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Financial Spillover and Contagion Risks in the Euro Area in 2007-2019

Roman Garcia, Dimitri Lorenzani, Daniel Monteiro, Francesco Perticari, Bořek Vašíček and Lukas Vogel

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Abstract

This paper analyses empirically the main direct and indirect transmission channels of financial spillovers and contagion risks in the euro area, focusing on the sovereign-to-sovereign, sovereign-to-bank, and bank-to-bank channels. We employ correlation analysis, analysis of bank balance sheets, reduced-form models inferring the interconnectedness among agents from market data, and simulated structural models. The value added by this paper to the literature consists both in analysing the recent episodes of financial distress (until 2019), which happened after reforms of the Economic and Monetary Union (EMU) architecture were introduced in response to the euro area debt crisis, and in our reliance on complementary analytical tools ("tool kit"). Overall, the paper suggests that: (i) sovereign-to-sovereign spillover risks have weakened, arguably also due to a more limited role of redenomination risk; (ii) financial spillovers from sovereigns to banks (and vice versa) have become smaller in recent years; and (iii) the bank-to-bank transmission channel remains the most relevant in terms of financial spillovers and potential contagion. Finally, when analysing the impact of financial spillovers on the real economy, we find that higher financial risks can imply sizeable losses in terms of real GDP growth.

JEL Classification: C01, E43, G01, G21, G28.

Keywords: Spillover, financial contagion, sovereigns, banks, euro area, EU.

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CONTENTS

1. Introduction 5

2. Literature review 6

 2.1. Review of empirical methods 7

 2.2. Review of empirical results for the EU countries 8

3. Empirical analysis on spillover/contagion channels in the Euro Area 10

 3.1. Correlation analysis and redenomination risk 11

  3.1.1. Real time correlations 12

  3.1.2. Fixed-period correlation and redenomination risk 15

 3.2. Systemic & contagion risks due to interconnectedness in the banking system (CIMDO) 18

  3.2.1. Banks' distress dependence and Banking Stability Measures 20

  3.2.2. Quantifying systemic risk losses 24

 3.3. Banks' credit exposures and the SYMBOL model 26

  3.3.1. EBA data on the credit exposures of EA banks 26

  3.3.2. SYMBOL model simulations 29

 3.4. Macroeconomic effects of elevated financial risk 30

4. Conclusions 34

REFERENCES 36

LIST OF TABLES

3.1. Comparison of empirical models used in this paper 10

3.2. Real-time heatmap (focus on sovereign-to-sovereign and sovereign-to-banks channels) 12

3.3. Real-time heatmap (focus on bank-to-bank channel) 14

3.4. Fixed-period correlations (sovereign-to-sovereign, sovereign-to banks and bank-to-bank) 15
3.5. Distress Dependence Matrix 23
3.6. Credit exposures of EA-16 banking sectors to EA-19 sovereigns 27
3.7. Credit exposures of EA-16 banking sectors to the private sector of EA-19 Member States 27
3.8. QUEST simulations on the macroeconomic effects of strong financial contagion 32
3.9. QUEST simulations on macroeconomic effects of moderate financial contagion 33

LIST OF GRAPHS

3.1. Correlation between different asset classes 13
3.2. Correlation between selected banks 14
3.3. Quanto-based measure of redenomination risk (3M mov. avg.) 17
3.4. ISDA-based measure of redenomination risk.. 17
3.5. Comparison of sovereign spreads and ISDA-based measure of redenomination risk 18
3.6. Total assets of selected banking institutions over time 20
3.7. Share of sample in EU total bank assets over time 20
3.8. Relative size of selected institutions in the portfolio over time (as % of portfolio size) 20
3.9. Banking Stability Index & Joint Probability of Distress (Q1 2015-Q1 2019) 22
3.10. MSRC of all financial institutions of the sample 24
3.11. MCSR and relative size of financial institutions as of Q4 2018 24
3.12. Relative Systemic Risk Losses over time 26
3.13. Systemic risk losses for Q4 2018 in absolute terms 26
3.14. Largest cross-border counterpart Member State for private sector bank exposures 28
3.15. Largest cross-border exposures to Member States' private sectors: top banks 28
3.16. Credit exposures of EA banking sectors to the Italian private sector 28
3.17. Exposures of non-Italian banks to the Italian private sector 28
3.18. Excess losses from shocks to Italian banks and sovereign 29
3.19. Excess losses from shocks to periphery banks and sovereigns, with origin in Italy 29
3.20. QUEST simulations on the macroeconomic effects of strong financial contagion 32
3.21. QUEST simulations on macroeconomic effects of moderate financial contagion 33

LIST OF BOXES

4.1. CIMDO (Goodhard and Segoviano, 2009) 20

1. INTRODUCTION

Today's financial system is complex and capillary. Market interlinkages among its participants can magnify sector-specific losses and lead to (potentially systemic) cross-border effects, like financial spillover and contagion. The term "financial spillover" is commonly understood as a situation in which developments in one market, especially with regard to asset prices, are transmitted to other markets. The term "contagion", by contrast, is employed in a narrower sense, indicating the spread of market disturbances across sectors or regions in the absence of interlinkages through economic fundamentals (Dornbusch et al., 2000). Both spillovers and contagion can have an intra-country and an inter-country dimension. The intra-country dimension relates to the transmission of financial shocks among different domestic economic agents or sectors (e.g. government sector, banks, non-financial corporations, households). The inter-country dimension refers to the propagation of a shock from one country to another (e.g. from one sovereign bond market to another). Financial spillovers are an inherent component of the interlinked and integrated financial system, while contagion has an unambiguously negative connotation and is often associated with financial turmoil. The economic literature shows the empirical relevance of these phenomena, with the initial focus on emerging market countries gradually shifting towards advanced economies. The global financial crisis of 2007-2008 and the euro area debt crisis of 2010-2012 have brought financial spillovers/contagion back to the centre-stage of the economic policy debate also in Europe.

Interconnectedness is an inherent feature of the financial system, which can generate benefits and costs. Namely, linkages between financial institutions allow for more efficient channelling of funds from savers to borrowers and increase opportunities for risk sharing within the private sector. Interconnectedness can also be seen as a sign of diversification in financial intermediation. Cross-border financial linkages support the development of deeper and more efficient financial markets with a better allocation of capital to projects and businesses, which contributes to more sustainable economic growth. On the other hand, interconnectedness provides a basis for financial spillovers or contagion, which contributes in turn to systemic risks. In this regard, interconnectedness facilitates the propagation of financial shocks across markets and borders, with potentially significant economic losses.

Notwithstanding the global dimension of financial markets, the present analysis contributes to the academic and policy debate by focussing on the transmission channels of financial spillovers and contagion within the EU, and the euro area in particular. The focus on the euro area is justified by the latter's experience with spillover during the past decade and by the role that spillover and contagion play in the ongoing debate on economic resilience and convergence within the EMU. The analysis takes into account *direct* and *indirect* transmission channels for financial spillover and contagion risks. The direct transmission channels refer primarily to contractual and financial exposure, through different types of financial instruments, towards governments, banks, non-bank financial institutions, and corporate entities. Due to data limitations, the analysis of direct channels draws mostly on banks' credit exposure, based on banks' balance sheet data, and specific cross-border risk exposure across the banking system. The indirect transmission channels cover those channels that are not directly linked to existing exposures, but rather related to common risk factors and market price channels in equity and fixed income markets.

Overall, taking into account the features of financial markets in large EU Member States, including their size and systemic relevance, their interconnectedness, and the level of sovereign exposure of banks' balance sheets, this paper considers three main stylised transmission channels of financial spillover and contagion risks: (*i*) sovereign bond price co-movements (*sovereign-to-sovereign channel*); (*ii)* feedback loops between sovereigns and banks, and vice versa (*sovereign-to-bank channel*); and (*iii)* banks' credit default swaps (CDS) co-movements and their exposure to other banks' balance sheets (*bank-to-bank channel*). This analysis covers the entire euro area but often uses as an example the experience of specific Member States with financial spillover and contagion risks through one or more of the aforementioned transmission channels. For instance, Italy was subject to sovereign funding pressures during the euro area debt crisis as well as, more recently, in 2018. Future research could usefully try to analyse the impact of the pandemic on financial spillover and contagion risks, and on the functioning of the aforementioned transmission channels. The "real economy" focus of the pandemic crisis suggests that more consideration will have to be given to non-financial corporations in general and sectoral specialisation of individual Member States in particular in the analysis of spillover and contagion.

The contribution of this paper is twofold: (*i*) it updates the existing literature, which had mostly focused on the period of the global financial crisis and euro area debt crisis, on the basis of the experience of more recent years (2015-2019), which is particularly relevant in light of the gradual implementation of the financial regulatory reform agenda in the EU and world-wide; and (*ii*) it uses four complementary analytical tools to assess financial spillovers and contagion risks in the euro area, their transmission channels, and the possible impact of financial shocks on the euro area economy at large. The tools are the following: *(a)* cross-asset price correlations are used to estimate linkages among sovereign yields, equity, CDS and banks, building correlation heatmaps and matrices for different periods, which also allows analysing redenomination risks associated with the potential exit of individual Member States from the EMU, or the risk of a break-up of the euro area as a whole; *(b)* the CIMDO model (Segoviano and Goodhart, 2009) is used to analyse financial spillovers due to interconnectedness in the banking system using market data and estimate potential capital losses derived from banking interconnectedness structures; *(c)* the SYMBOL model (De Lisa et al., 2008), calibrated to European Banking Authority data on cross-border exposure between banks and sovereigns in the euro area, is used to evaluate linkages between banks and sovereigns; and *(d)* the QUEST model (Ratto et al., 2009) is used to evaluate the macroeconomic ("real economy") effects of elevated financial risk. Based on the combined use of these tools, the paper both describes the empirical relevance of the different transmission channels and assesses potential losses from financial spillover and contagion risk in the event of adverse shocks, without the ambition of testing the presence of contagion in the narrow sense of non-fundamental spreading of financial disturbances.

The remainder of the paper is organised as follows: Section 2 provides a review of the existing empirical literature on financial spillover and contagion, including main findings for the EU countries. Section 3 proposes a combined analysis, based on the abovementioned models and empirical approaches, of the relevance of financial spillovers and contagion risk within the euro area using data and episodes until 2019. Section 4 finally draws conclusions, based on the results from the different models employed in Section 3, and elaborates on possible policy implication of this analysis.

2. LITERATURE REVIEW

The global financial crisis demonstrated that what originally appeared as relatively small and localised losses in the financial system could easily be magnified to systemic dimensions. Systemic effects have the potential to amplify moderate exogenous shocks into substantial negative financial outcomes, with large negative welfare effects. In response, policymakers thus developed an extensive macroprudential policy toolkit. At the same time, diverse analytical approaches were used to quantify potential losses to the financial systems related to contagion and spillover effects, as well as due to the feedback mechanisms between the financial sector and the macroeconomy at large. However, data constraints and the complexity of interlinkages and of the amplification mechanisms have imposed significant impediments to both researchers and policymakers.

Systemic effects are diverse and complex and can vary in nature and magnitude at different points in time. The theoretical literature has identified various causes from which systemic effects can materialise. They can result from generalised shocks that affect several entities or markets at the same time and can give rise to negative feedback loops between the macroeconomic outlook and financial sector losses (Bernanke et al., 1999; Kiyotaki and Moore, 1997; Adrian and Shin, 2014). Systemic effects can also be due to the interconnectedness among financial entities and markets. Interconnectedness can either stem from contractual obligations among financial entities (Allen and Gale, 2000; Freixas et al., 2000; Eisenberg and Noe, 2001; Bhattacharya et al., 2007), which can cause “falling dominos” that amplify initial losses, or be induced by exposures to common risk factors, asset fire sales, especially when agents’ financial positions are bound by capital or collateral constraints (Bhattacharya and Gale, 1987; Aspachs et al., 2007; Lorenzoni 2008), asset sell-offs, or information asymmetries across agents (Jacklin and Bhattacharya, 1988; Khandani and Lo, 2011). The latter type might not be evident during calm periods but could resurface in periods of high volatility. Moreover, complex and interconnected financial structures may give rise to non-linear propagation of shocks, both in terms of magnitude and speed, including to the real economy (Balke, 2000).

2.1. REVIEW OF EMPIRICAL METHODS

The literature aiming at modelling financial spillover and contagion has evolved along two main tracks. The first covers the estimation of reduced-form indices of connectedness or systemic risk using publicly available market data, typically market prices. The second approach consists of simulated models of the banking system tracking its network features.

The first group of studies aims to provide a solution to the problem of limited information, mainly by relying on market data. Those studies (e.g. Acharya et al., 2012, 2017; Billio et al., 2012; Diebold and Yilmaz, 2014), exploiting high-frequency information on co-movements of stock prices or CDS spreads, allow capturing financial institutions' interconnectedness and building systemic risk indexes in real time. Nevertheless, identifying and interpreting the underlying mechanism generating the co-movements may be difficult (Glasserman and Young, 2016), as the changes in prices only represent its outcome. Moreover, those approaches often rely on empirical models, e.g. vector autoregressions (VAR), which can handle only a limited amount of variables, e.g. cover only a small sample of banks (Alter and Beyer, 2013; Diebold and Yilmaz, 2014). Although recent innovations in estimation techniques have allowed increasing sample sizes, market data still cover only listed companies. Simulated models have incorporated network features, recreating financial interconnectedness, to integrate and embed different systemic effects (Alessandri et al., 2015; Aikman et al., 2009). These include direct contagion through interbank loan exposures (Eisenberg and Noe, 2001), the role of common exposure and fire sales externalities (Cifuentes et al., 2005), and liquidity runs (Tressel 2010). These models have been useful to understand financial contagion through different amplification mechanisms. However, in order to avoid excessive complexity, these models tend to focus on specific transmission mechanisms and omit the inclusion of simultaneous effects that are likely to play a role in the context of real systemic crises. Besides, the level of data granularity required to implement many of these models is not currently available or might be difficult to obtain for most countries. The implementation of these models is therefore complex, and they are still unable to generate contagion loss estimates of the magnitude witnessed during the global financial crisis (Elsinger et al., 2013). Nonetheless, improvements have been incorporated in more recent models (Cont and Schaanning, 2016).

Another stream of the interconnectedness literature relies on bilateral exposures and bank balance sheet-based methodologies.[1] This approach allows studying the underlying mechanism of systemic risk formation and contagion stemming from concrete features of the network: the heterogeneity of the agents, the sources of risk, and their interplay. In general, balance sheet-based studies tend to focus on a few specific channels of possible contagion risk, to better disentangle its transmission. In particular, they focus on credit risk (Eisenberg and Noe, 2001; Rogers and Veraart, 2013), funding risk (Gai and Kapadia, 2010; Gai et al., 2011; Espinoza-Vega and Sole, 2010; Caballero and Simsek, 2013; Caccioli et al., 2014; Cont and Schaanning, 2017), cross-holdings of assets and fire sales (Espinoza-Vega and Sole, 2010; Caballero and Simsek, 2013; Caccioli et al., 2014; Cont and Schaanning, 2017). These approaches are more theoretical than empirical, as they aim at providing insights into the properties of

[1] See Hüser (2015) for a summary of this literature.

the network and their implications for financial stability, rather than at constructing contagion and vulnerability indexes for a systemic risk assessment. This is partially due to the lack of a complete set of bilateral exposures. Most empirical literature tends to focus on a specific market segment (i.e. repo market). Additionally, as access to confidential supervisory data is granted at the national level, most empirical analyses tend to be country-specific. This has resulted in the lack of a comprehensive analysis of cross-border financial exposures, thereby missing bidirectional linkages with institutions outside of a country's jurisdiction[2]. The development of simulated models has recently shifted its attention to agent-based models (ABM). The latter build on the contributions of behavioural economics to better explain the microeconomic behaviour of agents in financial markets.[3] These models include a heterogeneous set of agents, as well as a topology that describes their methods of interaction within an environment. Therefore, they attempt to go further than network models, by departing from mechanical behaviour and incorporating the heterogeneity of agents, including banks, and their specific behaviour. Because of these features, ABM are characterised by high computational complexity and data requirements, as more features are added to the models. However, these obstacles may matter less in the future, given the increasing availability of detailed data and the progress in computing power.

