalize the country factors with respect to the asset class and the global factors. This ensures for instance that the US factor is uncorrelated of the global factor and of the equity factor. The orthogonalization process, however, is not carried out within the groups of factors, so then the equity factor might have a nonzero correlation with the bond factor, and so the US factor with the EU factor. In the application, we show that the results are robust to the case in which one orthogonalizes the country factors with the global one and then the asset class factors with respect to the others.

3.3.2 Dynamic Multi-Factor Loading Estimation

The factor model proposed in Eqs. (3.1)-(3.2) allows for time-dependent exposures of the single assets to the different classes of factors. In the literature there are different approaches to accommodate this feature on the factor loadings. The specification we propose in Eq. (3.2) is within the class of the so-called "conditional time-varying factor loading approach" (see Bekaert et al., 2009), and it nests as a special cases both the static specification $\beta_t^{i,j} \equiv \beta^{i,j}$, which we consider as the baseline, and an alternative dynamic approach, which in the literature is known as "time-varying factor loading approach" (see Eq. 3.14 below) adopted inter alia by Bekaert et al. (2009) using fixed-length time windows. This section is designed to provide details on the main features of the alternative factor loading specifications.

In the "conditional time-varying factor loading approach", the factor loadings are assumed to follow a structural dynamic equation (see for instance Baele et al., 2010) of form:

$$\beta_t^{i,j} \equiv \beta(\mathcal{F}_{t-1}, X_t) \tag{3.9}$$

where $\{\mathcal{F}_t\}_{t=1,\dots,T}$ is the information flow and X_t is a set of conditional variables. Our explicit specification of Eq. (3.9) for the factor loadings $\beta_t^{i,j}$ is as in Eq. (3.2), that we re-write for convenience:

$$\beta_t^{i,j} = diag(\mathbf{1} - \phi^{i,j})\beta^{i,j} + diag(\phi^{i,j})\beta_{t-1}^{i,j} + \psi^{i,j} Z_{t-1} + u_t^{i,j} \tag{3.10}$$

where $\beta^{i,j}$ is the long-run value of $\beta_t^{i,j}$, $\phi^{i,j}$ and $\psi^{i,j}$ are 3-dimensional vectors of parameters to be estimated, $u_t^{i,j}$ is a white noise error term and Z_t is a control factor extracted from pure exogenous variables. Z_t measures market nervousness and accounts for potential increase in the factor loading during market distress periods. We estimate Z_t as the principal component extracted from the VIX, which is widely recognized as indicator of market sentiment, the TED spread and the Libor-OIS spread for Europe, which measure the perceived credit risk in the system. Widening spreads corresponds to a lack of confidence in lending money on the interbank market over short-term maturities, together with a flight to security in the form of overnight deposits at the lender of last resort.

The dynamic specification in Eq. (3.10) is convenient in the sense that it emphasizes that $\beta_t^{i,j}$ tends to its long-run value $\beta^{i,j}$ while following an autoregressive type of process of order one with a purely exogenous variable Z. Being Z a zero-mean variable, $\beta^{i,j}$ can indeed be interpreted as the long-run value for $\beta_t^{i,j}$.

Under the hypothesis:

$$H_0' : \begin{cases} \phi^{i,j} = \mathbf{0} \\ \psi^{i,j} = \mathbf{0} \\ u_t^{i,j} = 0 \end{cases} \quad \forall i = 1, \ldots, I \quad \forall j = 1, \ldots, J \quad \forall t = 1, \ldots, T \tag{3.11}$$

Model (3.10) boils down to the following static specification:

$$\beta_t^{i,j} \equiv \beta^{i,j}, \quad \forall i = 1, \ldots, I, \quad \forall j = 1, \ldots, J \tag{3.12}$$

This corresponds to the assumption that the exposure of all modelled variables to the different groups of factors are held at constant through time.

On the contrary, under the null hypothesis:

$$H_0'' : \psi^{i,j} = \mathbf{0} \quad \forall i = 1, \ldots, I \quad \forall j = 1, \ldots, J \tag{3.13}$$

Model (3.10) reduces to:

$$\beta_t^{i,j} = diag(\mathbf{1} - \phi^{i,j})\beta^{i,j} + diag(\phi^{i,j})\beta_{t-1}^{i,j} + u_t^{i,j} \tag{3.14}$$

This specification follows the so called "time-varying factor loading approach". No exogenous variables are generally considered in the process they follow. Typically, under this approach, subsamples of fixed length are used to estimate dynamic betas, so that the factor loadings are constant within pools of observations (see Bekaert et al., 2009). This corresponds to the following specification for the factor loadings:

$$\beta_t^{i,j} \equiv \beta^{i,j,s} \quad s = 1, \ldots, S \tag{3.15}$$

where $\beta^{i,j,s}$ is the static factor loading estimate referred to subsample s, while S is the number of subsamples considered. Bekaert et al. (2009) partition their sample in semesters and re-estimate the model every six months. On the contrary, in the specification in Eq. (3.14), we do not make any arbitrary choice about the inertia as to which factor loadings evolve through time.

We estimate the unconstrained version of model in Eqs. (3.3)-(3.4) as well as under the hypotheses H_0' and H_0''. H_0' corresponds to the static case, which we consider as the baseline. In this case, OLS gives consistent estimates. By considering the alternative specifications in Eqs. (3.10) and (3.14), we entertain the possibility that the factor loadings show evidence of contagion either in a conditioned way ($\psi^{i,j} \neq \mathbf{0}$) or in an unconditioned way ($\psi^{i,j} = \mathbf{0}$), according to the specified control variable. In these other two cases, consistent estimates are obtained by applying the Kalman filter. The models are nested and thus, the standard likelihood ratio test can be employed for model selection.

3.3.3 Heteroscedastic Factors

We set up the modelling framework so that we can contrast between spikes in comovements due to increasing exposures to common risk factors, from the case in which they are triggered by excess volatility in the common factors. For this reason, besides allowing for dynamic factor exposures, we allow for heteroscedastic factors. Namely, we model heteroscedasticity using Engle's (2002) Dynamic Conditional Correlations (DCC) model in its standard form, by choosing the order (1,1) for the DCC process, and employing a GARCH(1,1) for the marginals with normal innovations.

The extent that the three groups of factors are mutually uncorrelated by construction greatly simplifies the estimation. For the case of the global factor G_t, a univariate GARCH(1,1) with normal innovation is employed to estimate time-varying volatility. For the asset class and the country factors, we apply the Engle's DCC model separately on $\mathbf{A_t}$ and $\mathbf{C_t}$, defined by stacking the factors into matrices as follows: $\mathbf{A_t} \equiv [A_t^i]_{i=1,\ldots,I}$ and $\mathbf{C_t} \equiv [C_t^j]_{j=1,\ldots,J}$. We obtain consistent estimates of the time-varying covariance matrices of the factors, estimating the DCC model via quasi-maximum likelihood estimation.

3.3.4 Market Comovement Measures

Most of the key results of this chapter entail the dynamic behaviour of the comovements amongst the financial markets considered. On the basis of the proposed dynamic factor model, we derive the expression for the covariance between pairs of financial assets.

For the sake of simplifying the notation, let us introduce the one-to-one mapping $n \equiv n(i,j)$, with which we identify asset n ($n = 1, \ldots, N$), belonging to asset class i and country j. From Eq. (3.1), given the independence between the factors F_t and the error term ϵ_t, it follows immediately that the covariance between asset n_1 and asset n_2 (for $n_1 \neq n_2$) at time t is given by:

$$cov_t(R^{n_1}, R^{n_2}) = \mathbb{E}[\beta_t^{n_1\prime} F_t^{n_1\prime} F_t^{n_2} \beta_t^{n_2}] + \mathbb{E}[\epsilon_t^{n_1} \epsilon_t^{n_2}] \tag{3.16}$$

The first term on the right-hand side is what is generally referred to as *model-implied* covariance, whereas the second is called *residual* covariance. The empirical counterpart of Eq. (3.16) is given by:

$$\hat{cov}_t(R^{n_1}, R^{n_2}) = \hat{\beta}_t^{n_1}{}' \hat{\Sigma}_{F,t}^{n_1,n_2} \hat{\beta}_t^{n_2} + \hat{\Sigma}_{\epsilon,t}^{n_1,n_2} \tag{3.17}$$

which we rewrite for convenience, as:

$$\hat{cov}_{n_1,n_2,t} = \hat{cov}^F_{n_1,n_2,t} + \hat{cov}^{\epsilon}_{n_1,n_2,t} \tag{3.18}$$

where:

$$\hat{cov}^F_{n_1,n_2,t} \equiv \hat{\beta}_t^{n_1}{}' \hat{\Sigma}_{F,t}^{n_1,n_2} \hat{\beta}_t^{n_2} \tag{3.19}$$

$$\hat{cov}^{\epsilon}_{n_1,n_2,t} \equiv \hat{\Sigma}_{\epsilon,t}^{n_1,n_2} \tag{3.20}$$

Correspondingly, define the quantities $\hat{corr}^F_{n_1,n_2,t}$ and $\hat{corr}^{\epsilon}_{n_1,n_2,t}$ dividing by the appropriate variances. We provide the estimates of $corr^{\epsilon}_{n_1,n_2,t}$ via DCC. We deliberately do not adjust the residuals of the model by heteroscedasticity and/or serial correlation, which are instead treated as genuine features of the data. We denote the model-implied variance of the n-th market by $var_{n,t}$, which is defined as $var_{n,t} \equiv cov_{n,n,t}$.

During period of financial distress, soaring empirical covariances are in general observed. Eq. (3.17) shows that the covariance between R^{n_1} and R^{n_2} can rise through three different channels: an increase in the factor loadings $\beta_t^{n_1}$ and $\beta_t^{n_2}$, an increase in the covariance of the factors $\Sigma_{F,t}^{n_1,n_2}$, and an increase residual covariance $\Sigma_{\epsilon,t}^{n_1,n_2}$. Bekaert et al. (2005) and the related literature identify contagion as the comovement between financial markets in excess of what implied by an economic model. In this view, contagion is associated with spiking residual covariance between markets, which refers to Eq. (3.20), the second term on the right-hand side of Eqs. (3.17) and (3.18). In our modelling set-up, we take a different stand. Consistently with the case brought by Forbes and Rigobon (2002, pp.2230-1), contagion is thought as an episode of financial distress characterized by increasing interlinkages between markets. This extent finds its model equivalent in a surge in the factor loadings β_t. On the contrary, spiking volatility in the factor conditional covariances is associated with excess interdependence. We formalize this notion in Definitions 3.1 and 3.2 below.

Following Bekaert et al. (2009), we consider the average measure of model-implied comovements:

$$\Gamma_t^F \equiv \frac{2}{N(N-1)} \sum_{n_1=1}^{N} \sum_{n_2>n_1}^{N} c\hat{o}rr^F_{n_1,n_2,t} \tag{3.21}$$

and similarly we define Γ_t^ϵ as the residual comovement measure.

We can get further insights into the covariance decomposition outlined in Eq. (3.16), by recalling that the factors $F_t^{i,j} = [G_t \ A_t^i \ C_t^j]$ are by construction mutually uncorrelated. Thus, from Eq. (3.16), it follows that:

$$cov_t(R^{n_1}, R^{n_2}) = \mathbb{E}[\gamma_t^{n_1\prime} G_t' G_t \gamma_t^{n_2}] + \mathbb{E}[\delta_t^{n_1\prime} A_t^{i_1\prime} A_t^{i_2} \delta_t^{n_2}] + \mathbf{E}[\lambda_t^{n_1\prime} C_t^{j_1\prime} C_t^{j_2} \lambda_t^{n_2}] + \mathbb{E}[\epsilon_t^{n_1} \epsilon_t^{n_2}] \tag{3.22}$$

with empirical counterpart of the form:

$$cov_t(R^{n_1}, R^{n_2}) = \hat{\gamma}_t^{n_1\prime} \hat{\Sigma}_{G,t}^{n_1,n_2} \hat{\gamma}_t^{n_2} + \hat{\delta}_t^{n_1\prime} \hat{\Sigma}_{A,t}^{n_1,n_2} \hat{\delta}_t^{n_2} + \hat{\lambda}_t^{n_1\prime} \hat{\Sigma}_{C,t}^{n_1,n_2} \hat{\lambda}_t^{n_2} + \hat{\Sigma}_{\epsilon,t}^{n_1,n_2} \tag{3.23}$$

which for convenience we write as:

$$c\hat{o}v_{n_1,n_2,t} = c\hat{o}v^G_{n_1,n_2,t} + c\hat{o}v^A_{n_1,n_2,t} + c\hat{o}v^C_{n_1,n_2,t} + c\hat{o}v^\epsilon_{n_1,n_2,t} \tag{3.24}$$

Eq. (3.24) shows that within the proposed model framework, we can discriminate among comovements due to global, asset class or country specific shocks. We define a measure of comovement prompted by the global factor as:

$$\Gamma_t^G \equiv \frac{2}{N(N-1)} \sum_{n_1=1}^{N} \sum_{n_2>n_1}^{N} c\hat{orr}_{n_1,n_2,t}^G \tag{3.25}$$

where $c\hat{orr}_{n_1,n_2,t}^G$ is defined as:

$$c\hat{orr}_{n_1,n_2,t}^G \equiv \frac{c\hat{ov}_{n_1,n_2,t}^G}{\sqrt{v\hat{ar}_{n_1,t}^F v\hat{ar}_{n_2,t}^F}} \tag{3.26}$$

and can be seen as the part of the correlation between markets n_1 and n_2, due to the common dependence on the global factor. In the same manner, we define Γ_t^A and Γ_t^C as the measures of comovements prompted by asset class and country factors, respectively. By construction we have: $\Gamma_t^F \equiv \Gamma_t^G + \Gamma_t^A + \Gamma_t^C$.