2.2. REVIEW OF EMPIRICAL RESULTS FOR THE EU COUNTRIES

So far, most of the research has been focussing on the sovereign bond markets of euro area Member States, as the EMU is characterised by the existence of a common monetary policy, decentralised fiscal policies, and a non-bailout clause for government debts. The pre-crisis evidence (e.g. Beber et al., 2009) suggested that the bulk of sovereign yield spreads are explained by differences in credit quality, although liquidity also plays a role for low credit risk countries and during times of heightened market uncertainty. However, it is also apparent (e.g. Faini, 2006) that financial markets in general and interest rates spreads in particular did not have sufficiency disciplining effects on fiscal policy in the pre-crisis period.

The euro area debt crisis that followed the global financial crisis drew attention to cross-border interconnectedness between sovereign bond markets. Numerous studies tried to measure the linkages between European sovereign bond markets in terms of commonalities, spillovers and contagion, looking at sovereign bond yields or CDS prices (e.g. Alter and Beyer, 2013; Beirne and Fratzscher, 2013; Caporin et al., 2018; Claeys and Vašíček, 2014; De Santis, 2012; Kalbaska and Gatkowski, 2012). The studies agreed that, despite significant spillovers, the presence of pure contagion was largely limited to some short-lived episodes before the Outright Monetary Transaction (OMT) announcement, when the ECB, by providing liquidity to stressed sovereigns, started to act as a lender of last resort (De Grauwe, 2013). While there is no consensus on the role played by economic fundamentals in pricing the sovereign risk during the crisis, most studies agree on a greater sensitivity of sovereign yields to fundamentals in the peripheral countries. This premium on fundamentals seems to have been reinforced by the rise in domestic bank credit risk (Afonso et al., 2014; Aizenmann et al., 2013; Bernoth and Erdogan, 2012; Bruenau et al., 2013; Beirne and Franzcher, 2013; Delatte et al., 2017; de Grauwe and Ji, 2013; Paniagua et al., 2017) but also global risk aversion (Gómez-Puig et al., 2014). The flight to safety and liquidity is identified as an additional cross-border factor affecting the pricing of sovereign bonds during the euro area debt crisis (De Santis, 2014; Monfort and Renne,

[2] Garratt et al. (2011) and Espinoza-Vega and Sole (2010) manage to overcome this challenge by using the aggregate-level International Consolidated Banking Statistics database from BIS. This allowed them to assess the cross-border credit and funding risks of a banking system's default on another country's banking system. However, neither study includes bank and exposure level information, thereby ignoring the benefit that a specific distribution of exposures and bank-specific characteristics may bring to the overall stability of the system.

[3] Krishnamurthy (2010) designs a model to analyse how the uncertainty of investors in certain types of assets, especially assets coming from recent financial innovations, can lead to a run to safety after the shock occurred and a sudden escape from the new products.

2014), whereby a rise in yields in several stressed countries determined opposite movements in French and German yields. Some studies aim specifically at the effect of news and policy events (e.g. news about the rescue programmes in Greece) on bank stock and sovereign bond prices (Beetsma et al., 2013; Mink and de Haan, 2013). Other studies analyse the impact of rating actions on sovereign bond yields (Alsakka and Gwilym, 2013; Afonso et al., 2012; Candelon et al., 2011; De Santis, 2012) but also on the euro exchange rate (Baum et al., 2016). Finally, there is evidence that interest rate premia on some sovereign bonds also reflect a redenomination risk component. This represents the risk that one or more countries would exit the euro area and reintroduce their national currencies, which could consequently depreciate (De Santis, 2019; Klose and Weigert, 2014).

The spillovers between the sovereign bond and CDS markets came under scrutiny amid indications that CDS markets (namely, naked CDS position when a holder of CDS protection did not possess the underlying sovereign bond) behaved as a further shock transmitter (Calice et al., 2013). Arce et al. (2013) analysed the extent to which prices in the sovereign CDS and bond markets reflect the same information on credit risk during the euro area debt crisis. They find that flight to quality was one of the drivers of worsening efficiency of the bond market and one of the reasons for the deviation between CDS and bond spreads. In the same context, Fontana and Scheicher (2016) document a complex relationship between sovereign CDS and bond markets, which is characterised by sizable deviations from the no-arbitrage relationship. They aim at the CDS-bond basis (the difference between the premium on the CDS and the credit spread on the underlying bond) and show that this basis is larger for more creditworthy countries with more liquid government bonds (i.e. driven by a flight to quality), as more liquid bonds benefit from yield discount. Evidence of the flight to quality/liquidity phenomena is provided by the fact that CDS premia and bond spreads correlate negatively with the German Bund.

The feedback loop between banks and sovereigns has been identified as another important risk after the euro area debt crisis. Therefore, an extensive strand of empirical literature analysed the financial spillovers and contagion between sovereigns and banks (using mostly CDS prices). The feedback loop seems to have emerged alongside the government-sponsored rescue programs for the domestic financial sector (Acharya et al., 2014) as official lending strategies and the crisis resolution framework developed only gradually (Corstetti et al., 2017). The bank bailout programs seem to have reinforced the transmission from sovereign risk towards the risk of domestic banking systems (Alter and Schüler, 2012). Moreover, in some countries, the excessive government indebtedness was even the main driver of adverse shock that resulted in the provision of external financial assistance. Consequently, it seems that sovereign risk spills over to bank risk more strongly than vice versa (Erce, 2015; Fratzscher and Rieth, 2019). There is also some indication of pure contagion as a co-movement between sovereign and banking CDS was excessive in some periods, which could be attributed to a guarantee channel, an asset holdings channel and a collateral channel (De Bruyckere et al., 2013). Last, not the least, the financial spillovers between sovereign and banks were identified not only within countries but also across countries (Fratzscher and Rieth, 2019).

The impact of sovereign credit risk has been detected also in the case of non-financial corporations (Bedendo and Colla, 2015). Namely, a decline in sovereign credit quality seems to affect more adversely those firms likely to benefit from government aid, concentrated in the domestic market, and relying more heavily on bank financing. During crisis episodes, there is evidence for a contagion effect (Guidolin and Pedio, 2017) from sovereign bonds towards corporate bonds and equities, albeit economically weak, mostly driven by the flight-to-quality channel. There is also some evidence that in low-risk countries government bonds represent a natural hedge against equity risk (Dufour et al., 2017). On the other hand, government bonds of high-risk countries lost their "safe-asset" status and exhibited more equity-like behaviour during the euro area debt crisis, with positive and significant co-movements with the stock market. Finally, it seems that the non-financial sector suffered little contagion from domestic banking shocks, as it was often able to find alternative sources of financing (Dungey et al., 2020). On the contrary, the non-financial sector shock triggered contagious effects for the domestic banking sector.

Finally, several papers aim at the overall systemic risk[4] and evaluate the contribution of different sectors to it.[5] The structural increase of systemic risk in Europe can be associated with the increase of the size of the banking system as opposed to equity and private bond markets (Langfield and Pagano, 2016) and home bias of banks' sovereign portfolios (Battistini et al., 2014). The systemic riskiness of the banking sector is related to its decisive role in credit provision to households and corporates, but also its short-term funding. However, it seems that other financial services beyond banking contribute to overall systemic risk at the time of high stress as well (Bernal et al., 2014). Systemic sovereign risk represents an important component of the overall systemic risk in the euro area, but its role has decreased since the euro area debt crisis as crisis sovereigns decoupled from the others (Reboredo and Ogolini, 2015). At the same time, spikes in systemic sovereign risk seem, in turn, to be linked to financial market conditions rather than to macroeconomic fundamentals (Ang and Longstaff, 2013).

3. EMPIRICAL ANALYSIS OF SPILLOVER AND CONTAGION RISKS IN THE EURO AREA

Most existing academic literature focuses specifically on the analysis of the global financial crisis and the euro area debt crisis. In comparison to previous studies, the contribution of our paper consists in the combined use of a variety of methodologies to measure financial spillovers and contagion risks in the euro area and in the inclusion of data and episodes until 2019. The rationale for using different methods are the complexity and multidimensional nature of financial spillovers and contagion risks and the specific elements of each of the three transmission channels defined above (*sovereign-sovereign, sovereign-bank,* and *bank-bank*). Because of these features, the use of a single methodology, due to the limitations of each approach, does not allow capturing the complexity of financial spillovers and contagion. At the same time, some of the methods can be seen as complementary (the SYMBOL and CIMDO models, see Table 3.1), and the results obtained can be used as input for others (this is the case for cross-asset price correlations, where results have been used as input to QUEST simulations, see Table 3.1).

On this basis, financial spillovers and contagion risks are investigated, exploiting synergies among different models, by employing correlation and exposure heat maps, analysis of bank balance sheets, reduced-form models inferring the interconnectedness among agents from the market data, as well as simulated structural models. A comparison of the different methods used is presented in Table 3.1 below.

Table 3.1. **Comparison of empirical models used in this paper**

	Cross-asset price correlations and redenomination risk (Sect 3.1)	**CIMDO model (Sect 3.2)**	**SYMBOL model (Sect 3.3)**	**QUEST model (Sect 3.4)**
Inputs	Market-based, readily available market data (e.g. equity, fixed income and CDS market prices within and	Market-based. Readily available market data (equity, CDS and total assets).	EBA data (cross-border bank exposures to EA sovereigns) as well as sovereign CDS and debt data	Cross-asset price correlations.

[4] IMF (2009) defines systemic risk as a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and that has the potential to cause serious negative consequences for the real economy. Contagion can be seen together with bank run or liquidity crisis, one of the sources of systemic risk.

[5] The macprudential policymaking distinguishes between “cyclical” systemic risk and “cross-sectoral” systemic risk. The focus of this paper is more closely related to the latter. Likewise, we do not explicitely consider the impact of financial cycles on financial spillover and contagion risks that was found relevant by Adrian and Shin (2010).

	among euro area countries).		(among other data sources).	
Nature	Estimated correlation coefficients both static (fixed period) and dynamic (real time). Empirical model based on price differences between similar sets.	Empirical "reduced form" model[6] without structural assumption. Stochastic and non-parametric approach to model copulas.	Micro-simulation credit portfolio model.	Dynamic general-equilibrium model with linkages between financial variables and the "real" economy.
Transmission channels	Diagnostic test (necessary but not sufficient condition) for all contagion channels (sovereign-to-sovereign, sovereign-to-bank and bank-to-bank).	Bank-to-bank (direct and indirect contagion channel).	Sovereign-to-bank (and vice versa).	Sovereign-to-bank (and vice versa).
Outputs	Real time heatmaps and fixed period correlation charts.	Systemic risks due to interconnectedness across banking systems. Determination of systemic risk losses (likelihood and intensity of any possible state of nature following the realisation of a given default).	Total losses and recapitalisation needs faced by EA banking sectors. Impact on government debt.	Macroeconomic effects of identified systemic risk.

Source: Own compilation.

3.1. CORRELATION ANALYSIS AND REDENOMINATION RISK

Correlation analysis can be used as a diagnostic tool allowing a first assessment of financial data. With some degree of generalisation, it can be claimed that an increased correlation between certain asset classes can be seen as *necessary*, albeit not *sufficient* condition for phenomena such as financial spillover or contagion.[7] As a crucial *caveat*, it should be kept in mind that the lack of causality from the correlation coefficients, or the possibility of an omitted variable bias may occur (e.g. due to common driving factors, such as the presence of a certain monetary policy stance). In this section, both real-time (time varying) and fixed-period correlation analyses are used to measure the existence of financial spillovers in each of the three identified transmission channels. Specifically, the relevant correlation coefficients among equity, fixed income and CDS market prices within and among euro area countries are estimated. For instance, the correlation relationship between equity and fixed income markets provides a first indication of the existence and magnitude of spillovers through the sovereign-to-banks transmission channel. Moreover, analysing relevant fixed-time correlations among sovereign bonds may shed light on the weight of *redenomination risk* as a euro-area specific channel of contagion within the broader sovereign-to-sovereign transmission channel. Italy is considered only for illustrative purposes and as a case study, since it was subject to sovereign funding pressures not only during the euro area debt crisis but also, more recently, in 2018. By taking as benchmark other Member States, like Spain and Portugal, which were mostly subject to funding pressures during the

[6] Meaning that although they capture the aggregate effects of agents' behavior, they do not provide structural information on the specific agents' behaviors that define the channels of contagion that can lead to the materialisation of systemic risk.

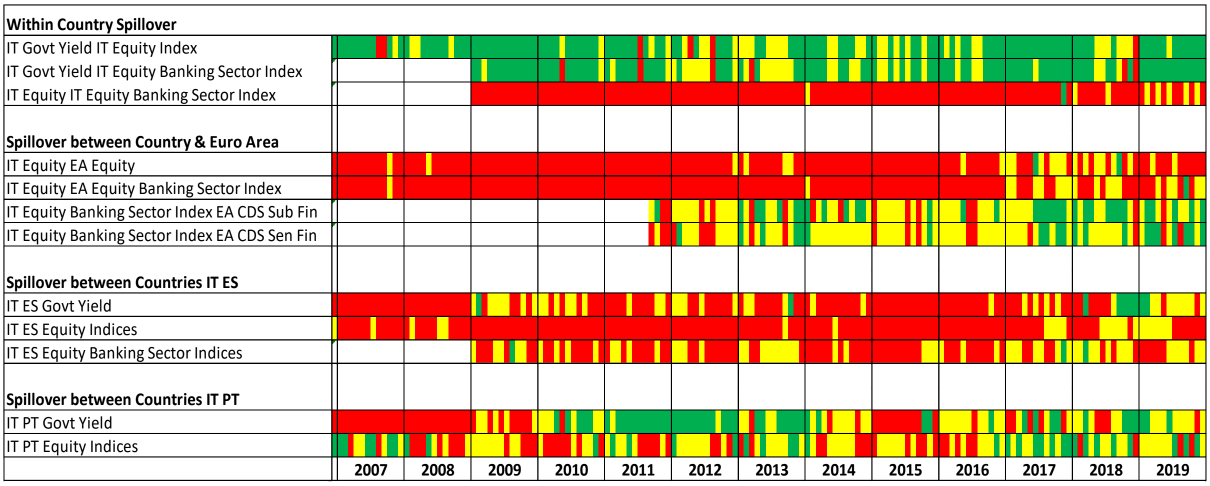
[7] For instance, a commonly used methodology is to examine the daily co-movements between asset prices, e.g. (sovereign) bond yields and equity prices, via GARCH-implied time-varying correlations (e.g. Hesse et al., 2018; Frank and Hesse, 2009).

euro area debt crisis, this provides a good starting point to assess the working of specific transmission channels of financial spillover and contagion risks in the euro area.

3.1.1. Real-time correlations

Computing time-varying correlations between pairs of asset prices is a simple but powerful tool to detect whether *real-time* spillovers occur across asset classes. We draw a *real-time correlation heatmap*, tracing co-movements between key asset price variables, including sovereign bond yields, equity prices, and bank credit indexes. The heatmap reports relatively low correlation (i.e. an estimated implied correlation coefficient below 0.55[8] in absolute terms) in green, moderate correlation (between 0.55 and 0.80) in yellow, and high correlation (above 0.80) in red. This calculation relies on daily Bloomberg data between January 2006 and end-December 2019, with daily correlation coefficients between pairs of assets calculated over 30-day periods. The heatmap in Table 3.2 shows, as example, correlations across asset prices within Italy, between Italy and the euro area, and between Italy and Spain or Portugal. As a mirror image, Graph 3.1 shows the estimated correlation coefficients in their absolute numbers over December 2006-December 2019.