We decline the same Γ-measures of comovements even at the asset class and county level. Let $\mathcal{I}_i$ be the set of indices from the sequence $n = 1, \ldots, N$ referred to markets belonging to the asset class i, and $\mathcal{J}_j$ be the indices referred to markets in county j, that is:

$$\mathcal{I}_i = \left\{ n \middle| n = n(i,j); j = 1, \ldots, J \right\} \tag{3.27}$$

$$\mathcal{J}_j = \left\{ n \middle| n = n(i,j); i = 1, \ldots, I \right\} \tag{3.28}$$

The model-implied comovement measure for asset class i is given by:

$$\Gamma_t^i \equiv \frac{2}{|\mathcal{I}_i| \left(|\mathcal{I}_i| - 1 \right)} \sum_{n_1 \in \mathcal{I}_i} \sum_{\substack{n_2 \in \mathcal{I}_i \\ n_2 > n_1}} c\hat{orr}_{n_1,n_2,t}^F \tag{3.29}$$

and in the same manner for country j, we have:

$$\Gamma_t^j \equiv \frac{2}{|\mathcal{J}_j| \left(|\mathcal{J}_j| - 1 \right)} \sum_{n_1 \in \mathcal{J}_j} \sum_{\substack{n_2 \in \mathcal{J}_j \\ n_2 > n_1}} c\hat{orr}_{n_1,n_2,t}^F \tag{3.30}$$

As in Bekaert et al. (2009), along with the definition of comovement measures introduced so far, we propose a modification of them, to test for contagion versus excess interdependence. In the case of Γ_t^F, besides the definition in Eq. (3.21), we consider also:

$$\Gamma^F_{t,ED} \equiv \frac{2}{N(N-1)} \sum_{n_1=1}^{N} \sum_{n_2>n_1}^{N} c\hat{o}rr^F_{n_1,n_2,t,ED} \tag{3.31}$$

$$\Gamma^F_{t,VD} \equiv \frac{2}{N(N-1)} \sum_{n_1=1}^{N} \sum_{n_2>n_1}^{N} c\hat{o}rr^F_{n_1,n_2,t,VD} \tag{3.32}$$

where $c\hat{o}rr^F_{n_1,n_2,t,ED}$ and $c\hat{o}rr^F_{n_1,n_2,t,VD}$ are the correlation coefficients respectively associated with the following covariances:

$$c\hat{o}v^F_{n_1,n_2,t,ED} \equiv \hat{\beta}_t^{n_1\prime} \hat{\Sigma}_F^{n_1,n_2} \hat{\beta}_t^{n_2} \tag{3.33}$$

$$c\hat{o}v^F_{n_1,n_2,t,VD} \equiv \hat{\beta}^{n_1\prime} \hat{\Sigma}_{F,t}^{n_1,n_2} \hat{\beta}^{n_2} \tag{3.34}$$

where $\hat{\Sigma}_F^{n_1,n_2}$ is an estimate of $\Sigma_F^{n_1,n_2} \equiv \mathbb{E}\left(F^{n_1\prime}F^{n_2}\right)$ and $\hat{\Sigma}_{F,t}^{n_1,n_2}$ is its time-varying counterpart.

$\Gamma^F_{t,ED}$ differs from Γ^F_t in the sense that the correlations used in its definition are computed assuming constant factor volatilities. In this case, the dynamics of the correlation between two markets is triggered by their time-varying exposures to common factors. We label this correlation measure as exposure driven (ED). On the contrary, $\Gamma^F_{t,VD}$ is an average measure of comovements triggered by factor volatility only, while the exposures to the factors are kept constant according to their long-run values. We tag this type of comovements as volatility driven (VD). We consider the same two definitions for Γ_t^G, Γ_t^A and Γ_t^C, as well as for Γ_t^i and Γ_t^j.

The tools used in the analysis of the resulting time series are based on the Impulse-Indicator Saturation (IIS) technique implemented in Autometrics^{TM}, as part of the software PcGive^{TM} (Hendry and Krolzig, 2005, Doornik, 2009, Castle et al., 2011).

Castle et al. (2012) show that Autometrics^{TM} IIS is able to detect multiple breaks in a time series when the dates of breaks are unknown. Furthermore, Authors demonstrate that the IIS procedure outperforms the standard Bai and Perron (1998) procedure. In particular, IIS is robust in presence of outliers close to the end and the start of the sample.

Following Castle et al. (2012), we look for structural breaks in the generic $\Gamma_t^{(\cdot)}$ average comovement measures, by estimating the regression:

$$\Gamma_t^{(\cdot)} = \mu + \eta_t \tag{3.35}$$

where μ is a constant and η_t is assumed to be white noise. We then saturate the above regression using the IIS technique. IIS will retain into the model individual impulse-indicators in the form of spike dummy variables, signalling the presence of instabilities in the modelled series. These dummies will occur in block between the dates of the breaks. In line with the procedure outlined in Castle et al. (2012), we group the dummy variables "with the same sign and similar magnitudes that occur sequentially" to form *segments* of dummies, whereas the impulse-indicators which can not be grouped will be labelled as *outliers*. We interpret the segments of spike dummies as a step dummy for a particular regime. We can now state the following:

Definition 3.1. (*Contagion*). A situation of *contagion* is defined as the case in which a segment of dummy variables is detected through the IIS procedure for the average comovement measure $\Gamma_{t,ED}^{(\cdot)}$.

Definition 3.2. (*Excess Interdependence*). A situation of *excess interdependence* is defined as the case in which a segment of dummy variables is detected through the IIS procedure for the average comovement measure $\Gamma_{t,VD}^{(\cdot)}$.

We set a restrictive significance level of 1%, which leads to a parsimonious specification, as shown in Castle et al. (2012). Section 3.4.3 gives account of the results of the outlined methodology applied to our data.

3.4 Empirical Results

In this section, we report the empirical estimates of the model formulated in Section 3.3. Section 3.4.1 outlines the results regarding the estimation of the factors and model selection, while in Sections 3.4.2 and 3.4.3 we provide an analysis of market comovements.

3.4.1 Factor Estimates and Factor Loading Selection

We start the empirical analysis by extracting the factors according to the methodology outlined in Section 3.3.1. We extract the first principal component at a global, asset class and country level from the estimate of the covariance matrix of the demeaned return time series. The factors have by construction zero mean.

The extracted factors account in total for 83.28% of the overall variance, thus explaining a substantial amount of the variation of the considered return series. In particular, the global factor extracts as much as the 37.27% of the overall variance, whereas the asset class and the country factors account for a quota in the 50-80% range of the variation in the groups they are extracted from.

We then orthogonalize the extracted factors, so that the system $\hat{F}_t^{i,j} \equiv [\hat{G}_t \; \hat{A}_t^i \; \hat{C}_t^j]$ with $i = 1, \ldots, I$ and $j = 1, \ldots, J$ consists of orthogonal factors. We first orthogonalize each of the asset class factors with respect to the global factor and then orthogonalize the country factors with respect to both the global and the asset class factors. In Section 3.4.2, we show that all our main results do not depend on the particular way the orthogonalization is carried out.

To validate the interpretations we attached to the factors, we map the contributions of the original variables onto the factors via linear correlation analysis. The result of this analysis is reported in Tab. 3.3.

[Tab. 3.3 about here.]

We find that the stock indices are the most correlated with the global factors, with correlations in the 80-90% range. This characterizes the global factor as the momentum factor. Such an interpretation seems reasonable in view of the fact that the equity asset class can be thought as the most direct indicator of the financial activity among the asset classes here considered.

More generally, when we sort the different markets by the magnitude of their correlation with the global factor, they tend to group by asset class, rather than by country, with the government bond and the FX market figure in the 30-50% range and the money market and the corporate bond market in the 0-30% range. This again supports the evidence that the asset class effect is more pervasive then the country effect. The extent that the global factor contains part of the asset class effect, however, does not pollute the interpretation of the asset class factors, which remain positively and strongly correlated with the variables which they are extracted from, even after the orthogonalization process.

To test for excess interdependence prompted by changes in the volatility of the factors, we entertain the possibility that the factor time series might be characterized by volatility clustering. The Engle test for residual heteroscedasticity suggests that at the 5% confidence level this is indeed the case for 7 out of the 11 estimated factors. See Tab. 3.4 for details.

[Tab. 3.4 about here.]

We fit the Engle's DCC model on the series of the estimated factors to get a time-varying estimate of their covariance matrix.

In Section 3.3.2, we proposed three alternative specifications for the factor loadings $\beta_t^{i,j}$ in Model (3.1) that we report below for convenience:

$$\beta_t^{i,j} = \beta^{i,j} \tag{3.36}$$

$$\beta_t^{i,j} = diag(\mathbf{1} - \phi^{i,j})\beta^{i,j} + diag(\phi^{i,j})\beta_{t-1}^{i,j} + u_t^{i,j} \tag{3.37}$$

$$\beta_t^{i,j} = diag(\mathbf{1} - \phi^{i,j})\beta^{i,j} + diag(\phi^{i,j})\beta_{t-1}^{i,j} + \psi^{i,j} Z_{t-1} + u_t^{i,j} \tag{3.38}$$

which we labelled as static, time-varying and conditional time-varying factor loading specification, respectively.

We estimate Eq. (3.3) via OLS when we use the static formulation in Eq. (3.36) for the factor loading, while when the factor loadings are specified as in either the time-varying model (Eq. 3.37) or the conditional time-varying factor loading model (Eq. 3.38), we estimate Eq. (3.3) via the Kalman filter using maximum likelihood estimation method. The models are nested and thus the likelihood ratio test can be employed for model selection. The likelihood ratio statistics are reported in Tab. 3.5.

[Tab. 3.5 about here.]

The test strongly rejects the static alternative in favour of the dynamic ones. The conditional time-varying factor loading approach dominates the time-varying factor loading approach. Thus, there is evidence that the fitting of the model improves when we control for market nervousness by means of the control factor Z.

3.4.2 Comovements Dynamics

We turn now to analyse the average measures of comovements introduced in Section 3.3.4. We start with the comparison between Γ_t^F and Γ_t^ϵ. The two measures are plotted in Fig. 3.2.

[Fig. 3.2 about here.]

As it can be clearly seen, the residual component is negligible throughout the sample period and on average does not convey any information about the dynamics of the comovements of the considered markets. We observe only a little jump in the idiosyncratic component in correspondence to the late 2008, which has been considered by many the harshest period of the 2007-09 global financial crisis. The model-implied measure of average comovements Γ_t^F fluctuates around what can be regarded as a constant long-run value of roughly 20%. This erratic behaviour does not allow us to identify any peak in correlation possibly associated to crisis periods. During the period 2007-09 a slightly lower average correlations seem to be observed instead. We give account of this fact in what follows, by disaggregating the model-implied covariation measure Γ_t^F.

We start doing this by considering the decomposition of the overall comovement measure Γ_t^F into Γ_t^G, Γ_t^A and Γ_t^C, which is presented in Fig. 3.3. The global factor appears to be the most pervasive of all the three factors considered, shaping the dynamics of the average overall measure. The asset class factor is slightly less pervasive, but it is the most persistent of the three, meaning that its contribution is more resilient to change over time. This expresses the fact that the characteristics which are common to the asset class contribute in a constant proportion to the average overall market correlation. The least important factor is the country one, which is almost negligible. Thus, comovements typically propagate through two channels:

a global one, in a time varying manner, and an asset class channel, according to a constant contribution.

[Fig. 3.3 about here.]

We consider robustness check of these conclusions, by pursuing an alternative strategy in orthogonalizing the system of factors here considered. We first orthogonalize the country factor against the global and then the asset class one with respect to the other two. Then we re-estimate the model and construct the comovement measures. Embracing this alternative approach, Fig. 3.3 gets modified into the Fig. 3.4. The dynamics of the comovements is similar. The decomposition changes in favour of the global factor, which is even more pervasive than before. However, the country contribution is almost absent, even when the country factors are extracted and orthogonalized with priority, thus validating our orthogonalization method.

[Fig. 3.4 about here.]

3.4.3 Testing for Contagion versus Excess Interdependence

In this section, we propose an empirical analysis of the comovement measures introduced above by testing for the presence of different regimes in the resulting time series by means of Autometrics^{TM}. Figs. 3.5 to 3.7 report the time series analysed. Tabs. 3.6 to 3.8 show the result of this procedure applied to our data.

[Figs. 3.5-3.7 and Tabs. 3.6-3.8 about here.]

Let us start with the analysis of the results for Γ_t^F, $\Gamma_{t,ED}^F$ and $\Gamma_{t,VD}^F$ as reported in Tab. 3.6. As previously noted for Fig. 3.2, not surprisingly, we do not find any structural clear pattern in the IIS retained by Autometrics^{TM} when applied to Γ_t^F. We find outliers only, instead. However, when looking at $\Gamma_{t,VD}^F$ we find evidence of excess interdependence, that is excess average correlation prompted by the heteroscedasticity of common factors, in correspondence of the most severe period of the 2007-09 crisis, i.e. the last part of 2008, as well as in August 2011, when the sovereign debt crisis spread from the peripheral countries in Europe to the rest of the continent and ultimately to the US. On the other hand, we detect a significant negative break in the contagion measure $\Gamma_{t,ED}^F$ from late 2007 to the end of 2008, which offsets the peak in $\Gamma_{t,VD}^F$, so that no peaks are detected in Γ_t^F, as shown before. When only factor exposures are concerned, we observe an average de-correlation of more than 6%. To explore this issue, in what follows, we further disaggregate the Γ-measures at the asset class and country level. Along with the detected segments, we observe a few outliers, too. In the case of $\Gamma_{t,ED}^F$, we find a couple of outliers in proximity of the Dot-Com bubble burst, witnessing de-correlation on the market. All the other IIS identified by Autometrics^{TM} are in proximity of the start and the end of the sample, a fact observed also in Castle et al. (2012).

We turn our attention to Tab. 3.7 which reports the results referred to the single asset classes. For stock indices, we find evidence of contagion from Aug-07 to mid-09, with correlation significantly up by 5% from the average level of 79%. We also find evidence of excess interdependence for three less extended periods, in correspondence of the most dramatic months of 2008 and 2009, as well as in May-2010 and from Aug-2011 on, with a surge of 13-15% in the average correlation. We associate the former extent to the first EU intervention in the Greece's bailout programme, which marked the triggering of the sovereign debt crisis in Europe. The latter identified period has already been epitomized as the moment in which the sovereign debt crisis spread across and outside Europe. At the aggregate level, the 2007-09 crisis and the debt crisis remain the most relevant episodes in terms of average market correlations.

Detecting contagion and excess interdependence in the stock markets during crises is very much in line with the mainstream literature on comovements. For the other asset classes, the same periods are detected, but most of them are associated with *decreasing* market correlations. This is particularly evident at the aggregate level for corporate bonds (with average slumps in correlation as high as 41.34% in the last part of 2008) and foreign exchange rates (-39.93% in roughly the same period). This phenomenon is still present when we look for contagion and excess interdependence. The de-correlation observed in the case of foreign exchange rates is due to the contrasting effects of the crisis on the different currencies. Because of the low costs related to a borrowing position in Yen, since the early 2000s, the Japanese currency has been, together with the US Dollar, the currency used by investors to finance their positions in risky assets. The massive outflow from the markets experienced in the late 2000s, led to the unwinding of these borrowing positions, which fuelled a steady appreciation of the Japanese currency. This results in a massive de-correlation of the Yen against the other currencies. As part of the same phenomenon, the Japanese corporate bond market, even though it experienced a sharp capital outflow during the first period of the late 2000s financial crisis, continued to grow rapidly (see Shim, 2012), proving to be a safe haven during this period of generalized financial distress. This again triggered de-correlation of the Japan market with the other countries. See Fig. 3.8 for a graphic comparison of the market dynamics in these periods.

[Fig. 3.8 about here.]

Similarly, the money markets are pervaded by comovement shocks of alternate signs, especially at the aggregate level and when testing for excess interdependence. The series here considered are indicative of the status of the country interbank markets as well as a proxy of the conduct of the monetary policy. The negative breaks in comovements reflect the asymmetries in the shocks on the interbank markets and the differences in the reactions of the monetary policy to the spreading of the crisis, as documented in Chapter 2 for the Fed, the ECB and the BoE. We detect a positive sign at the aggregate level and at the volatility driven level in correspondence to the joint monetary policy intervention in October 2008 by the Fed, the ECB, the Bank of England and the Bank of Japan together with other 3 industrialized countries' Central Bank (Canada, Switzerland and Sweden). See Section 2.3 for more details on this topic. We find no breaks for the government bond yield series at the aggregate level.

We now move on to Tab. 3.8 and analyse the same average comovement measures at the country level. We find evidence of a peak in the overall comovements in US during the 2007-09 crisis. In particular there is strong evidence of contagion at the national level characterized by an escalation in the magnitude of the breaks in correspondence to the worsening of the crisis in late 2008. Similarly, in the other countries, we observe peaks during financial crises. In particular, in Europe excess interdependence is detected for most of the period between 2008 and 2012. In the UK we find positive breaks in the correlations at the aggregate level and at the volatility driven level both for the 2007-09 crisis and for the sovereign debt crisis. For Japan we observe the de-correlation phenomenon described above, with the stock market correlated with the other stock markets, while the national currency was following a steady appreciation path.

The first evidence of contagion during the late 2000s economic and financial crisis was observed for equity markets and the US, as early as in the August 2007, anticipating the all-time peak of the S&P500 in October, epitomizing the beginning of the 2007-09 global financial crisis. This combined evidence is in line with what has been observed in reality: the crisis originated in the US, spread across the country and then propagated to the global financial markets, affecting first the global stock markets. On the contrary, there is evidence that the sovereign debt crisis originated in Europe was characterized by excess interdependence, rather than as an example of contagion. Indeed, in this case the most extended episode of excess interdependence was recorded for equity indices and for Europe.

3.5 Final Remarks

This chapter studied the determinants of the comovements between different financial markets, with a particular focus on the late 2000s global crisis and the current European sovereign debt crisis. We proposed a dynamic factor model with multiple sources of shocks, at global, asset class and country level and use it to test for the presence of contagion versus excess interdependence. The model is specified with time-varying factor loadings, to allow for time-dependent exposures of the single assets to the different shocks. We statistically validated the supremacy of this model as compared to a standard static approach and an alternative dynamic approach.

The main findings of the empirical analysis can be summarized as follows. First, the global factor is the most pervasive of the considered factors, shaping the dynamics of the comovements of the considered financial markets. On the contrary, the asset class factor is the most persistent through time, suggesting that the structural commonalities of markets belonging to the same asset class systematically contributes in a constant proportion to the average overall comovements. In our multiple asset class framework, the country factor is negligible. In a robustness check, we showed that this result does not depend on the order in which the system of factors is orthogonalized.

Secondly, we found evidence of contagion stemming from the US and the stock market jointly in correspondence to the harshest period of the 2007-09 financial crisis. On the contrary, the currency and sovereign debt crisis originated in Europe characterized for the presence of excess interdependence from mid-2010 onwards. According to the literature on comovements, this let us characterize the spillover effects during the 2007-09 financial crisis as persistent, altering the strength of the financial linkages worldwide. On the other hand, the shock transmission experienced during the recent debt crisis has *so far* to be understood as temporary, being prompted by excess factor volatilities, which do not display trend in the long-term.

Finally, at the overall average level, we did not find any evidence of contagion nor excess interdependence. We like to interpret this result as follows. During the crises some of the securities considered in the study, the Japanese currency and corporate bond market in particular, displayed a diverging dynamics as result of the unwinding of carry positions, previously built to finance risky investments.

The findings in this chapter suggest several developments. First, as most of the described dynamics were prompted by the worsening of credit conditions, an interesting extension of this work would be the inclusion of credit indices in the analysis, provided the availability of the relevant data. Second, we modelled heteroscedasticity in the factors using the DCC approach. It would be interesting also to explicitly model high order moment dynamics as well as high order comovements between financial markets. Third, part of the conclusions entails the on-going sovereign debt crisis which broke out in the Euro Zone. The results of this chapter might be worth reconsidering when the turmoil period will be over. Finally, it may be useful to use this model set-up to forecast financial market comovements, to support asset allocation and risk management decisions. We leave these developments to future research.

TABLE 3.1: **Variables used in the empirical application.** We report the acronyms used to identify each variable (ID variable), the asset class and the country to which they belong, the name of the series, together with the data provider and the ticker for series identification.

ID variable	***Asset class***	***Country***	***Name***	***Source (Ticker)***
CorpBond/US	Corporate Bond	US	BOFA ML US CORP	Datastream^{TM} (MLCORPM)
CorpBond/EU	”	Euro Area	BOFA ML EMU CORP	Datastream^{TM} (MLECEXP)
CorpBond/UK	”	UK	BOFA ML UK CORP	Datastream^{TM} (ML£CAU$)
CorpBond/JP	”	Japan	BOFA ML JAP CORP	Datastream^{TM} (MLJPCP$)
CorpBond/EM	”	Emerging Countries	BOFA ML EMERG CORP	Datastream^{TM} (MLEMCB$)
EqInd/US	Equity Indices	US	MSCI USA	Datastream^{TM} (MSUSAML)
EqInd/EU	”	Euro Area	MSCI EMU U$	Datastream^{TM} (MSEMUI$)
EqInd/UK	”	UK	MSCI UK U$	Datastream^{TM} (MSUTDK$)
EqInd/JP	”	Japan	MSCI JAPAN U$	Datastream^{TM} (MSJPAN$)
EqInd/EM	”	Emerging Countries	MSCI EM U$	Datastream^{TM} (MSEMKF$)
FX/EU	Foreign Exchange	Euro Area	FX Spot Rate	Bloomberg^{TM} (EURUSD Curncy)
FX/UK	”	UK	FX Spot Rate	Bloomberg^{TM} (GBPUSD Curncy)
FX/JP	”	Japan	FX Spot Rate	Bloomberg^{TM} (JPYUSD Curncy)
FX/EM	”	Emerging Countries	FX Spot Rate	Bloomberg^{TM} (BRLUSD, CNYUSD, INRUSD, RUBUSD, TRYUSD Curncy)
MoneyMkt/US	Money Market	US	3 month US Libor	Bloomberg^{TM} (US0003M Index)
MoneyMkt/EU	”	Euro Area	3 month Euribor	Bloomberg^{TM} (EUR003M Index)
MoneyMkt/UK	”	UK	3 month UK Libor	Bloomberg^{TM} (BP0003M Index)
GovBond/US	Government Bond	US	US Govt 10 Year Yield	Bloomberg^{TM} (USGG10YR Index)
GovBond/EU	”	Euro Area	EU Govt 10 Year Yield	Bloomberg^{TM} (GECU10YR Index)
GovBond/UK	”	UK	UK Govt 10 Year Yield	Bloomberg^{TM} (GUKG10 Index)

Table 3.2: **Descriptive statistics for market returns.** We report summary statistics for the variables used in the empirical application. The numbers reported refer to the entire sample, which consists of weekly observations from Jan-1999 to Mar-2012.

	Mean	***Standard Deviation***	***Min***	***Max***	***Skewness***	***Kurtosis***
CorpBond/US	0.119%	0.748%	-5.355%	3.171%	-0.935	8.553
CorpBond/EU	0.103%	1.558%	-5.815%	5.385%	-0.194	3.512
CorpBond/UK	0.100%	1.612%	-13.152%	5.628%	-1.075	10.651
CorpBond/JP	0.092%	1.347%	-5.356%	8.924%	0.572	6.755
CorpBond/EM	0.163%	0.826%	-9.332%	3.724%	-3.717	38.973
EqInd/US	0.014%	2.747%	-20.116%	11.526%	-0.748	8.850
EqInd/EU	-0.011%	3.502%	-26.679%	12.245%	-1.073	9.576
EqInd/UK	-0.009%	3.091%	-27.618%	16.243%	-1.249	14.920
EqInd/JP	0.009%	2.887%	-16.402%	11.016%	-0.258	4.823
EqInd/EM	0.184%	3.380%	-22.564%	18.538%	-0.775	8.889
FX/EU	0.017%	1.468%	-6.048%	4.992%	-0.213	3.831
FX/UK	-0.009%	1.341%	-8.348%	5.195%	-0.588	6.546
FX/JP	0.050%	1.498%	-6.027%	7.445%	0.253	4.304
FX/EM	-0.142%	1.517%	-17.401%	4.786%	-2.961	29.634
MoneyMkt/US	-0.350%	3.814%	-27.877%	21.137%	-1.850	16.873
MoneyMkt/EU	-0.187%	2.087%	-11.989%	15.021%	-0.717	11.723
MoneyMkt/UK	-0.262%	2.091%	-26.170%	8.374%	-4.357	43.968
GovBond/US	-0.126%	3.596%	-19.122%	12.110%	-0.045	5.511
GovBond/EU	-0.116%	3.056%	-17.838%	14.018%	-0.353	6.476
GovBond/UK	-0.105%	2.805%	-16.758%	11.153%	-0.362	5.943

TABLE 3.3: **Correlations between the market returns and the extracted factors.** We report the correlation between the factors and the market returns from which the factors are extracted. There are 20 series displayed in the rows and 11 factors (one global, 5 asset class and 5 country factors), which are displayed in the columns. The numbers reported are in-sample linear correlations.

		Asset class factors					***Country factors***				
	Global factor	***CorpBond***	***EqInd***	***FX***	***MoneyMkt***	***GovBond***	***US***	***EU***	***UK***	***JP***	***EM***
CorpBond/US	-0.188	0.595	0.684	0.325	-0.337	-0.714	-0.234	0.017	0.032	0.098	0.059
CorpBond/EU	0.237	0.884	0.350	0.822	-0.211	-0.472	0.028	0.150	-0.120	-0.039	-0.044
CorpBond/UK	0.185	0.882	0.425	0.700	-0.131	-0.550	0.038	-0.163	0.145	0.052	-0.022
CorpBond/JP	-0.300	0.450	0.279	0.402	-0.128	-0.245	-0.106	0.107	-0.027	-0.129	0.015
CorpBond/EM	0.281	0.587	0.413	0.377	-0.248	-0.475	-0.007	-0.078	-0.153	0.061	0.278
EqInd/US	0.816	-0.072	0.248	-0.146	0.004	-0.214	0.138	-0.029	-0.035	-0.136	-0.167
EqInd/EU	0.907	0.193	0.275	0.127	-0.066	-0.284	-0.008	0.263	-0.024	-0.129	-0.156
EqInd/UK	0.875	0.206	0.290	0.119	-0.057	-0.307	-0.016	-0.011	0.312	-0.118	-0.188
EqInd/JP	0.541	0.177	0.350	0.096	-0.063	-0.288	-0.143	-0.181	-0.101	0.624	0.036
EqInd/EM	0.854	0.143	0.289	0.078	-0.072	-0.290	0.009	-0.177	-0.167	0.016	0.422
FX/EU	0.313	0.730	0.167	0.830	-0.117	-0.293	-0.012	0.226	-0.114	-0.078	-0.099
FX/UK	0.373	0.683	0.133	0.720	-0.032	-0.260	-0.061	-0.185	0.328	0.027	-0.092
FX/JP	-0.205	0.379	0.226	0.441	-0.104	-0.186	-0.089	0.044	-0.024	-0.026	0.022
FX/EM	0.557	0.225	0.122	0.421	-0.061	-0.222	0.119	-0.131	-0.169	0.088	0.212
MoneyMkt/US	-0.021	-0.241	-0.175	-0.139	0.973	0.187	0.133	-0.019	-0.034	-0.059	0.040
MoneyMkt/EU	0.092	-0.061	-0.138	-0.030	0.551	0.108	-0.360	0.152	-0.021	0.193	-0.096
MoneyMkt/UK	0.065	-0.104	-0.150	-0.010	0.697	0.118	-0.332	-0.031	0.176	0.120	-0.109
GovBond/US	0.559	-0.474	-0.716	-0.350	0.153	0.738	0.309	-0.142	-0.123	-0.025	0.028
GovBond/EU	0.577	-0.403	-0.700	-0.224	0.130	0.708	-0.229	0.248	-0.045	0.016	-0.025
GovBond/UK	0.536	-0.439	-0.695	-0.239	0.118	0.712	-0.250	-0.059	0.266	0.023	-0.017

TABLE 3.4: **Test for residual heteroscedasticity for the estimated factors.** We report the results of the Engle test for residual heteroscedasticity for the 11 extracted factors (one global, 5 asset class and 5 country factors). The first columns reports the name of the factor, the second reports the test statistics in the Engle test for residual heteroscedasticity. In the third column, ***, ** and * indicate rejection of the null of no ARCH effect at the 1%, 5% and 10% significance level, respectively.