Table 3.2. **Real-time heatmap (sovereign-to-sovereign and sovereign-to-banks channels, 2007-2019)**



Note: This heatmap shows the estimated correlation between pairs of asset prices (based on daily data and a 30-day window for the correlation calculations) within Italy (IT), between Italy and the euro area (EA), and between Italy and Spain (ES)/Portugal (PT); green is used for correlation coefficients of up to 0.55 in absolute terms, yellow for coefficients between 0.55 and 0.80, and red for coefficients higher than 0.80. "CDS Sub Fin" and "CDS Sen Fin" refer to Credit Default Swaps for Subordinate Financial and Senior Financial, respectively.

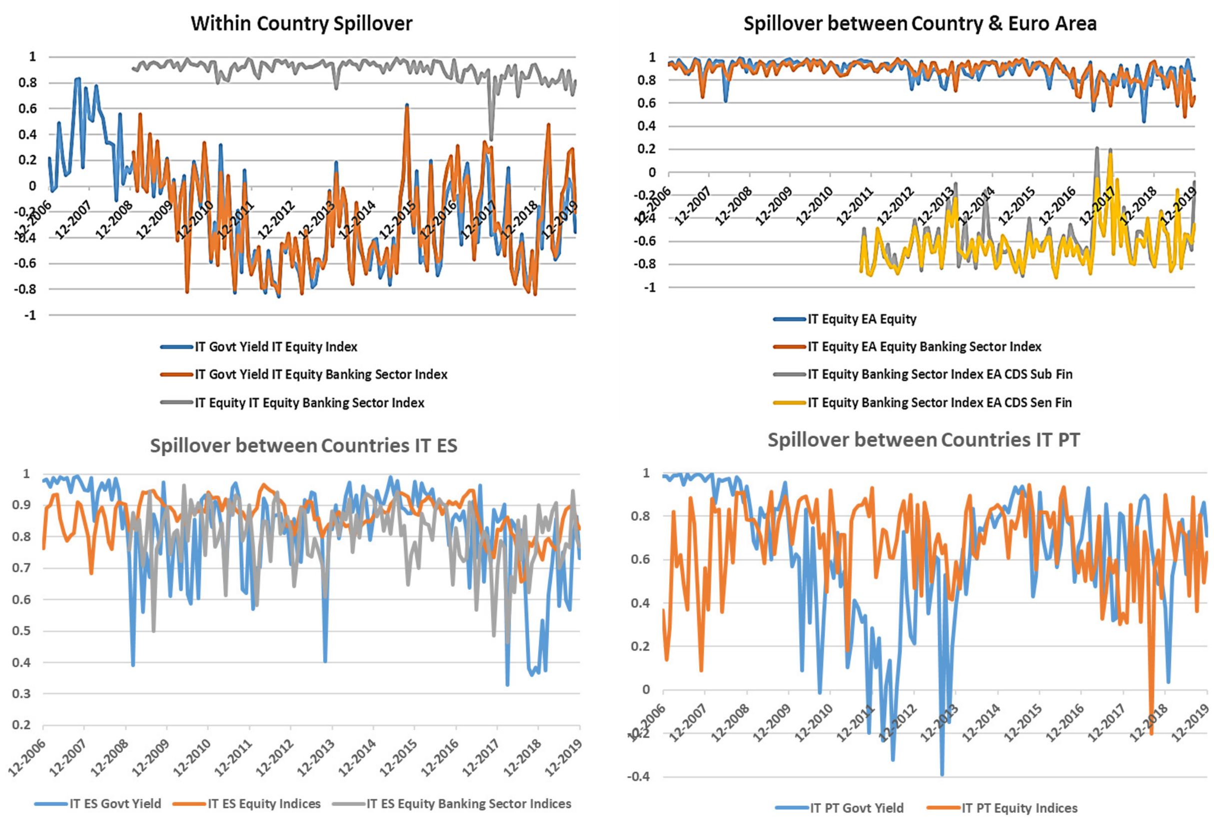
Source: Bloomberg, own calculations.

The estimated correlations, as reported in the heatmap, suggest limited cross-border spillover from Italy over 2018-2019, despite the idiosyncratic policy uncertainty that marked the Member State since the election of a new government in early 2018. In particular, the heatmap seems to suggest a recent decoupling between the dynamics of Italy's 10-year sovereign bond yields and those of Spain or Portugal, as opposed to persistently high co-movements during the previous normal and crisis periods. Moreover, also equity market correlations among the same Member States seem to drop as of late May 2018. That notwithstanding, asset price spillovers increased in Italy in May 2018, as indicated by higher co-movements between sovereign yields and equity prices, including bank shares' prices. This reflected possible market concerns about rising risks of a sovereign-bank doom loop, in a context where Italian banks had raised their exposure to national sovereign bonds (BTP) and suffered moderate declines in their capital buffers from mark-to-market losses in their BTP portfolio, while being

[8] The correlation threshold of 0.55 is the one that corresponds to a two-way significance test of 1%. This means that the identified correlation (or lack thereof) is statistically significant with a very high level of confidence.

prevented from accessing unsecured market funding[9]. Furthermore, there is evidence of spillovers to subordinated and senior bank credit markets, possibly caused by market uncertainty about banks. This may be related to the fact that the correlation between Italian banks' share prices and EU banks' credit spreads also rose as of early 2018. Such findings seem to align with the anecdotal evidence, whereby, as many Italian banks had largely lost market access to unsecured wholesale funding (including issuing unsecured senior or subordinated debt securities) since May 2018, it became more expensive for European banks to meet the subordinated part of the minimum requirements for own funds and eligible liabilities (so-called MREL) targets by issuing eligible debt, as well as to adjust to the phase out of the ECB targeted longer-term refinancing operations starting in 2020.

Graph 3.1: **Correlation between different asset classes**



Note: This graph shows the daily co-movement/correlation between pairs of asset prices, as shown in the correlation heatmap of Table 1, within Italy (IT), between Italy and the euro area (EA), and between Italy and Spain (ES)/Portugal (PT).

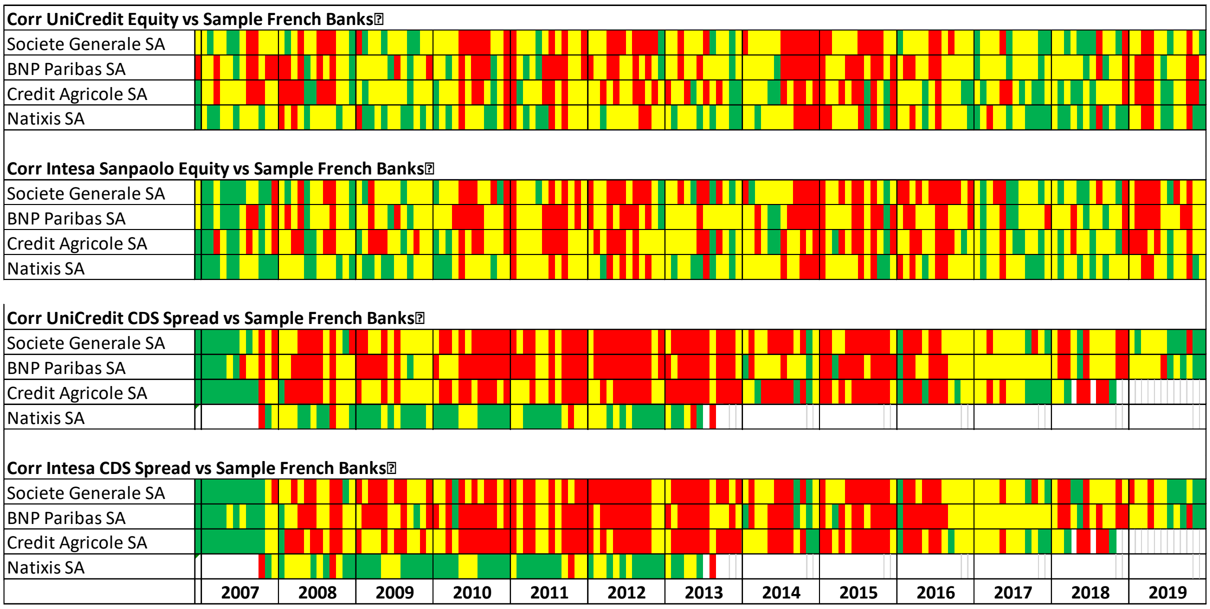
Source: Bloomberg, own calculations.

Given the large exposure of French banks *vis-a-vis* the Italian sovereign risk, both via their subsidiaries and through direct BTP holdings, Table 3.3 and Graph 3.2 report the implied correlations between major Italian banks' (Intesa and Unicredit) equity prices and CDS spreads and those of their French counterparts (Societe Generale, BNP Paribas, Credit Agricole, and Natixis). The aim is to provide a concrete example of the functioning of the bank-to-bank channel. During the 2011-2012 euro area debt

[9] Persistently high sovereign yields are likely to negatively impact banks' cost of funding, their market access, and hence credit provision. Banks could be adversely affected by the higher sovereign risk through a number of channels, such as capital losses from their sovereign exposures, higher funding costs, limited market access, lower collateral valuation and credit ratings, or reduced funding benefits from government guarantees. The liquidity position of Italian banks has remained adequate, however, mainly supported by the increase in domestic deposits and the reliance on ECB refinancing operations. See also European Commission, 2019 Country Report on Italy.

crisis, the heatmap clearly illustrates that the CDS spreads of Italian and French banks highly co-moved, which may reflect as much market concerns on specific financial institutions as a more generalised risk aversion towards banks. Instead, our findings suggest declining correlations between Italian and French banks' equity prices as of May 2018, while no decoupling of co-movements is observed for CDS spreads. The loss of correlation might suggest the presence of credit market spillovers, reflecting the fact that it became more expensive for European banks to issue senior and subordinated debt around that period, even in the absence of strong bank-to-bank equity market spillovers. However, the possible presence of common factors driving bilateral correlations suggests interpreting these findings with caution.

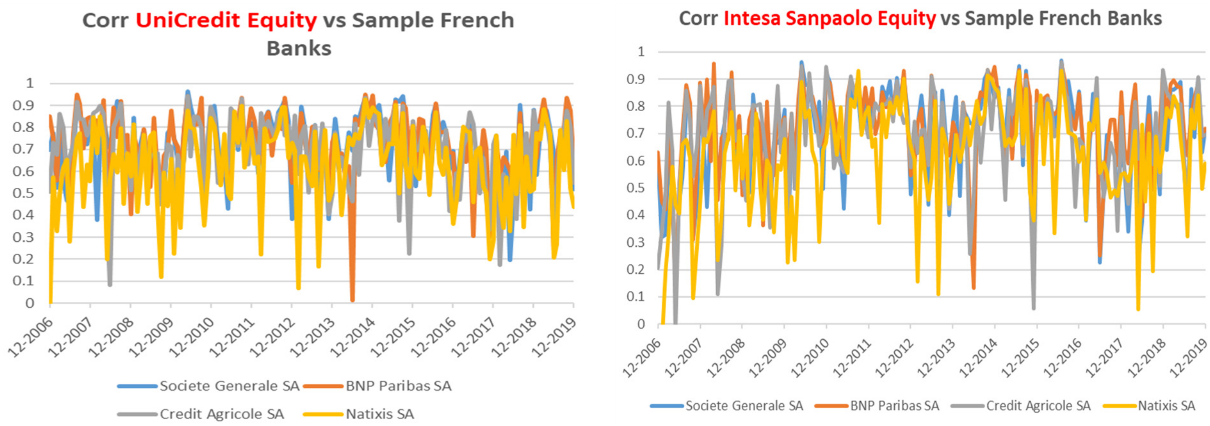
Table 3.3. **Real-time heatmap (banks-to-banks channel, 2007-2019)**

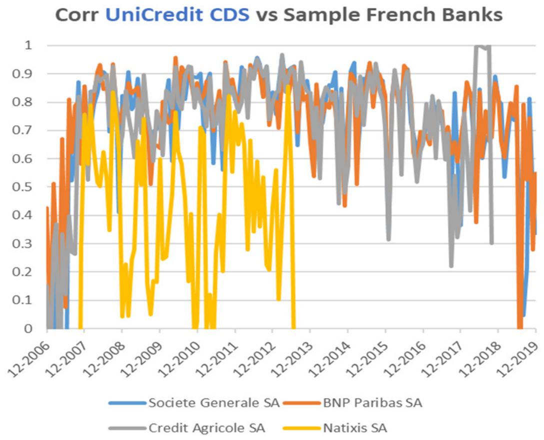


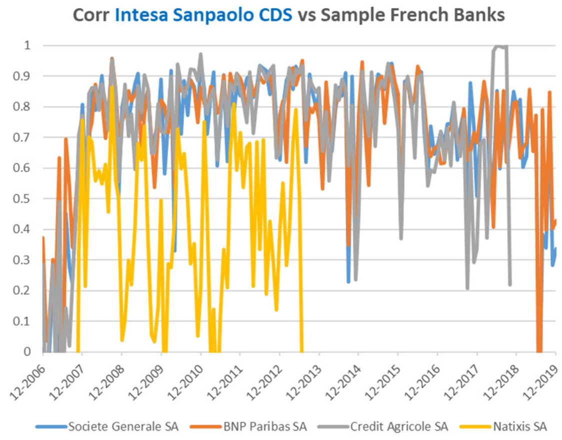
Note: This heatmap shows the estimated correlation between Italian (Unicredit/Intesa) and French banks' equity and CDS spreads based on daily Bloomberg data and a 30-day window for the correlation calculation; green captures a correlation coefficient of up to 0.55 in absolute terms; yellow between 0.55 and 0.80; and red higher than 0.80. The corresponding correlation figures are in annex.

Source: Bloomberg, own calculations.

Graph 3.2. **Correlation between selected banks**







Note: This graph shows the daily co-movement/correlation, as shown in the correlation heatmap (bank-by-bank).

Source: Bloomberg, own calculations.

3.1.2. Fixed-period correlation and redenomination risk

In this section, we compute fixed-period correlations between different indicators of sovereign risk (including so-called "redenomination risk") and bank credit risk (e.g. banks' CDS spreads) and build an all-encompassing correlation matrix to explore the existence of different indirect transmission channels both during the euro area debt crisis (2010-2012) and over the more recent non-crisis period (2016-2019). Table 3.4 presents the fixed-period correlation matrix, which allows observing financial spillovers across all three major transmission channels analysed in this paper:

(i) The *sovereign-to-sovereign channel*: Correlation among euro area sovereign CDS spreads was generally high in 2010-2012 and generally lower in 2016-2019, with very few exceptions (moderate for Italy/France to Spain/Portugal). As such, it suggests financial spillover being at work during the crisis and normal times. *Inter alia*, the inter-sovereign channel appears to have been stronger during the 2010-2012 crisis compared to recent years (2016-2019).

(ii) The *sovereign-to-banks channel*: Correlation among CDS of sovereign and banks was high in 2010-12 but much weaker in 2016-2019. This supports the idea of a weakening in the overall sovereign-bank nexus. However, recent co-movements between sovereign and bank risk indicators remain systematically higher in relative terms for Italy than for the other Member States.

(iii) The *banks-to-banks channel*: This channel seems to have been largely at work both in 2010-2012 and over the more recent period 2016-2019. For the latter, however, correlation appears to be more "concentrated" around a few countries, as witnessed by relatively stronger co-movements between Italian, French and Spanish banks.

Table 3.4: **Fixed-period correlations (sovereign-to-sovereign, sovereign-to-banks and banks-to-banks)**

2010-2012 corre	BNP Parib	Credit Agr	Banco Sar	Societe Ge	Lloyds	HSBC Bar	Allianz SE	Axa SA	Unicredit	Royal Ban	Intesa San	Banco Bilb	Nordea Ba	Standard (	Natixis	Danske Ba	Commerzb	Bank of Sc	IT CDS ch	ES CDS c	5Y FR CD	5Y PT CD	5Y DE CD
BNPParibas	1																						
CreditAgri~e	0.8735	1																					
BancoSanta~r	0.7625	0.7805	1																				
BankofAmer~a	0.5842	0.5839	0.5257																				
SocieteGen~e	0.896	0.8973	0.7415	1																			
Lloyds	0.79	0.7759	0.7356	0.7877	1																		
HSBCBank	0.6994	0.6822	0.6903	0.6655	0.6973	1																	
AllianzSE	0.7938	0.7601	0.7448	0.7687	0.7332	0.689	1																
AxaSA	0.8006	0.7481	0.7131	0.7659	0.7502	0.659	0.833	1															
Unicredit	0.8389	0.8148	0.8026	0.8162	0.7952	0.6949	0.7751	0.7709	1														
RoyalBanko~d	0.7618	0.77	0.761	0.758	0.8558	0.7111	0.7309	0.7247	0.7546	1													
IntesaSanp~o	0.8484	0.8091	0.8143	0.8126	0.7741	0.7061	0.7931	0.7794	0.9098	0.7576	1												
BancoBilba~a	0.7636	0.7782	0.9629	0.7348	0.7331	0.6913	0.7592	0.7168	0.807	0.7565	0.817	1											
NordeaBank	0.3505	0.3867	0.371	0.3528	0.4209	0.4472	0.343	0.3828	0.399	0.4125	0.3644	0.3717	1										
StandardCh~d	0.7197	0.7242	0.6476	0.6893	0.7091	0.6981	0.6867	0.6785	0.6866	0.7116	0.6728	0.6492	0.4828	1									
Natixis	0.5012	0.5043	0.4364	0.4986	0.4729	0.414	0.489	0.5199	0.4783	0.4885	0.4631	0.4239	0.294	0.441	1								
DanskeBankAS	0.593	0.6014	0.5023	0.5933	0.5905	0.4667	0.565	0.596	0.6051	0.5229	0.6147	0.4947	0.3871	0.5341	0.461	1							
Commerzban~G	0.757	0.7321	0.7239	0.7477	0.7189	0.6443	0.7263	0.7205	0.743	0.736	0.7496	0.7263	0.3335	0.6218	0.4304	0.5267	1						
ITCDSch	**0.7315**	**0.7113**	**0.704**	**0.7072**	**0.6539**	**0.574**	**0.6908**	**0.6716**	**0.7261**	**0.6349**	**0.748**	**0.7178**	**0.3247**	**0.6141**	**0.3922**	**0.4694**	**0.6203**	**0.6123**	***1***				
ESCDSch	**0.658**	**0.6469**	**0.7255**	**0.6439**	**0.6089**	**0.5461**	**0.6462**	**0.608**	**0.6643**	**0.5959**	**0.6796**	**0.7422**	**0.2882**	**0.5267**	**0.3515**	**0.4169**	**0.586**	**0.5731**	***0.8718***	***1***			
YFRCDS	**0.7221**	**0.6656**	**0.614**	**0.6728**	**0.6405**	**0.5422**	**0.668**	**0.6753**	**0.6753**	**0.5982**	**0.6646**	**0.6225**	**0.3277**	**0.5744**	**0.4204**	**0.4856**	**0.5696**	**0.5739**	***0.7227***	***0.6904***	***1***		
YPTCDS	**0.4846**	**0.4803**	**0.4636**	**0.4806**	**0.4319**	**0.3435**	**0.4825**	**0.4847**	**0.4819**	**0.4337**	**0.4902**	**0.467**	**0.1946**	**0.4124**	**0.2566**	**0.3185**	**0.4084**	**0.4393**	***0.591***	***0.604***	***0.4903***	***1***	
YDECDS	**0.6391**	**0.5745**	**0.5273**	**0.5833**	**0.5624**	**0.4866**	**0.5863**	**0.5993**	**0.598**	**0.5384**	**0.597**	**0.5162**	**0.3064**	**0.5179**	**0.3606**	**0.4144**	**0.5221**	**0.4884**	***0.6225***	***0.6024***	***0.7225***	***0.4687***	***1***

2016-2019 corre	BNP Parib	Credit Agr	Banco Sar	Societe Ge	Lloyds	HSBC Bar	Allianz SE	Axa SA	Unicredit	Royal Ban	Intesa Sar	Banco Bilt	Nordea Ba	Standard (	Natixis	Danske Ba	Commerzb	Bank of Sc	***IT CDS ch***	***ES CDS c***	***5Y FR CD***	***5Y PT CD***	***5Y DE CD***
BNPParibas	1																						
CreditAgri~e	0.6944	1																					
BancoSanta~r	0.6902	0.6028	1																				
SocieteGen~e	0.8957	0.7429	0.6715	1																			
Lloyds	0.4967	0.6325	0.6425	0.5062	1																		
HSBCBank	0.5317	0.663	0.6249	0.5722	0.7948	1																	
AllianzSE	0.6912	0.5415	0.7456	0.6223	0.553	0.5438	1																
AxaSA	0.6943	0.617	0.7087	0.6638	0.5443	0.5515	0.7813	1															
Unicredit	0.691	0.5304	0.8168	0.6748	0.4928	0.5113	0.6781	0.6576	1														
RoyalBanko~d	0.63	0.5647	0.7111	0.5864	0.7441	0.6544	0.6643	0.6222	0.6007	1													
IntesaSanp~o	0.6772	0.4856	0.7971	0.6544	0.4711	0.4808	0.6726	0.6376	0.9473	0.592	1												
BancoBilba~a	0.6471	0.5596	0.8666	0.6304	0.5825	0.5595	0.6881	0.6381	0.8041	0.6367	0.7691	1											
NordeaBank	.	.	.	.	.	.	.	.	.	.	.	.	.										
StandardCh~d	0.2723	0.2249	0.2451	0.2347	0.21	0.371	0.2532	0.3037	0.2098	0.2827	0.2044	0.2544	.	1									
Natixis	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.								
DanskeBankAS	0.0781	0.0988	0.0597	0.0677	0.0895	0.128	0.1384	0.1026	0.0649	0.0328	0.0663	0.0397	.	0.1727	.	1							
Commerzban~G	0.6182	0.4384	0.6989	0.5665	0.4739	0.4421	0.6821	0.6253	0.6286	0.6151	0.6223	0.6323	.	0.2468	.	0.0868	1						
ITCDSch	**0.4701**	**0.3439**	**0.5029**	**0.4484**	**0.2689**	**0.3042**	**0.4375**	**0.5475**	**0.5927**	**0.3707**	**0.6075**	**0.5042**	.	**0.1557**	.	**0.0403**	**0.3533**	.	***1***				
ESCDSch	**-0.0896**	**-0.202**	**0.1236**	**-0.1126**	**0.0404**	**-0.1946**	**0.1164**	**0.0375**	**0.035**	**0.1088**	**0.0318**	**0.1714**	.	**0.0571**	.	**0.013**	**0.2105**	.	***0.0856***	***1***			
YFRCDS	**0.1239**	**0.0274**	**0.0966**	**0.1316**	**-0.0327**	**-0.1776**	**0.0965**	**0.149**	**0.0542**	**0.0977**	**0.0273**	**0.1264**	.	**0.0547**	.	**-0.0417**	**0.1904**	.	***0.1198***	***0.7091***	***1***		
YPTCDS	**0.1978**	**0.2312**	**0.2286**	**0.1946**	**0.2171**	**0.2279**	**0.1715**	**0.3708**	**0.1937**	**0.2073**	**0.1753**	**0.2134**	.	**0.0829**	.	**0.0242**	**0.0857**	.	***0.5623***	***-0.0564***	***-0.0056***	***1***	
YDECDS	**0.087**	**0.0754**	**0.0695**	**0.0849**	**0.0261**	**0.0731**	**0.0718**	**0.1006**	**0.0174**	**0.0703**	**0.0172**	**0.0301**	.	**0.0273**	.	**0.0077**	**0.0784**	.	***0.074***	***0.0344***	***0.0589***	***0.0258***	***1***

Source: Bloomberg, own calculations.

Fixed-period correlations allow investigating the "redenomination risk" as an indirect channel specific to the euro area. In general, redenomination risk refers to the possibility, for which the investors tend to ask for compensation in the form of extra return, that a country changes its currency and its assets are thus redenominated in a new and devalued legacy currency, including due to the following reasons: (*i*) significant inflation and currency devaluation; (*ii*) the formation of a currency union; (*iii*) the break-up of a currency union (De Santis, 2019); or (iv) the unilateral exit of a country from a currency union, which continues to exist.

In the euro area, the redenomination risk was associated with the possibility of a break-up of the currency area during the 2010-2012 euro area debt crisis. The ECB's announcement of the OMT programme seemed to significantly contribute to a decline in redenomination risk. At that time, the possibility of a sovereign default of one or more euro-area governments was perceived largely as an extraordinary development that could trigger the break-up of the euro area. While a credit event (i.e. default) of a Member State government does not automatically imply the break-up of the euro area or the obligation of payments in a devalued currency, the markets have long perceived those events as connected. In the case of the Greek sovereign debt restructuring of 2012, the credit event did not imply the exit of the debtor from the euro area. However, such an event may increase the market perception of redenomination risk for sovereign assets into a (devalued) legacy currency.

As redenomination risk is *per se* unobservable, combinations of observable indicators (e.g. market news, euro/dollar exchange rate, bond yields/spreads, and CDS spreads[10]) have been proposed to capture it. To analyse redenomination risk as an additional contagion channel in the euro area, two alternative measures of redenomination risk are used here: (i) the “International Swaps and Derivatives Association ISDA-based measure” of redenomination risk, which can isolate redenomination risk in the context of a unilateral euro area exit; and (ii) the “Quanto-based measure” of redenomination risk, which implies the euro area break-up.

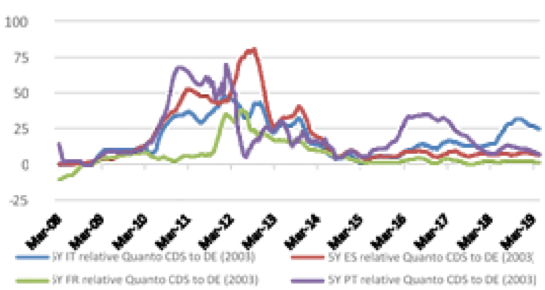
The “ISDA-based measure” exploits the fact that, since 2014, a CDS also implicitly insures the buyer against redenomination risks. In fact, according to the ISDA 2014 definitions, both sovereign default and redenomination constitute default events triggering CDS activation. On the other hand, before 2014, under the pre-existing ISDA 2003 definitions, the redenomination of a government bond issued by a G7 country was not an event triggering a CDS. As such, the price difference (or CDS spread) between the two types of the same sovereign CDS denominated in the same currency can be used as a measure of redenomination risk in the context of the euro area (Nolan, 2014, 2018; Scaggs, 2018; Smith, 2018). This measure has the advantage of being directly observable and offers the possibility to

[10] A CDS is a derivate product that offers protection against credit losses from specific events on an underlying instrument (e.g. bond, loan). A CDS on government bonds typically promises a predetermined payment in a specified currency to the buyer of the CDS under a credit event.

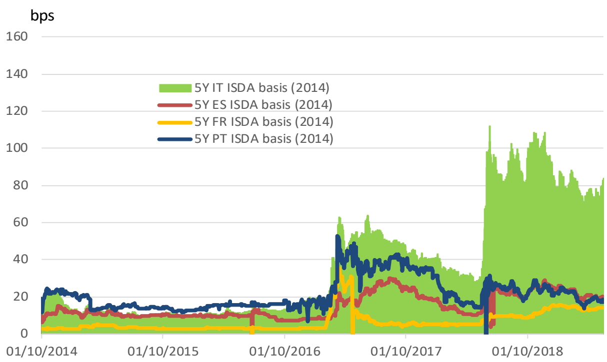
isolate redenomination risk from default risk. It may be biased, however, by the fact that the CDS issued under the 2014 definitions are likely to be more liquid than those issued under the 2003 ones, potentially leading to overestimation of the redenomination risk. Moreover, as 2014 CDS definitions were introduced only in September 2014, this comparison cannot be used to analyse developments prior to that date.

The “Quanto-based measure” (De Santis, 2019) tracks the redenomination risk for the euro area, taking a sample of euro area sovereign CDS before the introduction of the ISDA 2014 definitions. The measure is the difference in the differential between US dollar- and euro-denominated CDS spreads (also called *quanto* CDS) between a euro area Member State and Germany. The quanto CDS reflects the risk associated with a change in the euro exchange rate against the dollar. The difference between the quanto CDS of a Member State and the quanto CDS of Germany can be used as a measure of the redenomination risk associated with the break-up of the euro area as perceived by the markets. The difference between the two quantos should be close to zero if market perceptions of the break-up of the euro area are minor. Conversely, the existence of two different exchange rate risks would imply a difference between the two quantos, indicating the risk of a break-up of the euro area and a return to national currencies, also leading to a redenomination of existent CDS contracts (initially denominated in euro) in those currencies. That also implies that the Quanto-based measure should not capture redenomination risks related to unilateral exits that do not affect the existence of the euro as the currency in which CDS payments are made, but only the redenomination risk associated with a full break-up of the euro area. Instead, the ISDA-based measure should cover the redenomination risk associated with both a break-up of the euro area and a unilateral exit from it. Graphs 3.3 and 3.4 below report, respectively, the Quanto-based and the ISDA-based measure of redenomination risk for a sample of euro area Member States, including Italy, France, Spain, and Portugal.

Graph 3.3. **Quanto-based measure of redenomination risk (3M mov. avg.)**



Graph 3.4. **ISDA-based measure of redenomination risk in the EA**



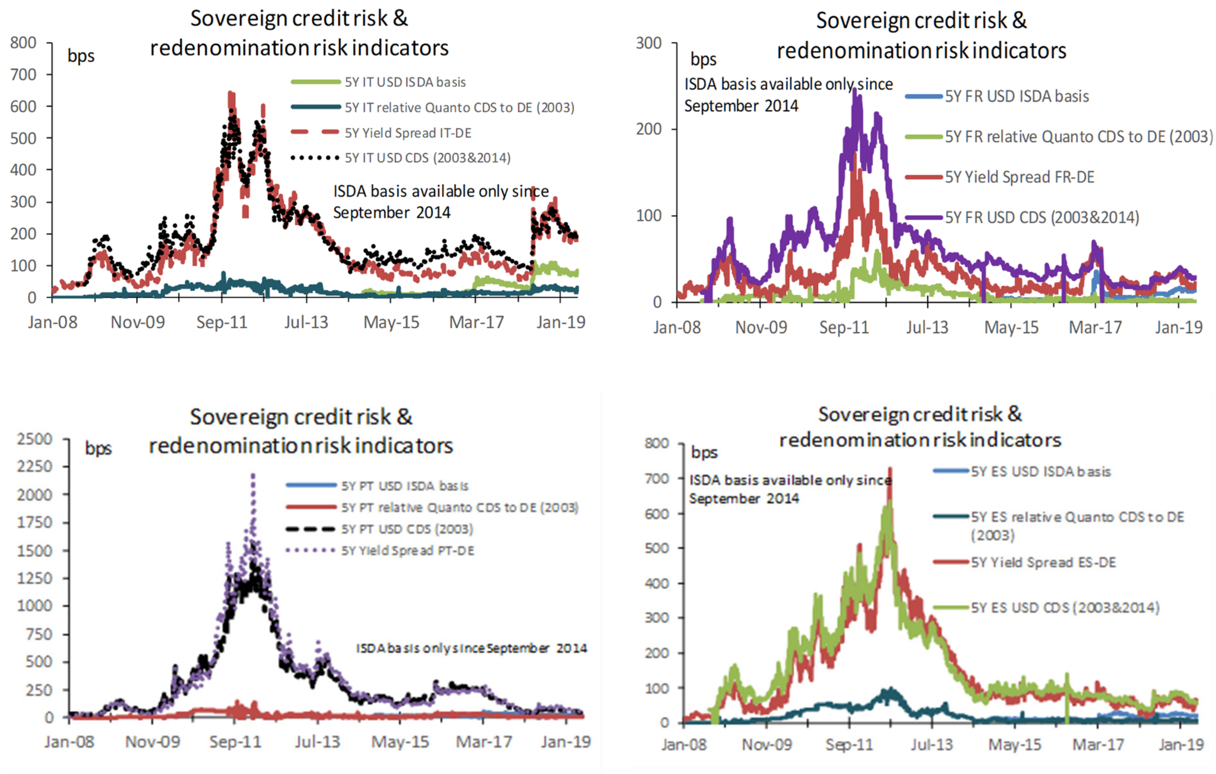
Source: Bloomberg, own calculations.