Global	51.982	***
CorpBond	7.577	***
EqInd	0.458	
FX	3.254	*
MoneyMkt	59.335	***
GovBond	0.318	
US	31.535	***
EU	21.421	***
UK	26.668	***
JP	3.386	*
EM	25.878	***

TABLE 3.5: **Likelihood ratio test for the alternative models.** We report the test statistics for the likelihood ratio test comparing the proposed alternative models. The test is employed to evaluate the null hypothesis that the *Null model* provides a better fit than the *Alternative model*. The models refer to the following alternative formulation for the factor loadings: the static factor loading in Eq. (3.36), the time-varying factor loading in Eq. (3.37) and the conditional time-varying factor loading in Eq. (3.38). *** indicates rejection of the null model at the 1% significance level.

	Alternative model	
Null model	***Time-varying factor loading***	***Conditional time-varying factor loading***
Static factor loading	260142.36***	261869.86***
Time-varying factor loading		1727.50***

Table 3.6: **IIS results for the overall average comovement measures.** Γ_t^F is the average comovement measure at the overall level, defined as the mean of the model-implied correlations between all the couples of asset considered. $\Gamma_{t,ED}^F$ ($\Gamma_{t,VD}^F$) considers the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time). We present the results of the saturation of model in Eq. (3.35) by means of Autometrics^{TM}. We report the dates detected via the IIS technique, together with the estimated coefficients. *Segment* refers to group of sequential dummies with the same size and similar magnitude. *Outliers* are dummies which can not be grouped. *Constant* refers to the constant term μ in Eq. (3.35). ***, ** and * indicate significance of the coefficient at the 1%, 5% and 10% significance level, respectively.

Γ_t^F		
Outliers		
26/02/1999	-0.0583	**
...		
16/12/2011	-0.0584	**
Constant	0.2230	***

$\Gamma_{t,ED}^F$		
Segments		
17/08/2007 - 21/11/2008	-0.0670	***
Outliers		
07/04/2000	-0.0608	**
30/06/2000	-0.0607	**
09/03/2001	-0.0746	***
25/11/2011	-0.0646	***
02/12/2011	-0.0583	**
Constant	0.2282	***

$\Gamma_{t,VD}^F$		
Segments		
31/10/2008 - 05/12/2008	0.0564	***
12/08/2011 - 26/08/2011	0.0594	***
Outliers		
23/04/1999	-0.0507	***
Constant	0.2320	***

Table 3.7: **IIS results for the average comovements measures at the asset class level.** $\Gamma_t^{CorpBond}$ is the average comovement measure within the corporate bond market, defined as the mean of the model-implied correlations between all the couples of securities in the corporate bond asset class. Γ_t^{EqInd}, Γ_t^{FX}, $\Gamma_t^{MoneyMkt}$ and $\Gamma_t^{GovBond}$ are analogously defined for the other asset classes. Exposure-driven (middle panel) and volatility-driven (bottom panel) comovement measures consider the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time). Refer to the caption of Tab. 3.6 for a legend of the results of the estimation.

$\Gamma_t^{CorpBond}$			Γ_t^{EqInd}			Γ_t^{FX}			$\Gamma_t^{MoneyMkt}$			$\Gamma_t^{GovBond}$		
Segments			*Segments*			*Segments*			*Segments*			*Outliers*		
24/08/2007 - 26/09/2008	-0.1614	***	10/10/2008 - 27/03/2009	0.1664	***	26/05/2006 - 04/08/2006	-0.1623	***	29/01/1999 - 20/04/2001	-0.0748	***	15/01/1999	-0.4502	***
03/10/2008 - 23/01/2009	-0.4134	***	12/08/2011 - 03/02/2012	0.1447	***	16/03/2007 - 25/07/2008	-0.1681	***	14/03/2008 - 28/03/2008	-0.9199	***	...		
06/02/2009 - 04/06/2010	-0.1867	***	*Outliers*			19/09/2008 - 15/05/2009	-0.3993	***	11/04/2008 - 19/09/2008	-0.0650	***	16/12/2011	-0.7062	***
12/08/2011 - 03/02/2012	-0.3610	***	01/01/1999	0.1596	***	12/08/2011 - 27/01/2012	-0.2528	***	26/09/2008 - 14/11/2008	0.0521	**	*Constant*	0.8238	***
Outliers			18/02/2000	-0.1695	***	*Outliers*			06/02/2009 - 22/01/2010	-0.1794	***			
22/01/1999	-0.1643	***	24/03/2000	-0.1718	***	22/01/1999	-0.1107	**	07/05/2010 - 28/05/2010	0.0525	**			
21/04/2000	-0.1535	***	*Constant*	0.7408	***	07/04/2000	-0.1149	***	15/04/2011 - 29/07/2011	-0.1010	***			
28/09/2001	-0.1812	***				09/03/2001	-0.1756	***	12/08/2011 - 19/08/2011	-1.2057	***			
05/10/2001	-0.1859	***				28/09/2001	-0.1433	***	11/11/2011 - 27/01/2012	-0.1060	***			
12/10/2001	-0.1343	***				21/05/2004	-0.1340	***	*Outliers*					
Constant	0.8557	***				24/07/2009	-0.1781	***	28/09/2001	0.0570	**			
						21/05/2010	-0.1111	**	16/11/2001	0.0550	**			
						Constant	0.7481	***	22/11/2002	-0.1174	***			
									21/02/2003	-0.0593	**			
									28/03/2003	-0.1570	***			
									04/04/2003	-0.0613	**			
									27/06/2003	-1.2632	***			
									01/02/2008	0.0524	**			
									29/02/2008	-0.0606	**			
									05/12/2008	-0.3098	***			
									26/12/2008	0.0502	**			
									02/07/2010	-0.0835	***			
									03/09/2010	0.0522	**			
									26/11/2010	-0.0771	***			
									14/01/2011	-0.0900	***			
									Constant	0.9421	***			

$\Gamma_{t,ED}^{CorpBond}$			$\Gamma_{t,ED}^{EqInd}$			$\Gamma_{t,ED}^{FX}$			$\Gamma_{t,ED}^{MoneyMkt}$			$\Gamma_{t,ED}^{GovBond}$		
Segments			*Segments*			*Segments*			*Segments*			*Outliers*		
24/08/2007 - 05/09/2008	-0.0805	***	24/08/2007 - 15/05/2009	0.0448	***	19/03/1999 - 09/07/1999	-0.1037	***	08/11/2002 - 29/11/2002	-0.0623	***	08/01/1999	-0.1247	**
19/09/2008 - 03/04/2009	-0.1858	***	*Outliers*			20/05/2005 - 19/09/2008	-0.1385	***	14/02/2003 - 20/06/2003	-0.0190	***	...		
10/04/2009 - 18/09/2009	-0.0686	***	01/01/1999	0.1132	***	26/09/2008 - 02/01/2009	-0.2525	***	17/08/2007 - 01/02/2008	-0.0207	***	16/12/2011	-0.7230	***
12/08/2011 - 23/12/2011	-0.0628	***	26/03/1999	0.0267	***	09/01/2009 - 15/05/2009	-0.1326	***	14/03/2008 - 21/03/2008	-1.3015	***	*Constant*	0.8304	***
Outliers			18/06/1999	0.0387	***	12/08/2011 - 25/11/2011	-0.1176	***	04/04/2008 - 24/04/2009	-0.0313	***			
22/01/1999	-0.0803	***	02/03/2001	-0.0931	***	*Outliers*			05/06/2009 - 27/11/2009	-0.0204	***			
22/10/1999	-0.0574	***	28/09/2001	-0.0413	***	22/01/1999	-0.0871	**	14/05/2010 - 29/07/2011	-0.0311	***			
21/04/2000	-0.0419	***	05/10/2001	-0.0386	***	14/01/2000	-0.1109	***	12/08/2011 - 19/08/2011	-1.2619	***			
15/09/2000	0.0415	***	15/03/2002	0.0367	***	07/04/2000	-0.1090	***	26/08/2011 - 16/12/2011	-0.0321	***			
10/11/2000	0.0403	***	09/03/2007	-0.0312	***	09/03/2001	-0.2604	***	*Outliers*					
08/12/2000	0.0493	***	17/07/2009	-0.0435	***	16/03/2001	0.1068	***	18/06/1999	-0.0142	***			
05/01/2001	0.0440	***	14/08/2009	-0.0267	***	*Constant*	0.7349	***	30/07/1999	-0.0134	***			
02/08/2002	-0.0440	***	12/03/2010	-0.0257	***				17/09/1999	0.0157	***			
01/08/2003	0.0403	***	14/05/2010	-0.0460	***				08/10/1999	-0.0175	***			
Constant	0.8276	***	21/05/2010	-0.0336	***				12/01/2001	-0.0233	***			
			20/08/2010	0.0271	***				10/08/2001	-0.0259	***			
			08/04/2011	-0.0345	***				28/12/2001	-0.0165	***			
			15/04/2011	-0.0522	***				08/02/2002	-0.0148	***			
			26/08/2011	0.0293	***				27/06/2003	-1.2770	***			
			23/09/2011	0.0290	***				28/03/2008	-0.2650	***			
			11/11/2011	0.0305	***				01/05/2009	-1.0106	***			
			Constant	0.7860	***				29/05/2009	-0.2165	***			
									Constant	0.9720	***			

$\Gamma_{t,VD}^{CorpBond}$			$\Gamma_{t,VD}^{EqInd}$			$\Gamma_{t,VD}^{FX}$			$\Gamma_{t,VD}^{MoneyMkt}$			$\Gamma_{t,VD}^{GovBond}$		
Segments			*Segments*			*Segments*			*Segments*			*Segments*		
28/09/2001 - 26/10/2001	-0.1392	***	18/02/2000 - 14/04/2000	-0.1367	***	28/09/2001 - 02/11/2001	-0.1156	***	29/01/1999 - 30/04/1999	-0.0511	**	01/10/1999 - 05/05/2000	-0.0650	***
23/12/2005 - 27/01/2006	0.0485	*	12/09/2008 - 13/03/2009	0.1491	***	01/04/2005 - 15/04/2005	0.0495	*	17/12/1999 - 10/03/2000	-0.0891	***	06/12/2002 - 21/03/2003	-0.0536	***
24/08/2007 - 28/09/2007	-0.1147	***	14/05/2010 - 28/05/2010	0.1366	***	19/09/2008 - 04/12/2009	-0.1399	***	26/09/2008 - 16/01/2009	0.0540	**	31/10/2008 - 07/11/2008	0.0571	***
17/10/2008 - 31/07/2009	-0.1823	***	12/08/2011 - 10/02/2012	0.1347	***	14/05/2010 - 16/07/2010	-0.0955	***	06/02/2009 - 20/03/2009	-0.1680	***	17/04/2009 - 11/09/2009	-0.0502	***
14/05/2010 - 11/06/2010	-0.1108	***	*Constant*	0.7437	***	15/07/2011 - 17/02/2012	-0.1452	***	22/05/2009 - 29/05/2009	0.0534	**	*Outliers*		
08/07/2011 - 24/02/2012	-0.1627	***				*Outliers*			17/07/2009 - 11/09/2009	0.0525	**	29/01/1999	-0.0454	**
Outliers						14/05/1999	-0.0794	***	16/10/2009 - 20/11/2009	-0.0697	***	12/08/2011	0.0545	***
21/04/2000	-0.0857	***				18/10/2002	-0.1335	***	07/05/2010 - 03/09/2010	0.0541	**	*Constant*	0.8791	***
04/07/2003	0.0503	*				25/10/2002	-0.0899	***	*Outliers*					
12/12/2003	0.0499	*				30/07/2004	0.0523	*	15/10/1999	0.0491	**			
30/09/2005	0.0513	*				*Constant*	0.7604	***	19/09/2008	-0.0521	**			
15/02/2008	-0.0854	***							19/06/2009	-0.0690	***			
Constant	0.8623	***							08/01/2010	-0.0504	**			
									26/11/2010	-0.0522	**			
									11/11/2011	-0.0583	**			
									06/01/2012	-0.0865	***			
									13/01/2012	-0.1019	***			
									Constant	0.9401	***			

Table 3.8: **IIS results for the average comovements measures at the country level.** Γ_t^{US} is the average comovement measure within the US market, defined as the mean of the model-implied correlations between all the couples of securities in the US group. Γ_t^{EU}, Γ_t^{UK}, Γ_t^{JP} and Γ_t^{EM} are analogously defined for the other countries. Exposure-driven (middle panel) and volatility-driven (bottom panel) comovement measures consider the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time). Refer to the caption of Tab. 3.6 for a legend of the results of the estimation.

Γ_t^{US}		
Segments		
22/10/1999 - 29/10/1999	0.0576	***
04/02/2000 - 18/02/2000	0.0643	***
24/11/2000 - 22/12/2000	0.0516	***
28/09/2001 - 02/11/2001	-0.0532	***
19/07/2002 - 27/09/2002	0.0568	***
24/08/2007 - 26/09/2008	0.0566	***
03/10/2008 - 19/12/2008	0.1524	***
02/01/2009 - 16/07/2010	0.0545	***
Outliers		
08/08/2003	-0.0515	***
Constant	-0.1399	***

Γ_t^{EU}		
Outliers		
27/06/2008	-0.2400	**
05/12/2008	0.2282	**
19/12/2008	0.2436	**
10/07/2009	-0.2203	**
07/05/2010	-0.2203	**
07/01/2011	-0.2155	**
29/07/2011	0.2320	**
12/08/2011	0.2404	**
26/08/2011	0.2648	**
21/10/2011	0.2253	**
18/11/2011	0.2779	***
23/12/2011	0.2197	**
06/01/2012	0.2225	**
Constant	0.1667	***

Γ_t^{UK}		
Segments		
11/02/2000 - 21/04/2000	0.1197	***
04/07/2003 - 08/08/2003	-0.1149	***
10/10/2008 - 13/03/2009	0.1552	***
12/08/2011 - 18/11/2011	0.1079	***
Outliers		
06/11/2009	0.1012	***
16/07/2010	0.1076	***
03/12/2010	-0.0992	***
Constant	0.1988	***

Γ_t^{JP}		
Segments		
08/10/1999 - 12/05/2000	-0.2752	***
17/08/2007 - 24/07/2009	-0.3622	***
21/05/2010 - 25/06/2010	-0.2484	***
12/08/2011- 27/01/2012	-0.3288	***
Outliers		
30/05/2003	0.1582	*
16/06/2006	-0.2002	**
Constant	0.3496	***

Γ_t^{EM}		
Outliers		
22/01/1999	0.1323	***
...		
09/12/2011	0.0618	**
Constant	0.6248	***

$\Gamma_{t,ED}^{US}$		
Segments		
06/08/1999 - 08/12/2000	0.0331	***
19/07/2002 - 11/10/2002	0.0291	***
23/07/2004 - 14/04/2006	-0.0147	*
17/08/2007 - 05/09/2008	0.0436	***
12/09/2008 - 30/01/2009	0.0766	***
06/02/2009 - 17/07/2009	0.0447	***
12/08/2011 - 09/03/2012	0.0331	***
Outliers		
11/06/2010	0.0252	**
03/12/2010	0.0275	***
Constant	-0.1457	***

$\Gamma_{t,ED}^{EU}$		
Outliers		
13/08/1999	-0.2253	**
04/02/2000	-0.2319	**
03/03/2000	-0.2266	**
14/04/2000	-0.2216	**
23/06/2000	-0.2245	**
23/02/2001	-0.2252	**
07/06/2002	-0.2163	**
11/10/2002	-0.2222	**
07/03/2003	-0.2263	**
23/07/2004	-0.2145	**
20/08/2004	-0.2269	**
08/04/2005	-0.2288	**
Constant	0.1805	***

$\Gamma_{t,ED}^{UK}$		
Outliers		
01/01/1999	0.0567	***
...		
01/10/2010	-0.0249	***
Constant	0.1989	***

$\Gamma_{t,ED}^{JP}$		
Segments		
27/08/1999 - 02/06/2000	-0.2321	***
17/08/2007 - 10/07/2009	-0.3365	***
12/08/2011 - 20/01/2012	-0.2486	***
Outliers		
12/03/2004	0.2703	***
04/02/2005	0.1355	*
27/05/2005	0.1404	*
08/07/2005	0.1449	*
Constant	0.3521	***

$\Gamma_{t,ED}^{EM}$		
Outliers		
22/01/1999	0.1545	***
...		
21/10/2011	0.1071	***
Constant	0.6273	***

$\Gamma_{t,VD}^{US}$		
Segments		
28/09/2001 - 19/10/2001	-0.0484	***
26/07/2002 - 20/09/2002	0.0451	***
20/06/2008 - 25/09/2009	-0.0365	***
19/11/2010 - 17/12/2010	-0.0336	**
19/08/2011 - 09/03/2012	-0.0377	***
Constant	-0.1346	***

$\Gamma_{t,VD}^{EU}$		
Segments		
27/06/2003 - 08/08/2003	-0.0716	**
23/01/2004 - 01/10/2004	-0.0565	*
17/10/2008 - 26/12/2008	0.1748	***
02/01/2009 - 23/07/2010	0.1044	***
08/07/2011 - 27/01/2012	0.1300	***
Outliers		
31/08/2007	0.0796	**
Constant	0.2112	***

$\Gamma_{t,VD}^{UK}$		
Segments		
04/07/2003 - 08/08/2003	-0.1111	***
17/10/2008 - 20/03/2009	0.1308	***
06/11/2009 - 13/11/2009	0.0826	**
02/07/2010 - 16/07/2010	0.0863	**
12/08/2011 - 11/11/2011	0.1050	***
Outliers		
20/06/2008	-0.0976	***
03/12/2010	-0.0978	***
Constant	0.1994	***

$\Gamma_{t,VD}^{JP}$		
Segments		
20/06/2003 - 27/02/2004	0.1288	***
17/10/2008 - 19/12/2008	-0.1532	***
19/11/2010 - 14/01/2011	0.1434	***
12/08/2011 - 18/11/2011	-0.1162	***
Constant	0.2815	***

$\Gamma_{t,VD}^{EM}$		
Segments		
23/04/1999 - 04/06/1999	0.0683	***
30/07/1999 - 20/08/1999	-0.0542	***
26/01/2001 - 02/11/2001	0.0680	***
05/07/2002 - 01/11/2002	0.0660	***
07/05/2004 - 21/05/2004	0.0519	***
24/08/2007 - 14/09/2007	0.0688	***
18/04/2008 - 31/10/2008	0.0479	***
12/08/2011 - 11/11/2011	0.0505	***
Outliers		
29/09/2000	0.0593	***
Constant	0.6394	***

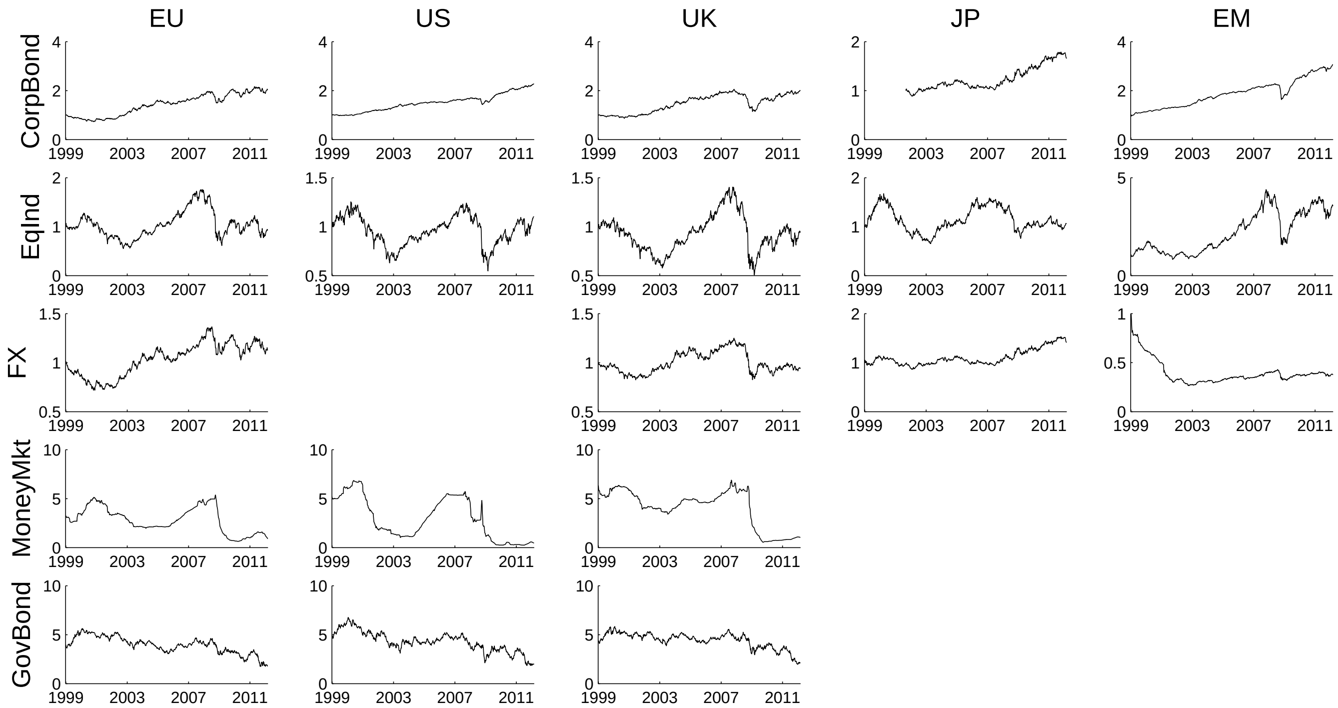


FIGURE 3.1: **Price data used in the empirical application.** We plot the weekly price series for the considered markets. Asset classes are displayed in the rows, whereas countries are in the columns. Corporate bond, equity indices and foreign exchange rates (top three rows) are rebased using the first available observation. US foreign exchange is excluded from the analysis because is used as the numeraire. The other missing series are not considered due to lack of data.

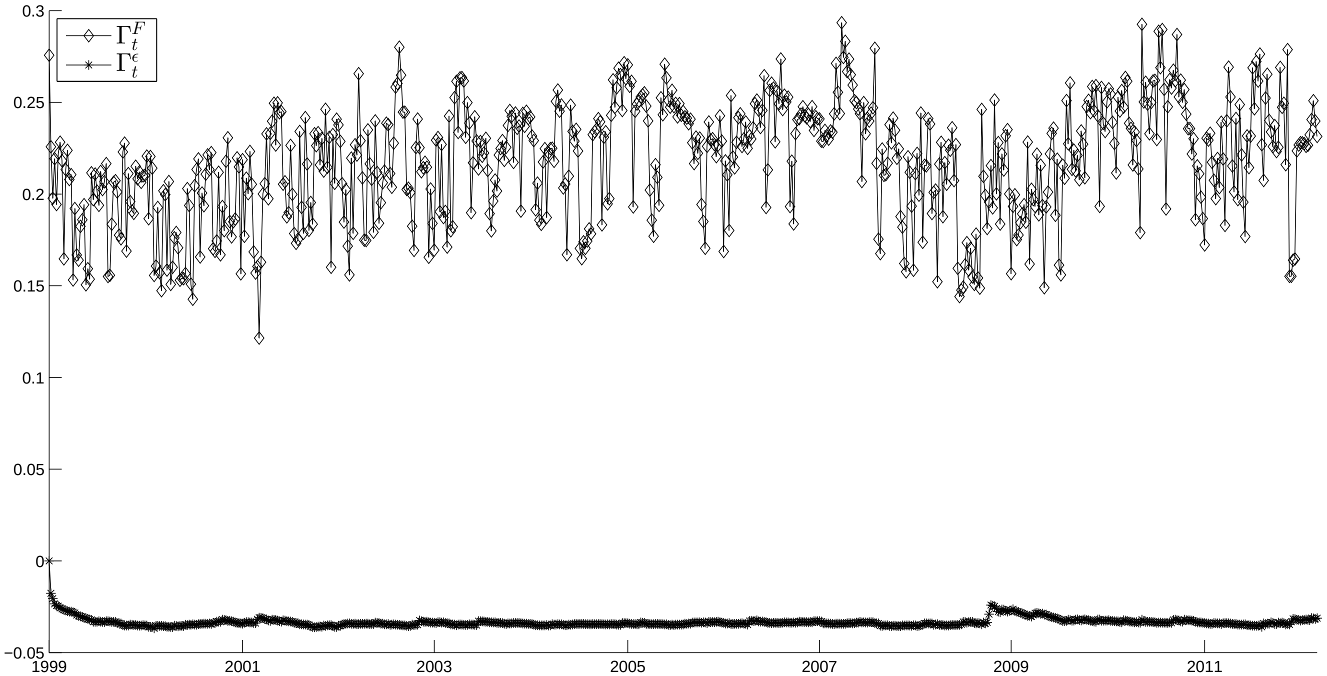


FIGURE 3.2: **Model-implied versus residual average correlation measures.** Γ_t^F is the average comovement measure at the overall level, defined as the mean of the model-implied correlations between all the couples of asset considered. Γ_t^ϵ is the average residual comovement measure, defined as the mean of the correlations between the error term in the model for all the couples of asset considered.

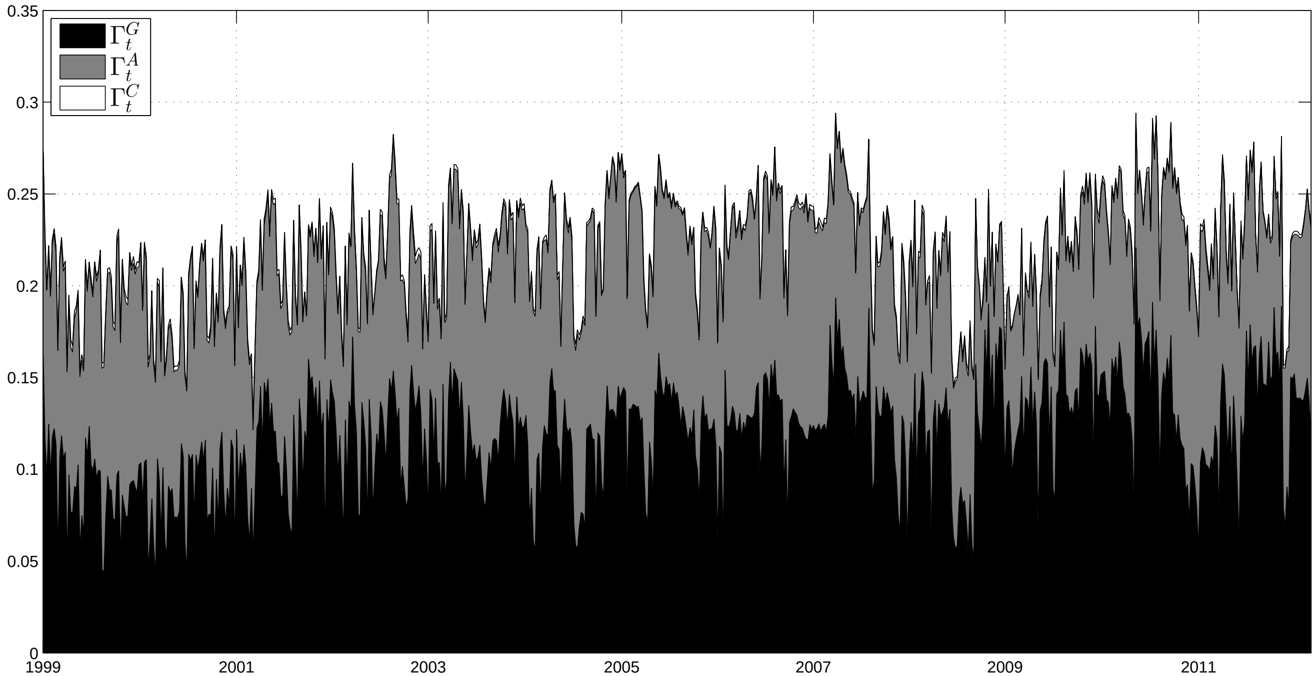


FIGURE 3.3: **Decompositions of the overall average comovements by source of the shock.** Γ_t^G, Γ_t^A Γ_t^C are the average measures of comovement prompted by the global, the asset class and the country factor, respectively.