The graphs suggest that redenomination risk appears to have been largely at play as an indirect transmission channel for contagion during the 2010-2012 euro area debt crisis. As shown in Graph 3.3, it was priced mostly as fear of a euro-area break-up due to financial turbulence and rising risk of sovereign default in some Member States (other than Greece - not reported here). Instead, redenomination as a risk of a break-up of the euro area appears to have become much less relevant at the euro area level in recent years, in particular over 2016-2019. Still, the Quanto-based measure of redenomination risk shows a few peaks related to country-specific events also in the most recent period. In particular, recent events that appear to have been associated with isolated rises in that measure include the banking rescue in Portugal in end-2016 and the formation of a new coalition government in Italy in 2018.

It thus appears that redenomination risk has changed its nature: (i) In 2010-2012, redenomination risk was priced as fear of a euro area break-up due to financial turbulence and the increasing risks of sovereign default in some Member States (e.g. Greece, Italy) and spillover to others (e.g. Spain and

Portugal); and (ii) in 2016-2019, redenomination risk has become more country-specific, "idiosyncratic", less related to euro break-up, and more to the individual Member States, repriced around specific national markets and political events) as well as concrete economic policies and announcements (e.g. by some political parties in France and Italy). This is confirmed by Graph 3.4, which shows that redenomination risk was largely perceived as fear of unilateral exit of specific countries, as it was the case for Italy in 2018. Here, redenomination risk seems to explain a significant part, up to 30% in the case of Italy, of the recent increase in sovereign spreads registered for a few euro area Member States (see also Confindustria, 2019) as shown in Graph 3.5 below.

Graph 3.5. Comparison of sovereign spreads and ISDA-based measure of redenomination risk for four Member States



Source: Bloomberg, own calculations.

3.2. FINANCIAL SPILLOVERS AND CONTAGION RISKS DUE TO INTERCONNECTEDNESS IN THE BANKING SYSTEM (CIMDO)

Financial supervisors recognise the importance of assessing not only the risk of distress, i.e. large losses and possible default of a specific bank but also the impact that such an event would have on other banks in the system. Therefore, estimating distress dependence among banks is key for the surveillance of the stability of the banking system. In this context, distress dependence can be understood as a precondition for contagion risk, which is one of the drivers of systemic risk as contagion between specific banks can increase the risk that the whole financial system collapses. Distress dependence is based on the fact that banks are linked, either directly, through e.g. the inter-bank deposit market, equity cross-ownership holdings, participation in syndicated loans, or indirectly, through e.g. lending to common sectors and proprietary trades. Banks' distress dependence varies across the economic cycle and tends to rise in the time of distress, since the fortunes of banks decline concurrently after financial shocks that are transmitted through the financial system. In such periods, the banking system's joint probability of distress (JPoD), i.e. the probability that all the banks in the system experience large losses simultaneously, which embeds banks' distress dependence, may experience larger and nonlinear increases than those experienced by the probabilities of distress (PoDs) of individual banks.

However, from a policy perspective it is also important to consider that interconnectedness also generates benefits, which need to be traded off against its negative implications in the form of contagion and spillover risks. Benefits of interconnectedness include, for instance, the channelling of funds from savers to borrowers and the provisioning of credit to the real economy. Moreover, higher interconnectedness can improve diversification and thus facilitate risk sharing. Cross-border financial integration, which may support the development of a deeper and more stable financial system, also leads to higher interconnectedness. Therefore, a fundamental question is then what is the optimal level of interconnectedness in the financial and banking system, or how the risks of increasing distress dependence and interconnectedness among banks can be mitigated.

By developing a robust and dynamic approach, this sub-section analyses: *i*) banks' distress dependence and the interconnectedness of the EU banking system by applying the CIMDO (Consistent Information Multivariate Density Optimising) method and model (Segoviano and Goodhart, 2009) to a sample of 18 financial institutions over the time period 2015-2018; *ii*) the marginal contribution of each financial institution to systemic risk over the same period; and, ultimately, *iii*) potential losses due to financial spillovers, considering previously estimated interconnectedness structures within the banking sector and the macroeconomy, in particular, the results obtained to estimate the banks' distress dependence. In order to do so, we calculate the probabilities of the distress for each entity and the interconnectedness structure (multivariate density) using the CIMDO approach and quantify expected losses suffered by specific entities conditional on other entities in the system falling in distress. The model uses Monte Carlo-type simulations[11] on a representative portfolio and projection on the banking system.

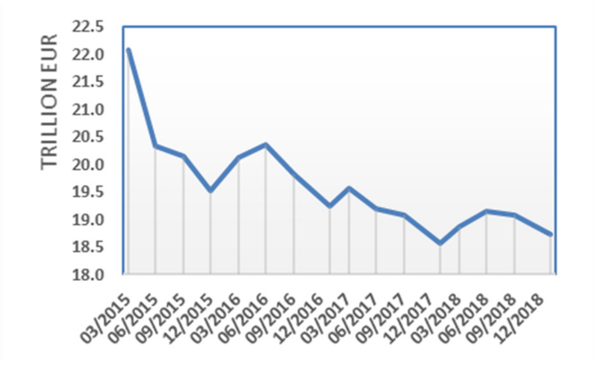
The analysis is based on a sample comprising 18 of the largest financial institutions in the EU (i.e. not only the euro area, but also the majority of institutions is incorporated in the euro area countries) over 16-time intervals, encompassing the years 2015-2018 on a quarterly basis. More specifically, the sample entails 17 banks and one insurance company (Allianz Group). The sample is mostly focused on the banking sector, even though vulnerabilities related to contagion risks might not be captured fully by analysing each financial sector independently. A non-banking institution was included in the sample to motivate a further expansion of the analysis beyond the sole banking sector. With a smaller level of distress dependence for the Allianz group relative to banking institutions (see the row average in Table 3.5 below), this intuition seems to be confirmed by our results.

The total assets of these institutions amounted, respectively, to 22 073 and 18 721 EUR billions at the beginning (Q1 2015) and at the end (Q4 2018) of the considered period (see Graph 3.6), marking a 15.2% reduction in value. At the same time, the share of the considered sample in the total bank assets of credit institutions headquartered in the EU went from 59.9% as of Q1 2015 to 57.5% as of Q3 2018 (see Graph 3.7). The reduction in asset value indicates a substantial movement of deleveraging among the institutions of the sample. Deleveraging, which appears more pronounced in the sample than in the EU banking sector taken as a whole, is also heterogeneous among the institutions of our sample. As shown by the evolution of the relative size[12] of financial institutions inside of the portfolio (see Graph 3.8), the UK and German institutions seem to have followed a particularly sustained path of deleveraging (The Royal Bank of Scotland Group Plc. Barclays Plc, Deutsche Bank and Commerzbank), while two banks in particular increased their balance sheets (Banco Santander and Intesa Sanpaolo).

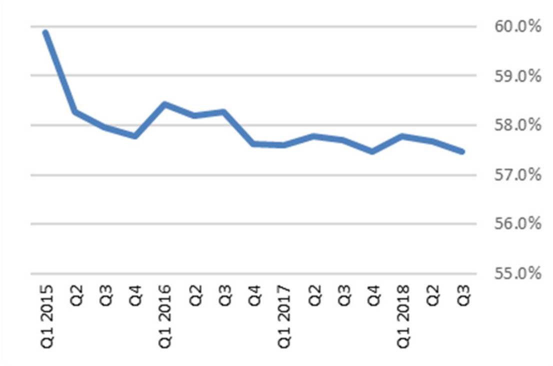
[11] A Monte Carlo simulation is a technique that consists in repeatedly generating random variables to model the risks or uncertainty of a system. The random variables, or inputs, are based on a specific probability distribution (e.g. normal). Different iterations are run for generating paths, and the long run outcome is obtained using suitable numerical computations.

[12] Measured as volume of an individual FI's asset divided by the total portfolio of assets held by the FIs in the sample.

Graph 3.6. **Total assets of selected banking institutions over time**

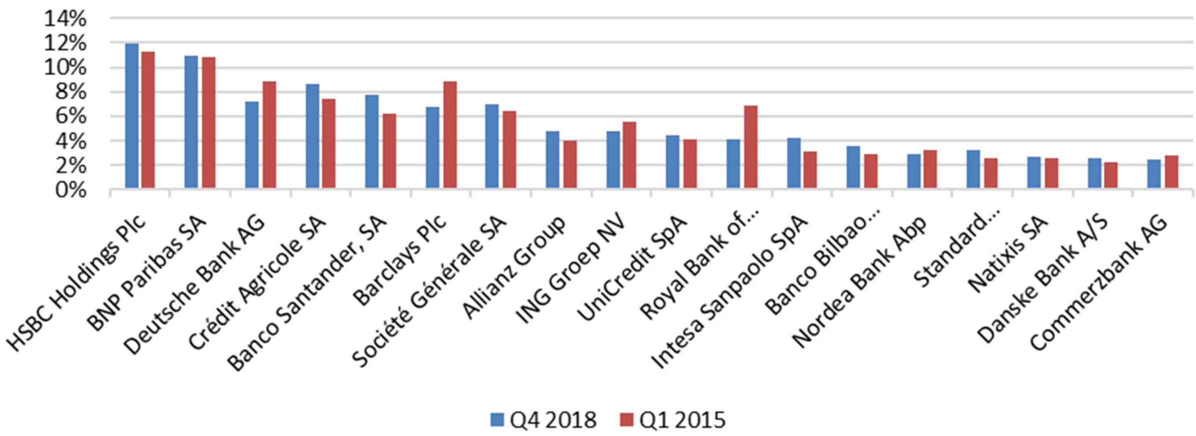


Graph 3.7. **Share of sample in EU total bank assets over time**



Note: Total assets of credit institutions headquartered in the EU.
Source: ECB Consolidated Banking Data, February 2019.

Graph 3.8. **Relative size of selected institutions in the portfolio over time (as % of portfolio size)**



Note: Share of the individual FI's assets in the total portfolio of assets held by the FIs in the sample.
Source: S&P, own calculations.

3.2.1. Banks' distress dependence and Banking Stability Measures

Consequently, it becomes essential for the proper estimation of the banking system's stability to incorporate banks' distress dependence and its changes across the economic cycle. Segoviano and Goodhart (2009) conceptualise the banking system as a portfolio of banks comprising the core, systemically important banks in a given country. In the next step, they infer the banking system's portfolio multivariate density (BSMD). The BSMD characterises the probability of distress of the individual banks included in the portfolio, their distress dependence, and changes across the economic cycle. Using the BSMD, a set of banking stability measures (BSMs) is constructed. The BSM allows analysing banking stability from two different, yet complementary, perspectives: *i)* common distress in the banks of the system, and *ii*) distress between specific banks. See Box 4.1 for more details.

Box 4.1. **CIMDO (GOODHART AND SEGOVIANO, 2009)**

For illustrative purposes, and to facilitate the understanding of the definitions below, we proceed by defining a banking system - portfolio of banks - comprising three banks, whose asset values are characterised by the random variables x and y and r. Hence, following the CIMDO method we infer the CIMDO-density function, which takes the form:

$$p(x,y,r) = q(x,y,r)\exp\left\{-\left[1+\mu+\left(\lambda_1\chi_{[x_d^x,\infty)}\right)+\left(\lambda_2\,\chi_{[x_d^y,\infty)}\right)+\left(\lambda_3\,\chi_{[x_d^r,\infty)}\right)\right]\right\}$$

where $q(x,y,r)$ and $p(x,y,r) \in \mathbb{R}^3$.

(1)

where λ_1 and λ_2 represent the Lagrange multipliers of the consistency constraints, μ represent the Lagrange multiplier of the probability additivity constraint, and χ indicating functions defined with the distress thresholds estimated for each bank in the portfolio. For a detailed derivation see Goodhart and Segoviano (2009).

Common distress in the banking system

The following measures are used to analyse common distress in the banks comprising the system: the Banking Stability Index (BSI), and the Joint Probability of Distress (JPoD). The BSI represents a probability measure that conditions on any bank becoming distressed, without indicating the specific bank, and reflects the expected number of banks becoming distressed, given that at least one bank has become distressed. A higher number means increased instability. For example, for a system of two banks, the BSI is defined as follows:

$$\mathrm{BSI} = \frac{P\left(X \geq x_d^x\right) + P\left(Y \geq x_d^y\right)}{1 - P\left(X < x_d^x, Y < x_d^y\right)}$$

(2)

The Index is based on the “conditional expectation of default probability” measure developed by Huang (1992). The author shows that this measure can also be interpreted as a relative measure of banking linkage. As the value of the BSI increases, banking linkage increases.

The Joint Probability of Distress (JPoD) represents the probability of all the banks in the system (portfolio) becoming distressed, i.e., the tail risk of the system. The JPoD embeds not only changes in the individual banks’ PoDs, it also captures changes in the distress dependence among the banks, which increases in times of financial distress; therefore, in such periods, the banking system’s JPoD may experience larger and nonlinear increases than those experienced by the (average) PoDs of individual banks. For the hypothetical banking system defined in equation [1], the JPoD is defined as $P(X \cap Y \cap R)$, and it is estimated by integrating the density (BSMD) as follows:

$$\int_{x_d^x}^{\infty}\int_{x_d^y}^{\infty}\int_{x_d^r}^{\infty} p(x,y,r)\,dx\,dy\,dr = JPoD$$

(3)

Distress between specific banks

For each period under analysis and with reference to each pair of banks in the portfolio, a set of pairwise conditional probabilities of distress can be calculated and presented in the Distress Dependence Matrix (DiDe). This matrix contains the probability of distress of the bank specified in the column, given that the bank specified in the row becomes distressed. Although conditional probabilities do not imply causation, this set of pairwise conditional probabilities can provide important insights into interlinkages and the likelihood of contagion between the banks in the system. For the hypothetical banking system defined in equation (1), at a given date, the DiDe is represented in Table 1

Table 1: **Distress Dependence Matrix**

	Bank X	Bank Y	Bank R
Bank X	1	P(X/Y)	P(X/R)
Bank Y	P(Y/X)	1	P(Y/R)
Bank R	P(R/X)	P(R/Y)	1

Where for example, the probability of distress of bank X conditional on bank Y becoming distressed is estimated by:

$$P\left(X \geq x_d^x \middle| Y \geq x_d^y\right) = \frac{P\left(X \geq x_d^x, Y \geq x_d^y\right)}{P\left(Y \geq x_d^y\right)}$$

(4)

Graph 3.9 presents an overview of the first category of findings regarding the Banking Stability Measures (BSI and JPoD) over the analysed period, 2015-2019. With a correlation coefficient for the time period of ca. 0.65, the two measures appear to correlate to a high degree. An increase in the BSI value implies increased instability, which in turn correlates with a higher JPoD. For example, the BSI and the JPoD jointly increase significantly between the announcement and the conduct of the Brexit referendum. While instability decreases in the following quarters, it picks up again during and in the direct aftermath of the 2016 US presidential election. Other peaks of the two measures appear shortly after the Italian election in 2018 and the beginning of the Turkish currency and debt crisis. The most recent peak took place shortly after the US administration imposed 10% tariffs on $200 billion of Chinese imports. Starting at the end of 2018 until the middle of March 2019, both the BSI and the JPoD decrease substantially which might be due to the relaxation of the trade tensions between the US and China.[13]

Graph 3.9. **Banking Stability Index & Joint Probability of Distress (Q1 2015-Q1 2019)**

Source: S&P, own calculations.