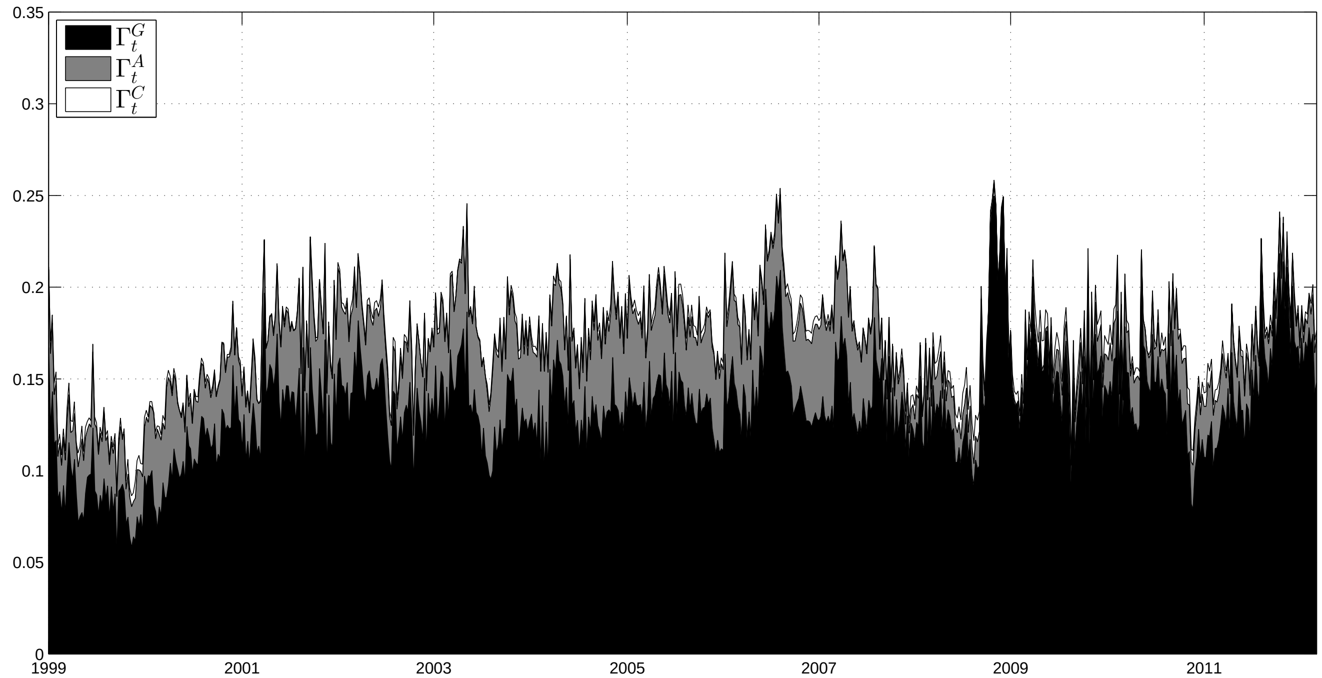


FIGURE 3.4: **Robustness check of the decomposition by source.** Fig. 3.3 reports the decompositions of the overall average comovements by source of the shock, for the case in which the asset class factors are first orthogonalized with respect to the global factor and then the country factors are orthogonalized with respect to the asset class and the global factors. Here we report the same decomposition for the case in which the country factors are orthogonalized with respect to the global factor and then the asset class factors are orthogonalized with respect to the others.

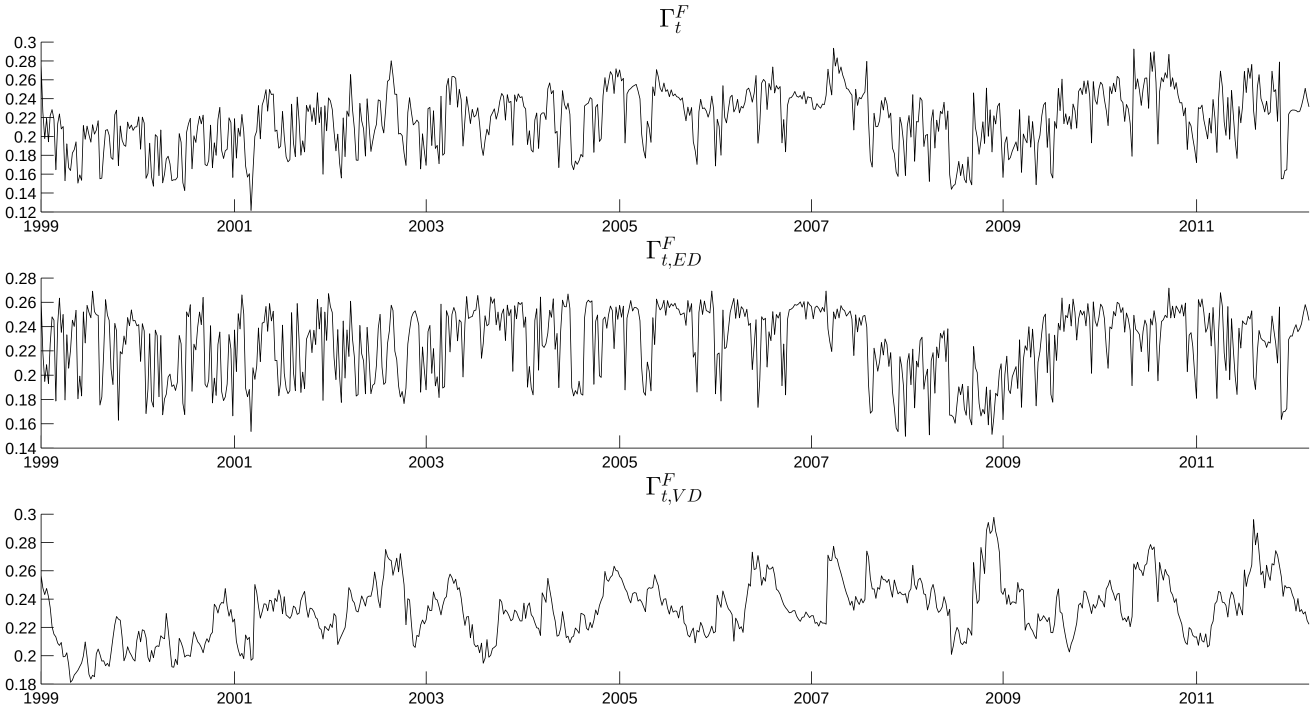


FIGURE 3.5: **Average correlation measures.** Γ_t^F (top panel) is the average comovement measure at the overall level, defined as the mean of the model-implied correlations between all the couples of asset considered. $\Gamma_{t,ED}^F$ -mid panel- ($\Gamma_{t,VD}^F$ -bottom panel-) considers the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time).

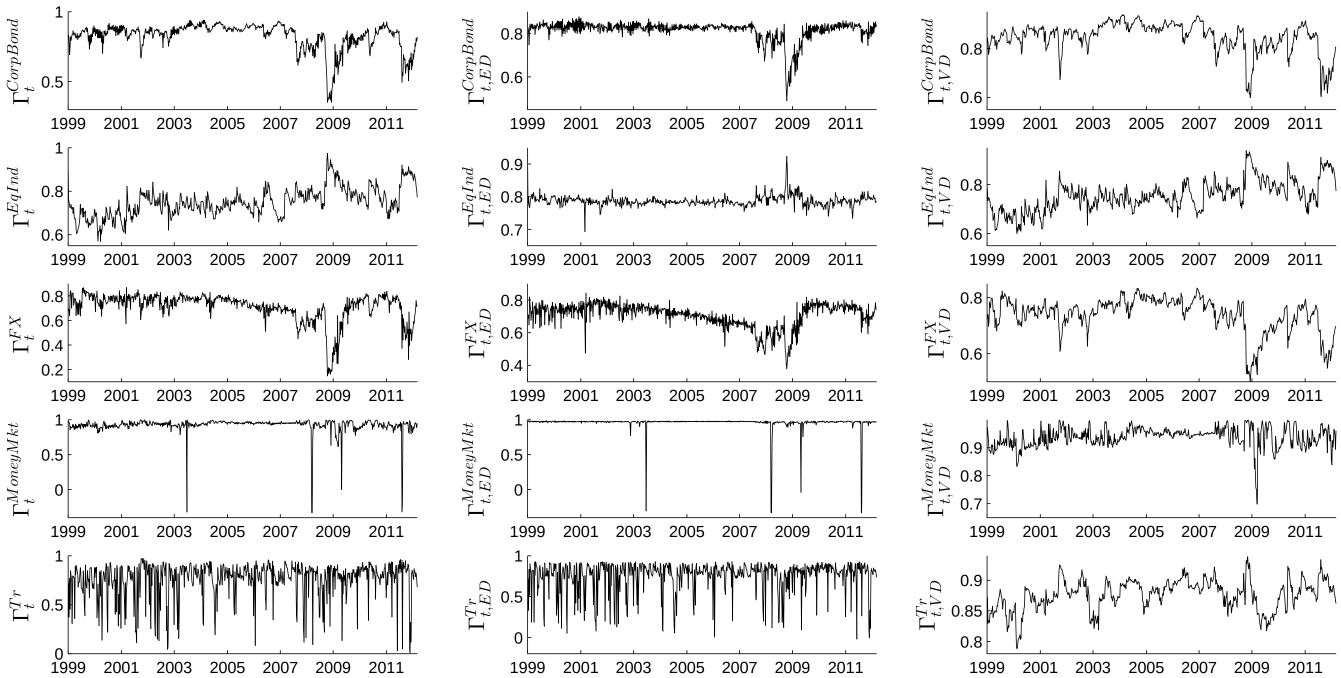


FIGURE 3.6: **Average correlation measures at the asset class level.** $\Gamma_t^{CorpBond}$ is the average comovement measure within the corporate bond market, defined as the mean of the model-implied correlations between all the couples of securities in the corporate bond asset class. Γ_t^{EqInd}, Γ_t^{FX}, $\Gamma_t^{MoneyMkt}$ and $\Gamma_t^{GovBond}$ are analogously defined for the other asset classes. Exposure-driven (second column) and volatility-driven (third column) comovement measures consider the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time).

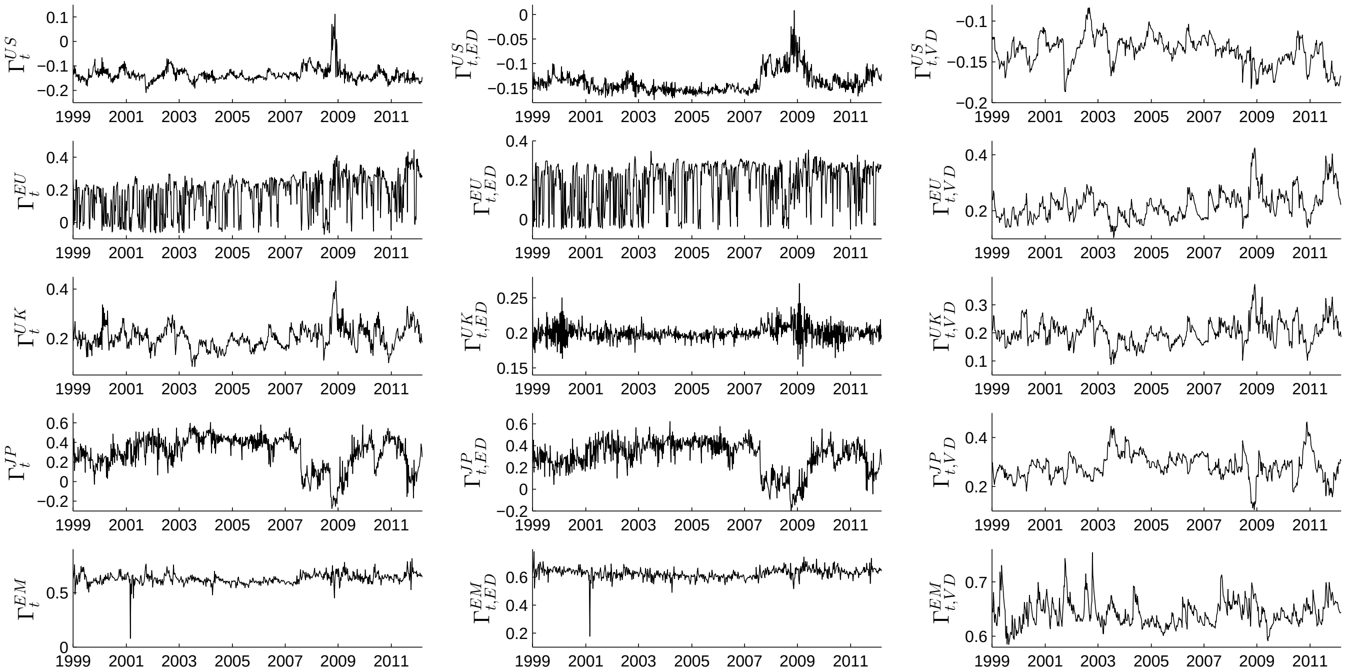


FIGURE 3.7: **Average correlation measures at the country level.** Γ_t^{US} is the average comovement measure within the US market, defined as the mean of the model-implied correlations between all the couples of securities in the US group. Γ_t^{EU}, Γ_t^{UK}, Γ_t^{JP} and Γ_t^{EM} are analogously defined for the other countries. Exposure-driven (second column) and volatility-driven (third column) comovement measures consider the correlations for the case in which factor exposures are allowed to vary with time (held at constant) and factor covariances are held at constant (allowed to vary with time).