In our case, the Distress Dependence Matrix presented in Table 3.5 shows the (pairwise) conditional probabilities of the distress of the bank in the column, given that the bank in the row falls into distress. The matrix is estimated daily. For the purposes of the analysis, we have chosen one day (29/06/2016) when the BSI and the JPoD peak shortly after the Brexit referendum. Any given probability of distress higher than 0.7, 0.6 or 0.5 is marked respectively in red, pink, and yellow. The main findings from the analysis of the distress dependence matrix are as follows. (i) On the chosen day, Deutsche Bank, Commerzbank, Banco Santander, RBS, and Unicredit (banks highlighted with a blue background in the table) were the banks most interconnected to the EU banking system and under the highest distress, with a conditional PoD higher than 50% on any other bank failing into distress (highest row average). (ii) Allianz (only insurance company in the sample) had the lowest conditional probability of distress (11%), which might point to its lower interconnectedness with the banking sector and the connectedness with FI under less distress on that date (lowest row average). (iii) French banks and ING Group appear to transmit the highest distressed to the system, prone to generate financial spillovers and losses with conditional PoD higher than 50% (highest column average). (iv) Financial institutions such as Standard Chartered or Unicredit transmitted less distressed to other banks (column average below 0.30).

[13] The relevance of the level of these indicators can be put into context by comparing them with analysis performed using the CIMDO model on a sample of US banks over the last financial crisis (2007Q1-2008Q4). The peak of the BSI for the European sample is 3.7 and dates back a few days after the Brexit referendum (29/06/2016), while 3.6 was approximately the level of the BSI during both the Bearn Sterns and Lehman Brothers collapses in 2008.

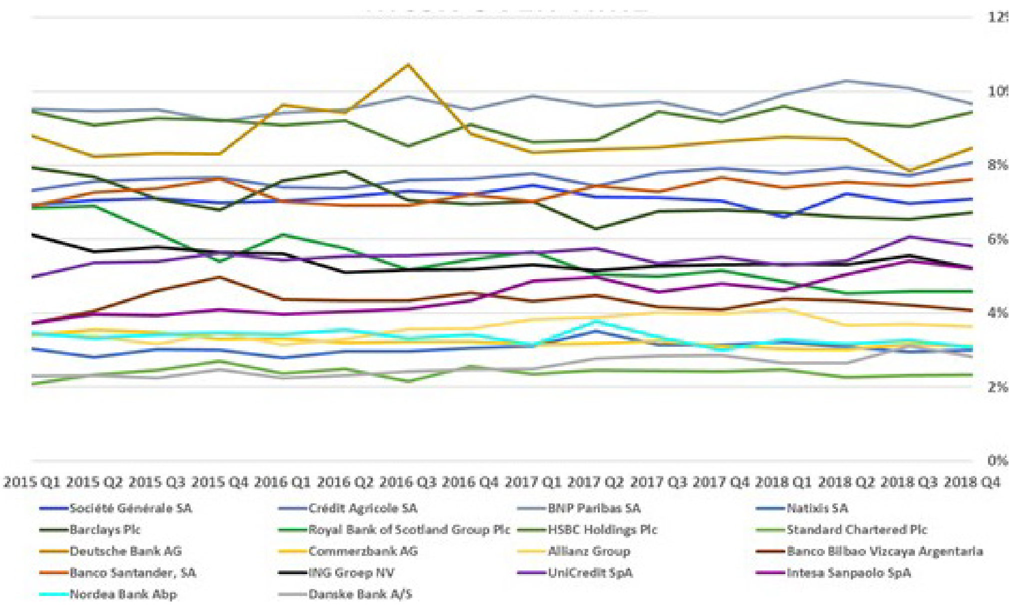
Table 3.5. **Distress Dependence Matrix** (conditional probabilities of distress for pairs of banks after the Brexit referendum on 29/06/2016)

Country	29-06-2016	DE	DE	DE	DK	ES	ES	FI	FR	FR	FR	FR	IT	IT	NL	UK	UK	UK	UK	
	Bank	Deutsche Bank AG	Commerzbank AG	Allianz Group	Danske Bank A/S	Banco Santander SA	Banco Bilbao Vizcaya Argentaria	Nordea Bank Abp	Societe Generale SA	BNP Paribas SA	Credit Agricole SA	Natixis SA	Intesa Sanpaolo SpA	UniCredit SpA	ING Groep NV	HSBC Holdings Plc	Barclays Plc	Royal Bank of Scotland Group Plc	Standard Chartered Plc	Row Average
DE	Deutsche Bank AG	.	0,73	0,47	0,63	0,70	0,70	0,63	0,78	0,79	0,78	0,75	0,62	0,58	0,76	0,63	0,62	0,55	0,27	0,65
DE	Commerzbank AG	0,42	.	0,40	0,56	0,58	0,59	0,54	0,69	0,69	0,70	0,71	0,50	0,43	0,68	0,50	0,46	0,43	0,20	0,53
DE	Allianz Group	0,06	0,09	.	0,17	0,10	0,10	0,13	0,14	0,12	0,14	0,14	0,10	0,07	0,13	0,12	0,09	0,07	0,06	0,11
DK	Danske Bank A/S	0,11	0,16	0,21	.	0,18	0,18	0,26	0,23	0,23	0,25	0,29	0,16	0,12	0,25	0,17	0,14	0,13	0,08	0,19
ES	Banco Santander SA	0,36	0,52	0,39	0,54	.	0,72	0,52	0,70	0,72	0,71	0,72	0,52	0,42	0,69	0,50	0,43	0,40	0,18	0,53
ES	Banco Bilbao Vizcaya Argentaria	0,31	0,46	0,35	0,48	0,63	.	0,47	0,62	0,63	0,63	0,65	0,45	0,36	0,61	0,45	0,38	0,35	0,16	0,47
FI	Nordea Bank Abp	0,20	0,30	0,32	0,49	0,32	0,33	.	0,40	0,40	0,44	0,49	0,29	0,22	0,41	0,34	0,26	0,34	0,13	0,33
FR	Societe Generale SA	0,27	0,41	0,36	0,48	0,47	0,47	0,43	.	0,66	0,63	0,63	0,41	0,31	0,58	0,40	0,35	0,31	0,15	0,43
FR	BNP Paribas SA	0,29	0,44	0,35	0,50	0,52	0,52	0,46	0,71	.	0,67	0,68	0,43	0,33	0,64	0,42	0,36	0,33	0,15	0,46
FR	Credit Agricole SA	0,23	0,36	0,31	0,43	0,40	0,41	0,40	0,53	0,53	.	0,60	0,34	0,25	0,50	0,33	0,29	0,26	0,12	0,37
FR	Natixis SA	0,11	0,18	0,16	0,26	0,21	0,21	0,22	0,27	0,27	0,30	.	0,18	0,13	0,25	0,18	0,15	0,13	0,07	0,19
IT	Intesa Sanpaolo SpA	0,30	0,41	0,34	0,46	0,48	0,48	0,43	0,56	0,55	0,55	0,57	.	0,39	0,55	0,40	0,38	0,33	0,15	0,43
IT	UniCredit SpA	0,50	0,64	0,46	0,60	0,69	0,68	0,59	0,76	0,76	0,73	0,74	0,70	.	0,72	0,56	0,53	0,50	0,23	0,61
NL	ING Groep NV	0,27	0,43	0,34	0,54	0,48	0,49	0,46	0,60	0,62	0,62	0,62	0,41	0,30	.	0,41	0,35	0,33	0,14	0,44
UK	HSBC Holdings Plc	0,25	0,35	0,36	0,42	0,39	0,40	0,42	0,46	0,45	0,45	0,50	0,34	0,27	0,46	.	0,41	0,30	0,16	0,37
UK	Barclays Plc	0,40	0,51	0,43	0,55	0,53	0,53	0,51	0,64	0,62	0,63	0,65	0,51	0,40	0,63	0,65	.	0,50	0,22	0,52
UK	Royal Bank of Scotland Group Plc	0,41	0,55	0,41	0,57	0,58	0,57	0,55	0,67	0,66	0,66	0,68	0,51	0,44	0,67	0,55	0,58	.	0,23	0,55
UK	Standard Chartered Plc	0,18	0,23	0,30	0,32	0,25	0,25	0,29	0,29	0,28	0,29	0,34	0,22	0,19	0,27	0,27	0,24	0,22	.	0,26
	Column Average	**0,28**	**0,38**	**0,34**	**0,46**	**0,43**	**0,43**	**0,42**	**0,52**	**0,51**	**0,53**	**0,56**	**0,38**	**0,29**	**0,50**	**0,39**	**0,34**	**0,30**	**0,15**	.
>0,5 < 0,59	> 0,6 < 0,69	> 0,7																		

Source: S&P, own calculations.

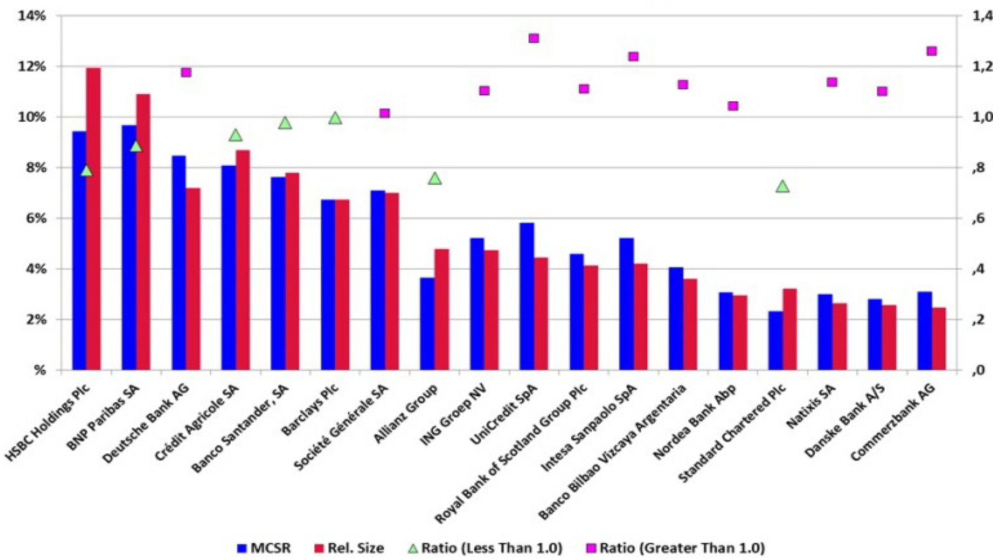
We also examine the different contributions of financial institutions to systemic risk within the sample to identify the institutions that contribute more to systemic risk. In order to do so, we compute the Marginal Contribution to Systemic Risk ("MCSR") of the 18 financial institutions of the sample, a metric expressed in relative terms and reflecting both the size of an institution and its interlinkages with other institutions. The results are to be analysed first from a chronological perspective. In a later step, the marginal contribution of financial institutions to the systemic risk has to be put into perspective with their respective size within the sample (see Graph 3.10). MSCR is stable over time for the majority of entities with some exceptions such as Deutsche Bank, where it fluctuates significantly or the RBS Group, where it decreased substantially, thereby most probably reflecting the particularly strong deleveraging path followed post-crisis by the bank. The ratio between relative size and MCSR appears to follow no clear pattern of correlation, with larger and smaller institutions all experiencing values below and above one in 2018Q4 (see Graph 3.11), meaning that for many FIs their marginal contribution to systemic risk does not correspond to their relative size (e.g. Deutsche Bank, Commerzbank, Unicredit, ING, RBS show a higher contribution to systemic risk than their relative sizes).

Graph 3.10. **MSRC of all financial institutions of the sample**



Source: S&P, own calculations.

Graph 3.11. **MCSR and relative size of financial institutions as of Q4 2018**



Source: S&P, own calculations.

3.2.2. Quantifying systemic risk losses derived from interconnectedness structures

Drawing on the "encompassing" approach developed in Akka et al. (2018), the CIMDO method combines the positive features of stress tests run on individual entities with an empirical approach to systemic risk measurement.[14] The quantification model of losses used in this method, therefore,

[14] Developed in Segoviano and Goodhart (2009), and Segoviano and Espinoza (2017) and based on Kullback (1959), this method incorporates the limited observed information on the entities' equity returns and empirically observed Probabilities of

calculates the losses of financial entities conditional on the distress of other entities in the system. In this spirit, systemic risk losses should be pictured at an individual level as the difference between the value of a given institution under an adverse macroeconomic scenario and its value assuming the realisation of both this adverse macroeconomic scenario and a given financial contagion event; in other words, as the difference between its unconditional and conditional valuation (expected value of the assets of a given bank A given the default of bank B). Hence, this method typifies the banking system as a sum of portfolios of interconnected entities (representing around 58% of EU total bank assets[15]) and extracts systemic risk losses from estimated losses suffered by specific institutions conditional on other entities falling in distress. It thereby clearly identifies and captures the losses directly caused by contagion effects ("second round" effects).[16]

Using the CIMDO method and the related CIMDO-copula approach allowing for an isolation of the dependence structure embedded in the multivariate density (through controlling for the marginal information of individual variables), we obtain a robust and empirically founded modelling of the multivariate density of losses and the interconnectedness structure of the banking system in times of crisis. Based on this as well as on market-based information regarding the probabilities of distress of financial institutions, we run Monte Carlo-type simulations randomly simulating distress sets. The conduct of this stochastic process (under certain assumptions concerning the distribution of losses) allows us to compute the relative (compared to bank asset value) and absolute levels of losses.

With respect to the recovery values assumed for assets under distress, this paper uses two distinct Loss Given Default (LGD) assumptions and compares the results associated with each of those two values: (i) a 45% rate, consistent with an equivalent risk scenario seen when Lehman collapsed in 2018 and the conventional regulatory value as defined in Article 163 of the of the Regulation (EU) No 575/2013 on prudential requirements for credit institutions and investments firms (so-called CRR); and (ii) a less risky scenario of 20% LGD rate. The comparative analysis provides some preliminary insights regarding the sensitivity of the LGD variable to systemic risk and bank interdependence in terms of distress to variations in the intensity of losses.

We first deliver an overview of maximum and average levels of losses overtime during the analysed period (2015-2018), expressed in relative terms with the total assets of the selected institutions used as the denominator. Under the scenario of LGD fixed at the conventional regulatory value of 45%, systemic risk losses are modelled according to a student-t distribution of losses (see Graph 3.12). The difference between the average and the maximum value of simulated losses provides us with the upper range of potential losses. With respect to the results, maximal losses relative to the sample's total assets peak at 6.2% in Q2 2016. Average losses values, for their part, peak at 2.6% in 2016Q1. The upper range of losses varies respectively between 2.4% (2018Q4) and 3.7% (2017Q1). While values appear to remain relatively stable over the period, a reduction of simulated systemic risk losses (expressed as a share of the total assets of the sample) is observable between 2017Q2-Q4.

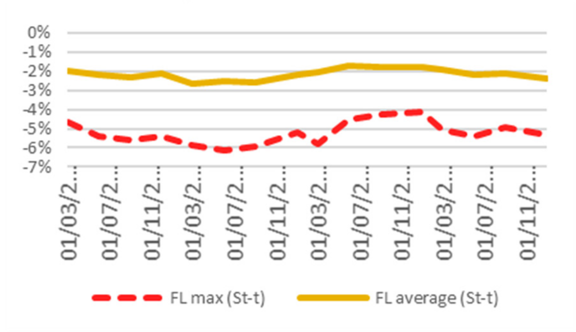
distress (PoD) of individual institutions to infer the dependence structure of the system (embedded in the multivariate density) instead of assuming parametric probabilities to characterise the information contained in the data.

[15] The ECB Consolidated Banking Data.

[16] The CIMDO method provides important benefits relative to parametric approaches in terms of implementation feasibility and estimation robustness. First, it guarantees the consistency of the inferred and modelled interdependence structure of the system with empirical PoD observations, reducing in this way the risk of density misspecifications. Moreover, as observed PoDs change over time, the interconnectedness structure and multivariate density of a given system instantaneously adapt. Systemic Risk Metrics (SRMs) estimated from the CIMDO Banking System Multivariate Density (BSMD) therefore directly incorporate changes in the interconnectedness structure. This constant update is essential to reflect non-linear increases in periods of high volatility. Finally, in using readily available market information, this method incorporates market estimates of risk spillovers due to direct or indirect transmission channels across financial entities (in this case mostly banks) and is therefore consistent with markets' real perceptions of risk.

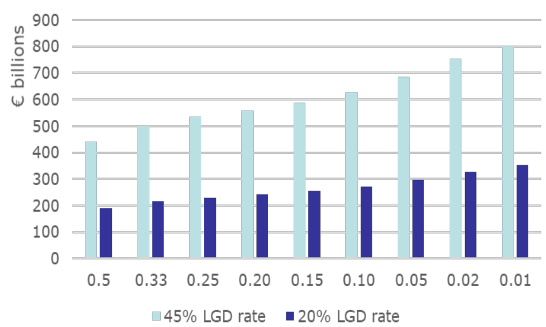
The next step of this analysis consists of a translation of these relative figures in absolute systemic risk losses. At the same time, we focus on the last interval (2018 Q4) of the period under consideration and present our analysis by considering the distribution of simulated losses in a probabilistic way. As was the case with relative figures, both the 20% and the 45% LGD rate are applied and results are computed based on a student-t distribution pattern of losses. Graph 3.13 provides estimates of absolute losses for 2018Q4 (under the assumption of a student-t type loss distribution). We now proceed to the analysis of absolute losses under a 45-LGD rate scenario. Results indicate that there is a 10% probability that losses exceed 625.98 EUR bn and a 5% probability that losses exceed 684.96 EUR bn. The results applying the 20%-LGD rate scenario assumption provide a 10% probability that losses exceed 270.29 EUR bn and a 5% probability that losses exceed 297.97 EUR bn. These results tend to indicate a strong sensitivity of simulated losses to variations in LGD-levels. Moreover, the effect of the LGD variable on the expected losses is not proportional.[17]

Graph 3.12. **Relative Systemic Risk Losses over time**



Note: FL means that for the estimation of losses a fixed LGD is assumed under the analysed time horizon.

Graph 3.13. **Systemic risk losses for 2018Q4 in absolute terms**



Note: Student-t (st-t) distribution of losses for the two distinct LGD rate scenarios (45% and 20%).

3.3. BANKS' CREDIT EXPOSURES AND THE SYMBOL MODEL

This section begins by exploring publically available bank-level data on cross-border credit exposures to private and government sectors in the euro area (EA). Subsequently, it uses part of the data to calibrate the European Commission's SYMBOL model (De Lisa et al., 2008). This allows us to simulate the impact on bank and sovereign balance sheets of stylised shocks in the presence of feedback-loop dynamics between these two sectors.

3.3.1. EBA data on the credit exposures of EA banks

The bank-level data presented in this section is taken from the 2018 Transparency Exercise conducted by the European Banking Authority (EBA). The underlying dataset provides detailed balance sheet data covering 102 EA banks on a consolidated basis as of June 2018. In particular, we explore banks' cross-border credit exposures to EA sovereigns and private sectors. Additionally, private sector exposures can be further distinguished into performing and non-performing status, and in subsectors: non-financial corporations, the retail sector (SMEs and households), and financial institutions. The heat maps presented in Tables 3.6 and 3.7 provide a summary of the main cross-border interlinkages and the degree of homes bias in bank lending.

[17] This analysis also inspires further research to explore the impact of variations in the LGD rate on potential losses in a more systematic and holistic way, which could be done by applying other LGD scenarios to the analysis in order to construct a systemic losses curve dependent on LGD scenarios as well as using empirical data from EU banks' LGD for different assets portfolios that would also help to calibrate further the output of the model.

Table 3.6. **Credit exposures of EA-16 banking sectors to EA-19 sovereigns**

Exposures from banking sector of (in % of tier 1 capital):	To sovereign of: AT	BE	CY	DE	EE	GR	ES	FI	FR	IE	IT	LT	LV	LU	MT	NL	PT	SI	SK
AT	49%	1%	0%	5%	0%	0%	2%	1%	2%	1%	2%	0%	0%	1%	0%	1%	0%	2%	16%
BE	1%	110%	0%	37%	0%	0%	19%	1%	35%	3%	59%	0%	0%	3%	0%	4%	11%	0%	7%
CY	0%	0%	28%	1%	0%	0%	0%	0%	9%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
DE	6%	3%	0%	130%	0%	0%	5%	1%	7%	1%	12%	0%	0%	1%	0%	3%	1%	0%	0%
EE	0%	0%	0%	0%	784%	0%	0%	0%	0%	0%	0%	16%	1%	0%	0%	0%	0%	0%	0%
GR	0%	0%	3%	0%	0%	44%	2%	0%	0%	0%	2%	0%	0%	4%	0%	0%	0%	0%	0%
ES	0%	0%	0%	1%	0%	0%	141%	0%	2%	0%	20%	0%	0%	0%	0%	0%	7%	0%	0%
FI	1%	1%	0%	15%	0%	0%	0%	270%	1%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%
FR	1%	9%	0%	10%	0%	0%	5%	1%	152%	1%	14%	0%	0%	3%	0%	2%	1%	0%	0%
IE	0%	4%	0%	8%	0%	0%	8%	0%	6%	47%	4%	0%	0%	0%	0%	1%	1%	0%	0%
IT	9%	1%	0%	19%	0%	0%	26%	0%	8%	0%	151%	0%	0%	1%	0%	0%	1%	1%	1%
LU	3%	17%	0%	4%	0%	0%	14%	1%	27%	7%	6%	1%	0%	128%	0%	1%	1%	1%	3%
MT	5%	3%	0%	17%	0%	0%	1%	2%	13%	0%	2%	0%	0%	0%	55%	2%	0%	1%	0%
NL	5%	18%	0%	20%	0%	0%	4%	5%	8%	0%	0%	0%	0%	1%	0%	110%	0%	0%	0%
PT	0%	0%	0%	2%	0%	0%	30%	0%	4%	1%	18%	0%	0%	0%	0%	0%	173%	0%	0%
SI	6%	7%	0%	3%	0%	0%	4%	2%	7%	4%	3%	2%	2%	2%	0%	5%	1%	86%	4%

Note: exposures as of June 2018. Based on a sample of 102 EA banks participating in the 2018 Transparency Exercise conducted by the EBA.

Source: EBA, own calculations.

Table 3.7: **Credit exposures of EA-16 banking sectors to the private sector of EA-19 Member States**

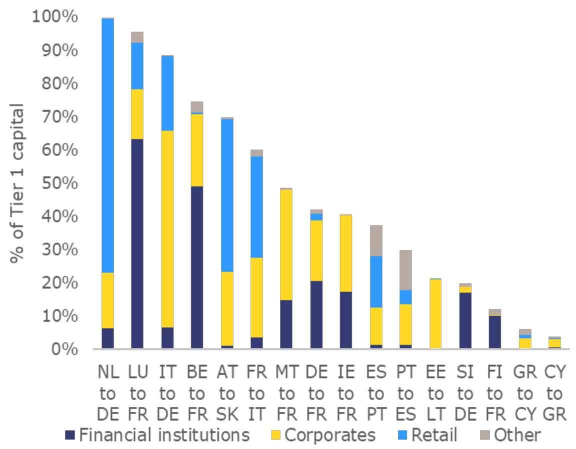
Exposures from banking sector of (in % of tier 1 capital):	To private sector of: AT	BE	CY	DE	EE	GR	ES	FI	FR	IE	IT	LT	LV	LU	MT	NL	PT	SI	SK
AT	443%	0%	0%	61%	0%	0%	2%	1%	3%	2%	0%	0%	0%	1%	0%	2%	0%	4%	70%
BE	0%	570%	0%	23%	0%	0%	21%	0%	74%	32%	26%	0%	0%	0%	0%	54%	2%	0%	21%
CY	0%	0%	310%	2%	0%	4%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%
DE	5%	1%	0%	674%	0%	0%	13%	0%	42%	1%	19%	0%	0%	18%	0%	25%	0%	0%	0%
EE	0%	0%	0%	0%	648%	0%	0%	0%	0%	0%	0%	21%	0%	0%	0%	0%	0%	0%	0%
GR	0%	0%	6%	0%	0%	435%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
ES	0%	0%	0%	21%	0%	0%	440%	0%	23%	0%	3%	0%	0%	0%	0%	0%	37%	0%	0%
FI	0%	0%	0%	8%	0%	0%	0%	797%	12%	0%	0%	7%	0%	0%	0%	3%	0%	0%	0%
FR	0%	41%	0%	39%	0%	0%	12%	0%	733%	0%	60%	0%	0%	21%	0%	13%	0%	0%	0%
IE	0%	0%	0%	9%	0%	0%	14%	0%	40%	345%	0%	0%	0%	0%	0%	10%	0%	0%	0%
IT	39%	0%	0%	88%	0%	0%	6%	0%	16%	0%	508%	0%	0%	4%	0%	1%	0%	0%	10%
LU	0%	19%	0%	32%	0%	0%	5%	0%	95%	1%	0%	0%	0%	419%	0%	28%	0%	0%	0%
MT	0%	4%	0%	33%	0%	0%	5%	0%	49%	5%	12%	0%	0%	11%	280%	37%	0%	0%	0%
NL	0%	88%	0%	99%	0%	0%	21%	0%	30%	0%	0%	0%	0%	0%	0%	714%	0%	0%	0%
PT	0%	0%	0%	1%	0%	0%	30%	0%	19%	0%	0%	0%	0%	0%	0%	0%	575%	0%	0%
SI	7%	3%	0%	20%	0%	0%	1%	0%	13%	0%	0%	0%	0%	0%	0%	5%	0%	292%	0%

Note: exposures as of June 2018. Based on a sample of 102 EA banks participating in the 2018 Transparency Exercise conducted by the EBA.

Source: EBA, own calculations.

The heat maps show a high degree of home bias in lending to public and private sectors, as highlighted by the red cells along the diagonal. Important cross-border linkages are visible in orange and yellow cells. Looking closer at private-sector exposures, Graph 3.14 shows for each national banking sector its main cross-border counterpart. A higher degree of cross-border integration is observed for "core" euro area Member States, such as the Netherlands, Luxembourg, Italy, Belgium, Austria, and France. Graph 3.15 zooms in on this picture by showing the top banks in the sample with the largest cross-border exposures.

Graph 3.14. **Largest cross-border counterpart Member State for private sector bank exposures**



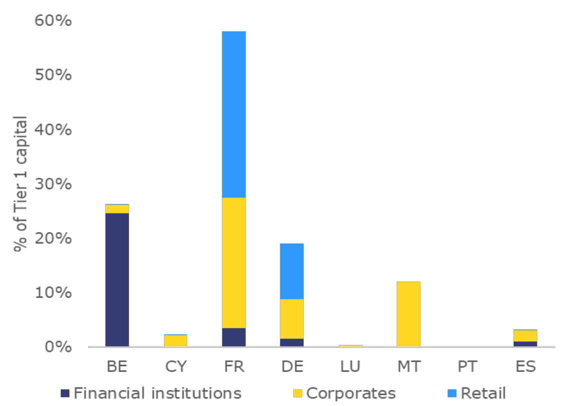
Graph 3.15. **Largest cross-border exposures to Member States' private sectors: top banks**

Note: exposures as of June 2018. Based on a sample of 102 EA banks participating in the 2018 Transparency Exercise conducted by the EBA.

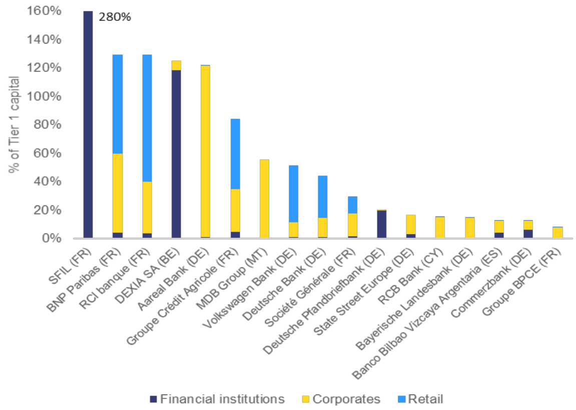
Source: EBA, own calculations.

The EBA data also allows examining in more detail the cross-border exposures to a given Member State. As an illustration, we focus on bank exposures to the Italian private sector, given that the next subsection simulates the effects of stylised shocks (with origin) in that country. In the consolidated banking data from the EBA, only banks from eight Member States register exposures to the Italian private sector (see Graph 3.16). Additionally, only 16 non-Italian banks show exposures worth more than 5% of their tier 1 capital (see Graph 3.17).

Graph 3.16. **Credit exposures of EA banking sectors to the Italian private sector**



Graph 3.17. **Exposures of non-Italian banks to the Italian private sector**



Note: exposures as of June 2018. Based on a sample of 102 EA banks participating in the 2018 Transparency Exercise conducted by the EBA. Graph 3.17 shows only institutions with total exposures greater than 5% of tier 1 capital.

Source: EBA, own calculations.

Among the euro area Member States, the largest exposures to the Italian private sector are concentrated in the banking sectors of France, Germany, and Belgium. France shows very large exposure of several of its banks, some of which are large institutions (BNP Paribas, Groupe Crédit Agricole, and Societé Generale).[18] Germany also shows a number of large exposures at the bank level,

[18] SFIL and RCI Banque also show very large exposures, but these are comparatively small institutions.

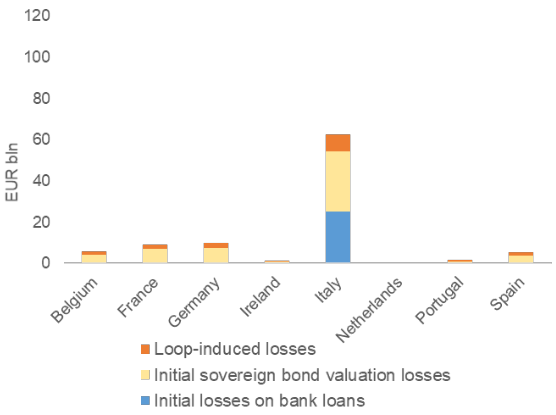
including in a large bank (Deutsche Bank). Belgium registers a large exposure of one bank (Dexia), via the financial institutions/interbank channel.