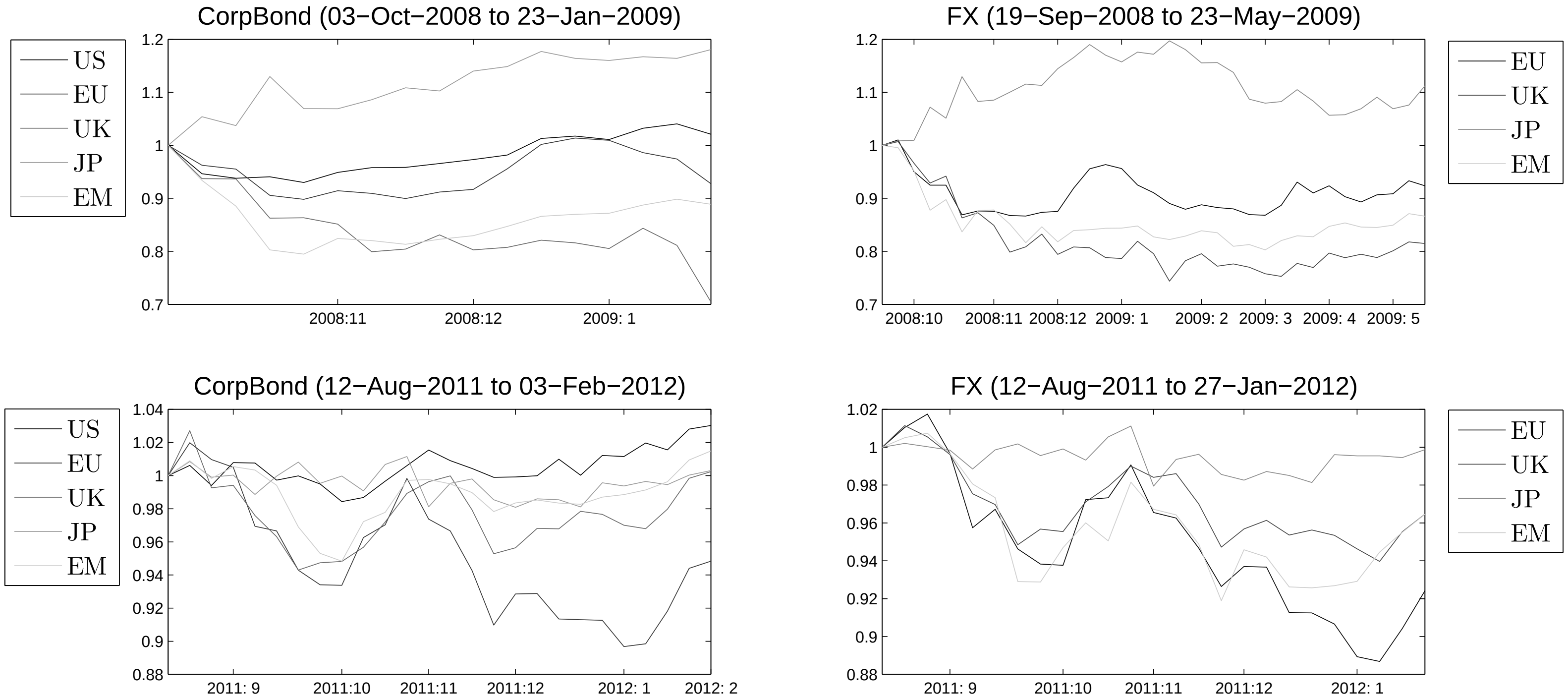


FIGURE 3.8: **Comparison among selected securities during the detected regimes.** We report corporate bond and foreign exchange price levels for periods in which de-correlation was detected. The price are rebased using the first observation in each subperiod.

List of Symbols

i	index for the i-th asset class with $i = 1, \dots, I$
j	index for the j-th country with $j = 1, \dots, J$
t	time index
$R_t^{i,j}$	weekly return for the asset belonging to asset class i and county j
$F_t^{i,j}$	three-dimensional row vector containing the global factor, the i-th asset class factor and the j-th country factor at time t
Z_t	factor controlling for period of market distress
$\epsilon_t^{i,j}$	idiosyncratic term for asset class i and county j
$\beta_t^{i,j}$	three-dimensional column vector of dynamic factor loadings
$\beta^{i,j}$	long-run value of $\beta_t^{i,j}$
$\phi^{i,j}$	three-dimensional column vector of parameters for the dynamics of $\beta_t^{i,j}$
$\psi^{i,j}$	three-dimensional column vector of parameters referred to the conditional variable Z_t in the specification of $\beta_t^{i,j}$
$u_t^{i,j}$	error term in the model for $\beta_t^{i,j}$
$\Sigma_{F,t}^{i,j}$	time-varying variance-covariance matrix of the factors $F_t^{i,j}$
G_t	global factor
A_t^i	i-th asset class factor
C_t^j	j-th country factor
$\gamma_t^{i,j}$	factor loading mapping from the global factor G_t onto $R_t^{i,j}$
$\delta_t^{i,j}$	factor loading mapping from the asset class factor A_t^i onto $R_t^{i,j}$
$\lambda_t^{i,j}$	factor loading mapping from the country factor C_t^j onto $R_t^{i,j}$
K	number of variables from which the factors are extracted
T	number of observations
$r_t^{i,j}$	demeaned counterpart of $R_t^{i,j}$
$\mathbf{r}$	matrix containing the demeaned returns $r_t^{i,j}$

$\mathbf{r^i}$	matrix containing the columns of $\mathbf{r}$ referred to asset class i
$\mathbf{r^j}$	matrix containing the columns of $\mathbf{r}$ referred to country j
$\Sigma_{\mathbf{r}}$	variance-covariance matrix of $\mathbf{r}$
$\Sigma_{\mathbf{r^i}}$	variance-covariance matrix of $\mathbf{r^i}$
$\Sigma_{\mathbf{r^j}}$	variance-covariance matrix of $\mathbf{r^j}$
l_k	k-th eigenvalue of the covariance matrix $\Sigma_{\mathbf{r}}$ with $k = 1, \ldots, K$
$\mathbf{w_k}$	eigenvector referred to the k-th eigenvalue of the covariance matrix $\Sigma_{\mathbf{r}}$ with $k = 1, \ldots, K$
$\mathbf{w_1^i}$	eigenvector corresponding to the largest eigenvalue of the covariance matrix $\Sigma_{\mathbf{r^i}}$
$\mathbf{w_1^j}$	eigenvector corresponding to the largest eigenvalue of the covariance matrix $\Sigma_{\mathbf{r^j}}$
$\mathcal{F}_t$	information set at time t
X_t	set of conditional variables in the general formulation of the model for the factor loadings
H_0'	null hypothesis in Eq. (3.11)
H_0''	null hypothesis in Eq. (3.13)
$\beta^{i,j,s}$	factor loading referred to subsample s with $s = 1, \ldots, S$
$\mathbf{A_t}$	matrix containing the asset class factors
$\mathbf{C_t}$	matrix containing the country factors
n	index referred to the n-th market for $n = 1, \ldots, N$
$\mathcal{I}_i$	set of indices from the sequence $n = 1, \ldots, N$ referred to markets belonging to asset class i
$\mathcal{J}_j$	set of indices from the sequence $n = 1, \ldots, N$ referred to markets belonging to country j
$var_{n,t}$	model-implied variance of the n-th market at time t
$cov_t(R^{n_1}, R^{n_2})$	covariance between asset n_1 and asset n_2 (for $n_1 \neq n_2$) at time t
$cov_{n_1,n_2,t}$	*ibidem*

$cov^F_{n_1,n_2,t}$	model-implied covariance
$cov^\epsilon_{n_1,n_2,t}$	residual covariance
$cov^G_{n_1,n_2,t}$	covariance prompted by the global factor
$cov^A_{n_1,n_2,t}$	covariance prompted by the asset class factors
$cov^C_{n_1,n_2,t}$	covariance prompted by the country factors
$cov^F_{n_1,n_2,t,ED}$	model-implied covariance triggered by exposure to common factors
$cov^F_{n_1,n_2,t,VD}$	model-implied covariance triggered by factor volatility
$corr^F_{n_1,n_2,t}$	model-implied correlation
$corr^\epsilon_{n_1,n_2,t}$	residual correlation
$corr^G_{n_1,n_2,t}$	correlation prompted by the global factor
$corr^F_{n_1,n_2,t,ED}$	model-implied correlation triggered by exposure to common factors
$corr^F_{n_1,n_2,t,VD}$	model-implied correlation triggered by factor volatility
Γ^F_t	average measure of model-implied comovements
Γ^ϵ_t	average measure of residual comovements
Γ^G_t	average measure of comovement prompted by the global factor
Γ^A_t	average measure of comovement prompted by the asset class factors
Γ^C_t	average measure of comovement prompted by the country factors
Γ^i_t	average measure of model-implied comovements for asset class i
Γ^j_t	average measure of model-implied comovements for country j
$\Gamma^F_{t,ED}$	average measure of model-implied comovements triggered by exposure to common factors
$\Gamma^F_{t,VD}$	average measure of model-implied comovements triggered by factor volatility
$\Gamma^i_{t,ED}$	average measure of model-implied comovements triggered by exposure to common factors for asset class i
$\Gamma^i_{t,VD}$	average measure of model-implied comovements triggered by factor volatility for asset class i

$\Gamma^j_{t,ED}$	average measure of model-implied comovements triggered by exposure to common factors for country j
$\Gamma^j_{t,VD}$	average measure of model-implied comovements triggered by factor volatility for country j
Σ^{n_1,n_2}_F	covariance matrix between F^{n_1} and F^{n_2}
$\Sigma^{n_1,n_2}_{F,t}$	time-varying counterpart of Σ^{n_1,n_2}_F
$\Sigma_{G,t}$	time-varying variance of the global factor G_t
$\Sigma^{n_1,n_2}_{A,t}$	time-varying covariance between $A^{i_1}_t$ and $A^{i_2}_t$ where i_1 and i_2 are the asset-class indices for markets n_1 and n_2 respectively
$\Sigma^{n_1,n_2}_{C,t}$	time-varying covariance between $C^{j_1}_t$ and $C^{j_2}_t$ where j_1 and j_2 are the country indices for markets n_1 and n_2 respectively
μ	constant in the regression used for break detection
η_t	error term in the regression used for break detection

Conclusions and Further Research

The main goal of this work was to contribute to the timely debate about the consequences of the materialization of financial instability on the soundness of the financial and the economic system. We developed a modelling framework to assess the degree of financial tension in the system and to gather early-warning signals of future systemic threats. We offered an in-depth dissection of the recent crisis periods together with an analysis of the orientation of the macro-prudential and stabilization policies adopted by Central Banks during this prolonged period of economic stress.

In Chapter 1, systemic risk is defined as the risk of a multiple default of large financial institutions and sovereign entities. For the sake of systemic risk assessment, an estimator for the joint default probability of multiple entities has been proposed. Pairwise default probabilities are bootstrapped from market data and then the single defaults are correlated through their common dependence on the financial macro-cycle, by means of a credit risk model with a factor model structure. This toolkit has been applied to the recent EU sovereign debt crisis, to find evidence of increasing systemic risk and danger of contagion from as early as 2007 and more significantly from late 2011 onwards. The estimates show to be very reactive to changes in market conditions and their magnitude is coherent with what found by Radev (2012) and Zhang et al. (2012). The forecasting power of the proposed estimates has been validated through an out-of-sample comparison with the dynamics of the EuroStoxx50, which epitomized the different phases of the recent sovereign debt crisis.

In spite of its predicting capability, the indicator presented in Chapter 1 do not consider signals from the real side of the economy, as the impact of the macroeconomic outlook is assessed only a-posteriori. However, the joint treatment of financial markets' and economic cycle's information to measure systemic risk appears a requirement for policy makers and global institutions alike: indeed recent crises show the limits of risk models for the financial crisis which neglect the economic cycle. Thus, in Chapter 2, we proposed a comprehensive indicator of global systemic risk, which integrates the dynamics of international financial markets with signals emerging from the economic cycle. The accuracy of the proposed indicator at peaking up episodes of financial instability has been validated on the basis of the crisis events occurred in the 1995-2011 time span. The other main contribution of Chapter 2 is the study of the reactions of monetary policy makers to systemic threats. There is evidence that the Bank of England and the Fed in particular, boldly reacted to the materialization of financial instabilities throughout the past two decades. On the contrary, the ECB showed a greater degree of commitment to its anti-inflationary mandate than to the goal of addressing financial instability, with the only exception of the recent period of economic and financial turmoil.

The update of the indicator proposed in Chapter 2 showed that the great recession of 2007-2009 had a much bigger impact on the stability of the global economic and financial system, when compared to the on-going sovereign debt crisis. This extent was further investigated in Chapter 3, which studied the determinants of the comovements within the global financial market during crisis periods. For this sake, we set up a dynamic factor model in a latent multi-factor framework, which is employed to test for the presence of contagion versus excess interdependence during crisis periods. The main findings of the empirical analysis can be summarized as follows. First, the global factor is the most pervasive of the considered factors, shaping the dynamics of financial comovements through time. On the contrary, the asset class factor characterizes as the most persistent, suggesting that the structural communalities of markets belonging to the same asset class systematically contributes in a constant proportion to the average overall comovements. Secondly, we found evidence of contagion stemming from the US and the stock market jointly during the burst of the 2007-09 financial crisis. On the other hand, the currency and sovereign debt crisis originated in Europe characterized for the presence of excess interdependence from mid-2010 onwards. This let us conclude that the spillover effect observed during the 2007-09 financial crisis altered the strength of the financial linkages worldwide, resulting in a prolonged period of financial distress. On the contrary, the shock transmission experienced during the recent debt crisis has *so far* to be understood as temporary, being prompted by excess factor volatilities, which do not display trend in the long-term. Finally, at the overall average level, we did not find any evidence of contagion nor excess interdependence, since, during the crises, some of the securities considered in the study, and in particular the Japanese currency and corporate bond market, displayed a diverging dynamics as result of the unwinding of carry positions, previously built to finance risky investments.

There are a number of areas for further research. In Chapter 1, we extracted information on counterparty risk from the basis and excluded the positive values, due to manifestation of market imperfections. It would be interesting to further explore the issue and model the determinants of this phenomenon. Also, alternative less parsimonious copula functions might be worth considering once an appropriate estimation method consistent with our methodology is derived. Developments on the model to test for the forecasting capability of our indicator might also be interesting to consider. The comprehensive approach adopted in Chapter 2, which integrates information from both the real and the financial side of the economy, can be extended in an early-warning fashion, with the idea of specifying a leading indicator to guide monetary policy in preventing systemic threats. Furthermore, it will be interesting to extend the analysis to unconventional monetary policy measures as a new tool to address systemic instabilities. Finally, the findings in Chapter 3 suggest several developments. First, since most of the described market dynamics were prompted by the worsening of credit conditions, in particular for the case of the sovereign debt crisis in Europe, an interesting extension of our work would be the inclusion of credit indices in the analysis, provided the availability of the relevant data. Second, we modelled heteroscedasticity in the factors using the DCC approach. It would be interesting also to explicitly model high order moment dynamics as well as high order comovements between financial markets. Third, part of the conclusions entails the on-going sovereign debt crisis which broke out in the Euro Zone. The results might be worth reconsidering when the turmoil period will be over. Finally, it may be useful to use this model set-up to forecast financial market comovements, to support asset allocation and risk management decisions. We leave these developments to future research.

Bibliography

Acharya, V., L. Pedersen, T. Philippon, and M. Richardson, 2010, Measuring systemic risk, Working paper, Federal Reserve Bank of Cleveland.

Adrian, T., and M. K. Brunnermeier, 2011, CoVaR, Working paper, National Bureau of Economic Research.

Allen, L., and A. Saunders, 2002, A survey of cyclical effects in credit risk measurement models, Working paper, BIS.

Amadei, L., S. Di Rocco, M. Gentile, R. Grasso, and G. Siciliano, 2011, Credit default swaps: Contract characteristics and interrelations with the bond market, Discussion paper, CONSOB.

Amihud, Y., and H. Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223–249.

Anderson, T. W., 2003, *An introduction to multivariate statistical analysis* (Wiley Series in Probability and Statistics).

Andrews, D. W. K., and J. C. Monahan, 1992, An improved heteroscedasticity and autocorrelation consistent covariance matrix estimator, *Econometrica* 60, 953–966.

Arnold, R., 2004, A summary of alternative methods for estimating potential GDP, Working paper, CBO.

Bae, K.-H., G. A. Karolyi, and R. M. Stulz, 2003, A new approach to measuring financial contagion, *Review of Financial Studies* 16, 717–763.

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

Bai, J., and P. Collin-Dufresne, 2011, The determinants of the CDS-bond basis during the financial crisis of 2007-2009, Discussion paper, Netspar.

Bai, J., and S. Ng, 2002, Determining the number of factors in approximate factor models, *Econometrica* 70, 191–221.

Bai, J., and P. Perron, 1998, Estimating and testing linear models with multiple structural changes, *Econometrica* 66, 47–78.

Bandopadhyaya, A., and A. L. Jones, 2006, Measuring investor sentiment in equity markets, *Journal of Asset Management* 7, 208–215.

Bates, B., M. Plagborg-Moller, J. H. Stock, and M. W. Watson, 2012, Consistent factor estimation in dynamic factor models with structural instability, Working paper, Harvard University.

Bekaert, G., M. Ehrmann, M. Fratzscher, and A. J. Mehl, 2012, Global crises and equity market contagion, Working paper, NBER.

Bekaert, G., C. R. Harvey, and A. Ng, 2005, Market integration and contagion, *Journal of Business* 78, 39–69.

Bekaert, G., and R. J. Hodrick, 1992, Characterizing predictable components in excess returns on equity and foreign exchange markets, *Journal of Finance* 47, 467–509.

Bekaert, G., R. J. Hodrick, and X. Zhang, 2009, International stock return comovements, *Journal of Finance* 64, 2591–2626.

Billio, M., and M. Caporin, 2010, Market linkages, variance spillovers, and correlation stability: Empirical evidence of financial contagion, *Computational Statistics & Data Analysis* 54, 2443–2458.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon, 2012, Econometric measures of connectedness and systemic risk in the finance and insurance sectors, *Journal of Financial Economics* 104, 535–559.

Bisias, D., M. Flood, A. W. Lo, and S. Valavanis, 2012, A survey of systemic risk analytics, Working paper, Office of Financial Research, US Department of Treasury.

Blair, B. J., S. H. Poon, and S. J. Taylor, 2001, Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high-frequency index returns, *Journal of Econometrics* 105, 5–26.

BoE, 2009, The Banking Act 2009. URL: http://www.bankofengland.co.uk/about/Pages/legislation/legis.aspx.

BoE, 2012, What is inflation? URL: http://www.bankofengland.co.uk/monetarypolicy/Pages/framework/framework.aspx.

Bollerslev T., 1986, Generalized autoregressive conditional heteroscedasticity, *Journal of Econometrics* 31, 307–327.

Brandt, M. W., A. Brav, J. R. Graham, and A. Kumar, 2010, The idiosyncratic volatility puzzle: Time trend or speculative episodes? *Review of Financial Studies* 23, 863–899.

Brownlees, C. T., and R. F. Engle, 2012, Volatility, correlation and tails for systemic risk measurement, Working paper, Stern School of Business, New York University.

Castle, J. L., J. A. Doornik, and D. F. Hendry, 2011, Evaluating automatic model selection, *Journal of Time Series Econometrics* 3, Article 8.

Castle, J. L., J. A. Doornik, and D. F. Hendry, 2012, Model selection when there are multiple breaks, *Journal of Econometrics* 169, 239–246.

Chen, L., D. A. Lesmond, and J. Wei, 2007, Corporate yield spreads and bond liquidity, *Journal of Finance* 62, 119–149.

Cherubini, U., S. Mulinacci, F. Gobbi, and S. Romagnoli, 2011, *Dynamic Copula Methods in Finance* (Wiley Finance Series).

Cousin, A., D. Dorobantu, and D. Rullière, 2012, An extension of Davis and Lo's contagion model, *Quantitative Finance* 13, 1–14.

Davidson, R., and J. G. MacKinnon, 2007, Improving the reliability of bootstrap tests with the fast double bootstrap, *Computational Statistics & Data Analysis* 51, 3259–3281.

Davis, M., and V. Lo, 2001, Infectious defaults, *Quantitative Finance* 1, 382–387.

De Nicoló, G., and M. Lucchetta, 2012, Systemic real and financial risks: Measurement, forecasting, and stress testing, Working paper, IMF.

De Wit, J., 2006, Exploring the CDS-bond basis, Working paper, National Bank of Belgium.

Doornik, J. A., 2009, Autometrics, in *J. L. Castle and N. Shephard, The methodology and practice of econometrics*, 88–121 (Oxford University Press).

Driessen, J., B. Melenberg, and T. Nijman, 2003, Common factors in international bond returns, *Journal of International Money and Finance* 22, 629–656.

Duffie, D., 1999, Credit swap valuation, *Financial Analysts Journal* 55, 73–87.

Dungey, M., R. Fry, B. González-Hermosillo, and V. L. Martin, 2005, Empirical modelling of contagion: a review of methodologies, *Quantitative Finance* 5, 9–24.

Dungey, M., and V. L. Martin, 2007, Unravelling financial market linkages during crises, *Journal of Applied Econometrics* 22, 89–119.

ECB, 2009, Credit default swaps and counterparty risk. URL: http://www.ecb.int/pub/pdf/other/creditdefaultswapsandcounterpartyrisk2009en.pdf.

ECB, 2011, The mission of the Eurosystem. URL: http://www.ecb.int/ecb/orga/escb/html/mission_eurosys.en.html.

Ehrmann, M., M. Fratzscher, and R. Rigobon, 2011, Stocks, bonds, money markets and exchange rates: Measuring international financial transmission, *Journal of Applied Econometrics* 26, 948–974.

Engle, R. F., 2002, Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroscedasticity models, *Journal of Business & Economic Statistics* 20, 339–350.

Engle, R. F., T. Ito, and L. Wen-Ling, 1990, Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market *Econometrica* 58, 525–542.

Fama, E. F., and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fed, 1917, Federal Reserve Act. URL: http://www.federalreserve.gov/aboutthefed/fract.htm.

Fontana, A., and M. Scheicher, 2010, An analysis of Euro Area sovereign CDS and their relation with government bonds, Working paper, ECB.

Forbes, K. J., and R. Rigobon, 2002, No contagion, only interdependence: Measuring stock market comovements, *Journal of Finance* 57, 2223–2261.

Fry, R., V. L. Martin, and C. Tang, 2010, A new class of tests of contagion with applications, *Journal of Business & Economic Statistics* 28, 423–437.

G10, 2001, G10 report on consolidation in the financial sector. URL: http://www.bis.org/publ/gten05.htm.

Gerlach, S., and J. Lewis, 2011, ECB reaction functions and the crisis of 2008, Discussion paper, CEPR.

Gerlach-Kristen, P., 2003, Interest rate reaction functions and the Taylor rule in the Euro Area, Working paper, ECB.

Giglio, S., 2011, Credit default swap spreads and systemic financial risk, Working paper, Harvard University.

Gnan, E., and J. C. Cuaresma, 2008, Four monetary policy strategies in comparison: how to deal with financial instability? *Monetary Policy & the Economy* 3, 65–102.

Haldane, A. G., and R. M. May, 2011, Systemic risk in banking ecosystems, *Nature* 469, 351–355.

Hayford, M. D., and A. G. Malliaris, 2005, How did the Fed react to the 1990s stock market bubble? Evidence from an extended Taylor rule *European Journal of Operational Research* 163, 20–29.

Hendry, D. F., and H.-M. Krolzig, 2005, The properties of automatic GETS modelling, *The Economic Journal* 115, C32–C61.

Hodrick, R. J., and E. C. Prescott, 1997, Postwar US business cycles: An empirical investigation, *Journal of Money, Credit and Banking* 29, 1–16.

Hollo, D., M. Kremer, and M. Lo Duca, 2012, CISS - A composite indicator of systemic stress in the financial system, Working paper, ECB.

Huang, X., H. Zhou, and H. Zhu, 2009, A framework for assessing the systemic risk of major financial institutions, *Journal of Banking & Finance* 33, 2036–2049.

Hull, J., and A. White, 2001, Valuing credit default swaps II: Modeling default correlations, *Journal of Derivatives* 8, 12–29.

IMF, 2009, Global financial stability report – Responding to the financial crisis and measuring systemic risks. URL: http://www.imf.org/external/pubs/ft/gfsr/2009/01/.

ISDA, 2012, ISDA Margin Survey. URL: http://www2.isda.org/functional-areas/research/surveys/margin-surveys/.

Jarrow, R. A., and S. M. Turnbull, 1995, Pricing derivatives on financial securities subject to credit risk, *Journal of Finance* 50, 53–85.

Jobst, A. A., and D. Gray, 2013, Systemic contingent claims analysis – Estimating market-implied systemic risk, Working paper, IMF.

Judd, J. P., and G. D. Rudebusch, 1998, Taylor's rule and the Fed: 1970-1997, *Economic Review – Federal Reserve Bank of San Francisco* 3, 3–16.

Karolyi, G. A., 2003, Does international financial contagion really exist? *International Finance* 6, 179–199.

King, M. A., and S. Wadhwani, 1990, Transmission of volatility between stock markets, *Review of Financial Studies* 3, 5–33.

Kumar, M. S., and A. Persaud, 2002, Pure contagion and investors shifting risk appetite: Analytical issues and empirical evidence, *International Finance* 5, 401–436.

Kurozumi, E., 2002, Testing for stationarity with a break, *Journal of Econometrics* 108, 63–99.

Lehar, A., 2005, Measuring systemic risk: A risk management approach, *Journal of Banking & Finance* 29, 2577–2603.

Longin, F., and B. Solnik, 2001, Extreme correlation of international equity markets, *Journal of Finance* 56, 649–676.

Mogliani, M., 2010, Residual-based tests for cointegration and multiple deterministic structural breaks: A Monte Carlo study, Working paper, Paris School of Economics.

O'Kane, D., and R. McAdie, 2001, Explaining the basis: cash versus default swaps, *Lehman Brothers Structured Credit Research* 5, 78–79.

Palladini, G., and R. Portes, 2011, Sovereign CDS and bond pricing dynamics in the Euro Area, Working paper, NBER.

Pesaran, M. H., and A. Pick, 2007, Econometric issues in the analysis of contagion, *Journal of Economic Dynamics & Control* 31, 1245–1277.

Radev, D., 2012, Systemic risk, banking and sovereign debt in the Euro Area, Discussion paper, Gutenberg School of Management and Economics.

Ravn, M. O., and H. Uhlig, 2002, On adjusting the Hodrick-Prescott filter for the frequency of observations, *Review of Economics and Statistics* 84, 371–376.

Ross, S. A., 1976, The arbitrage theory of capital asset pricing, *Journal of Economic Theory* 13, 341–360.

Schönbucher, P. J., 2001, Factor models: Portfolio credit risks when defaults are correlated, *Journal of Risk Finance* 3, 45–56.

Schwaab, B., S. J. Koopman, and A. Lucas, 2011, Systemic risk diagnostics: coincident indicators and early warning signals, Working paper, ECB.

Schwert, G. W., 1989, Why does stock market volatility change over time? *Journal of Finance* 44, 1115–1153.

Segoviano, M. A., 2006, Consistent information multivariate density optimizing methodology, Working paper, London School of Economics and Political Science.

Segoviano, M. A., and C. Goodhart, 2009, Banking stability measures, Working paper, London School of Economics and Political Science.

Shim, I., 2012, Development of Asia-Pacific corporate bond and securitisation markets, Working paper, BIS.

Stock, J. H., and M. W. Watson, 1998, Diffusion indexes, Working paper, NBER.

Stock, J. H., and M. W. Watson, 2002, Forecasting using principal components from a large number of predictors, *Journal of the American Statistical Association* 97, 1167–1179.

Stock, J. H., and M. W. Watson, 2009, Forecasting in dynamic factor models subject to structural instability, in *J. L. Castle and N. Shephard, The methodology and practice of econometrics*, 173–205 (Oxford University Press).

Taylor, J. B., 1993, Discretion versus policy rules in practice, in *Carnegie-Rochester conference series on public policy*, 195–214.

Trapp, M., 2009, Trading the bond-CDS basis: The role of credit risk and liquidity, Working paper, Centre for Financial Research - University of Cologne.

Wilmot, J., P. Mielczarski, and J. Sweeney, 2004, Global risk appetite index, Working paper, Credit Suisse First Boston.

Zhang, X., B. Schwaab, and A. Lucas, 2012, Conditional probabilities and contagion measures for Euro Area sovereign default risk, Working paper, Tinbergen Institute.