3.3.2. SYMBOL model simulations

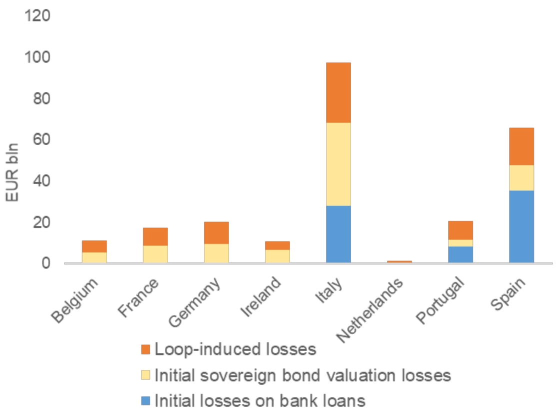
The SYMBOL model estimates[19] the level of bank losses and risks to public finances due to shocks to the balance sheets of banks and sovereign credit risk premia, as amplified by possible feedback loop dynamics between the two sectors. The model permits to take into account possible safety nets as bail-in and a Single Resolution Fund (SRF) are used to partly recapitalise banks. For a recent application, including a model description, see Bellia et al (2019).

Graphs 3.18 and 3.19 depict two scenarios, both of which assume a large increase in the credit risk of Italian banks' portfolios of a magnitude comparable to that observed in the worst periods of the crisis (namely, technically speaking, the risk-weighted assets of Italian banks are assumed to increase by 12.8%, which translates into an increase in their probability of default) as well as a rise in the sovereign risk premia of the Italian sovereign by annualised 200 bps. Graph 3.18 includes no further initial shocks while Graph 3.20 assumes, in addition, correlated increases in the sovereign risk premia of Spain and Portugal (by 100 bps each) and, respectively, in the credit risk of the portfolios of the banks located in these two countries. This increase in credit risk corresponds to raising the risk-weighted assets of Spanish and Portuguese banks by 5%. Both scenarios consider the partial use of bail-in and a SRF and rely on "worst-case" assumptions.[20] In particular, market pressure implies that investors tacitly consider all sovereign debt as marked-to-market, so that a bank may need to recapitalise when faced with valuation losses on their sovereign debt holdings.

Graph 3.18. **Excess losses from shocks to Italian banks and sovereign**



Graph 3.19. **Excess losses from shocks to periphery banks and sovereigns, with stronger magnitude in Italy**



Note: Excess losses correspond to the loss amounts bringing banks' tier 1 capital ratio below a regulatory minimum of 10.5% and which require, therefore, (government-sponsored) recapitalisation. Initial losses on bank loans.

Source: SYMBOL model simulations.

[19] The simulations shown in this subsection were kindly prepared in the Commission's Joint Research Center by M. Bellia, L. Cales, L. Frattarolo and M. Petracco.

[20] Bail-in was modelled such that total loss-absorbing capacity, consisting of bail-in capacity and regulatory capital, is set at 8% of total assets. The SRF is assumed to have been phased into 40% of its target level. The SRF contributes to resolution by absorbing losses up to 5% of the total assets of the insolvent ban,k provided that bail-in has already occurred.

A comparative reading of both graphs highlights the role of financial spillovers in potentiating losses. In Graph 3.18, total excess losses[21] remain largely restricted to Italy due to the comparatively low direct exposure of other EA banks to the Italian sovereign; in Graph 3.19, these losses are greatly augmented. The latter is due not only to the fact that the Portuguese and Spanish banks and sovereigns suffer (by assumption) correlated initial shocks to their portfolios and risk premia, but is also the result of stronger sovereign-bank loop dynamics.[22] These dynamics also show increasing losses in the other euro-area Member States that did not experience initial shocks to their banks or sovereigns.

3.4. SIMULATION OF MACROECONOMIC EFFECTS OF FINANCIAL SHOCKS

This final subsection contributes a quantitative characterisation of the macroeconomic implications of financial spillover (contagion). The discussion builds on simulations with the European Commission's macroeconomic model QUEST (Ratto et al., 2009). QUEST is a structural multi-region open-economy model in the New-Keynesian tradition with microeconomic foundations derived from utility and profit maximisation and including frictions in goods, labour, and financial markets. This section uses a model version with tradable and non-tradable goods and a residential construction sector and with four regions for illustrative purpose: Italy, where the financial shock assumingly originates; Spain and Portugal as potentially particularly exposed to contagion risk; the rest of the euro area (REA); and the rest of the world (RoW). Burgert et al. (2020) provides a detailed description of the multi-region version of QUEST with tradable and non-tradable goods, which includes trade in intermediate inputs. Breuss et al. (2015) develops a QUEST version with banking sector in which private loan default as well as sovereign risk can ignite a vicious bank-sovereign feedback loop. Bellia et al. (2019) provides an illustration of the adverse dynamics of the sovereign-bank feedback loop and the mitigating effects of asset diversification, but the model setting is limited to two stylised regions ("core" and "periphery").[23] In Bellia et al. (2019), the macroeconomic costs of spillover are in principle independent of whether the "doom loop" starts on either the bank or the sovereign side. The strength of spillover, however, depends on the precise nature of cross-border portfolio diversification (diversification of sovereign bond holdings versus diversification of bank equity/losses), which affects the cross-border transmission of the initial financial shock.[24]

The QUEST model simulations in this section aim at illustrating the propagation of financial shocks to the real economy. The structure of financial markets in the multi-region world-economy version of QUEST is rather parsimonious. There are liquidity-constrained ("hand-to-mouth"), credit constrained (credit is constrained by the value of housing collateral, and the constraint is binding) and Ricardian (full access to financial markets, with risk premia on corporate investment and sovereign bonds) households. Ricardian households also trade in an international bond, where the pricing of this bond includes a risk premium that depends on the relative net foreign asset position. For tractability, the model abstracts from international financial linkages through bank balance sheets and large gross asset exposure, which might otherwise imply powerful valuation effects. Instead, the simulations treat (assume) financial contagion as knock-on effect without providing a structural microeconomic

[21] Excess losses are losses requiring (government-sponsored) bank recapitalisation. They can be divided into the initial losses resulting from an increase in the credit risk of banks' portfolios, initial bond valuation losses resulting from initial shocks to sovereign risk premia, and other losses resulting from sovereign-bank loop dynamics.

[22] It can be observed that excess losses are particularly large for Spain. This is partly a consequence of the fact that the simulations rely on consolidated banking data and that Santander, a large international banking group, is headquartered in that country.

[23] Information on the QUEST macro model and its use for policy analysis at the European Commission, including a list of publications making use of the QUEST model, is available on https://ec.europa.eu/info/business-economy-euro/economic-and-fiscal-policy-coordination/economic-research/macroeconomic-models_en.

[24] Contagion and risk sharing are two sides of the same coin in Bellia et al. (2019), i.e. mitigation of domestic financial shocks through international portfolio diversification makes the domestic economy at the same time more vulnerable to foreign financial shocks. If investor loss functions are non-linear, such that a series of smaller losses is preferred to fewer large losses, there are gains from diversification to all parties as long as shocks are not concentrated in one region.

foundation of particular transmission channels inside the financial sector in this version of the model, contrary to the stylised "core-periphery" model in Bellia et al. (2019) in which spillover derives from cross-border portfolio diversification with respect to sovereign debt and bank equity.[25]

More precisely, we implement the illustrative scenario of financial contagion from Italy (IT) to Spain (ES) and Portugal (PT), as in the preceding SYMBOL scenario, by exogenous risk shocks on sovereign debt that are correlated across the two regional blocks (IT and ES+PT), and by correlated shocks on sovereign bonds and corporate financing costs (equity valuation) within each of the two regional blocks.

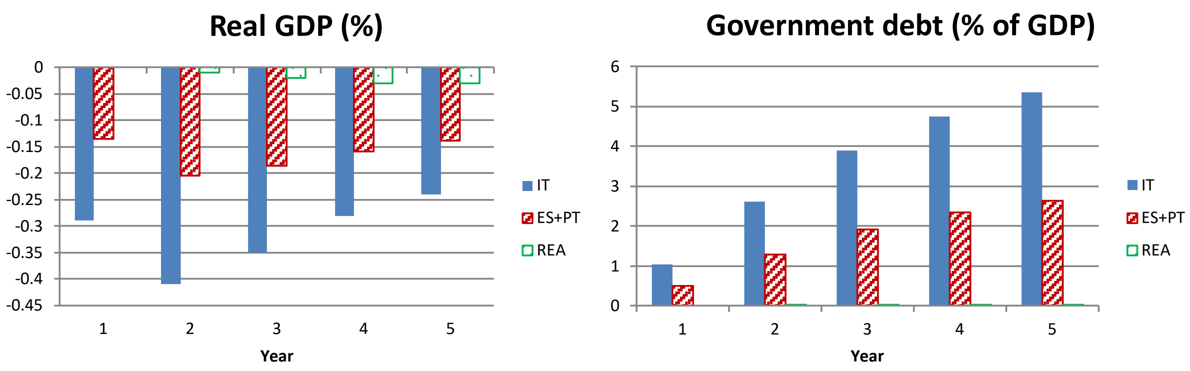
Building on the empirical analysis in the previous sections, we chose the following scenario for the simulation. The risk premium on Italian sovereign bonds increases by an annualised 200 basis points and remains at this elevated level for 2 years, after which it gradually declines. The sovereign risk increase only affects new issuance, which implies a very gradual increase in debt service costs in light of an average government debt maturity of around seven years. We assume that half of the increase in the sovereign premia spills over to private sector financing costs (corporate and housing investment) in Italy. The ½ spillover is in line with the evidence on sovereign-to-corporate risk spillover in Durbin and Ng (2005), implying an increase in Italian financing costs for private investment by annualised 100 basis points. The quantification of sovereign-to-private spillover in financing costs is also comparable to simulation results from the QUEST version with banking sector (Breuss et al., 2015) in which spillover of sovereign risk to loan supply and equity investment is endogenous and occurs through the balance sheet, notably the capital requirements, of banks.

Regarding cross-border financial contagion, we assume 50% transmission of the IT sovereign yield shock to sovereign risk in Spain and Portugal. The value of 50% is in line with evidence in Hesse et al. (2018), and it corresponds to the SYMBOL scenario with spread-out shocks in subsection 3.3.2 above. Cross-border transmission of 50% implies an increase in ES and PT sovereign risk by annualised 100 basis points for 2 years. In parallel to the assumption for Italy, half of the sovereign yield increase in Spain and Portugal spills over to elevated private sector (corporate and housing investment) financing costs. We switch off the government's debt stabilisation rule in the simulations for a period of 10 years. Temporary deactivation of the fiscal closure means the absence of tax increases (or spending cuts) in the short and medium term, which would be needed to offset the adverse budgetary effects associated with the sovereign risk increase (rollover costs) and the negative response of economic activity (primary government balance). Instead, the adverse impact on the government balance of higher financing costs and a deterioration in the primary balance (notably, lower tax revenue in response to negative investment, activity, and employment responses) is not offset, and it translates into an increase in government debt. As mentioned above, the budgetary impact of the increase in sovereign yields applies only to the newly issued sovereign bonds, where the model takes into account the average maturity of circa seven years of government debt in Italy, Spain and Portugal.

The simulation results are summarised in Graph 3.20 and Table 3.8. Graph 3.20 displays real GDP levels in per-cent deviations from the non-shock baseline, and the evolution of government debt in per cent of GDP relative to the baseline for the three EA sub-regions of the model (IT, ES+PT, REA) for the first five years. Higher financing costs lead to lower corporate and housing investment, which translates into lower domestic demand and aggregate activity. The decline in real GDP reaches its maximum, in absolute terms, at around -0.4% in IT and -0.2% in the ES+PT aggregate in the year 2.

[25] Besides the omission of a detailed modelling of the transmission channels in many macroeconomic models for the sake of simplicity, game theory and learning dynamics has been used to rationalise financial contagion in the absence of strong direct ("fundamental") financial linkages, i.e. to motivate financial contagion in the absence of direct balance sheet or portfolio exposure (e.g. Trevino, 2020). General-equilibrium macroeconomic models have not been able, so far, to integrate these appects. Another related aspect is contagion through sovereign and corporate credit ratings (e.g. Böninghausen and Zabel, 2015), which is also not part of the spillover channels in standard macroeconomic models.

Graph 3.20. **QUEST simulations on the macroeconomic effects of strong financial contagion**



Source: QUEST model simulations.

Table 3.8. **QUEST simulations on the macroeconomic effects of strong financial contagion**

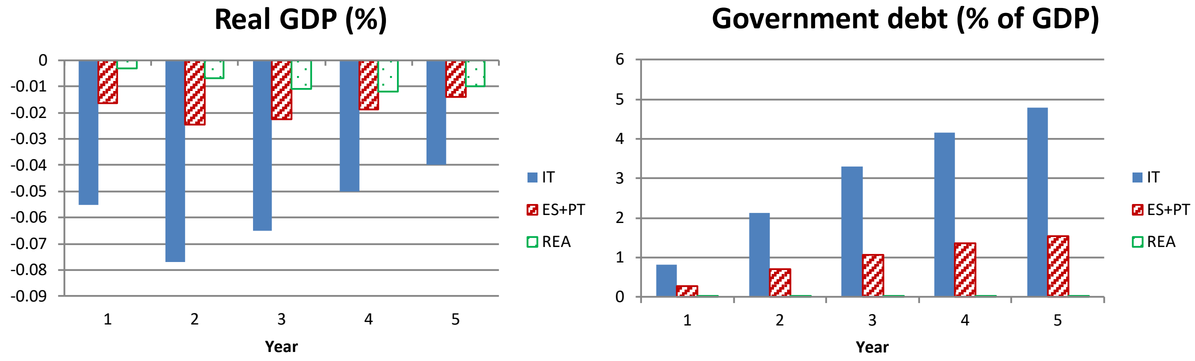
	IT					ES and PT				
Year	1	2	3	4	5	1	2	3	4	5
Real GDP (%)	-0.29	-0.41	-0.35	-0.28	-0.24	-0.14	-0.20	-0.19	-0.16	-0.14
Employment (%)	-0.19	-0.22	-0.11	-0.02	0.02	-0.09	-0.11	-0.06	-0.02	0.01
Consumption (%)	0.01	0.07	0.11	0.11	0.08	0.01	0.05	0.07	0.06	0.04
Corporate investment (%)	-3.37	-4.90	-4.20	-3.07	-2.12	-1.77	-2.61	-2.29	-1.72	-1.22
Housing investment (%)	-2.54	-3.69	-3.18	-2.32	-1.59	-0.98	-1.47	-1.36	-1.06	-0.78
Exports (%)	0.06	0.08	0.02	-0.06	-0.14	0.01	-0.01	-0.06	-0.10	-0.12
Imports (%)	-0.15	-0.45	-0.62	-0.64	-0.56	-0.08	-0.24	-0.33	-0.36	-0.33
Real wage (%)	-0.16	-0.31	-0.30	-0.23	-0.18	-0.06	-0.13	-0.14	-0.12	-0.11
GDP delator (%)	-0.09	-0.16	-0.14	-0.05	0.04	-0.05	-0.09	-0.09	-0.07	-0.04
Government debt (% of GDP)	1.04	2.62	3.89	4.75	5.35	0.52	1.30	1.92	2.34	2.64
Government balance (% of GDP)	-1.19	-1.33	-1.14	-0.87	-0.70	-0.53	-0.58	-0.49	-0.37	-0.30
Trade balance (% of GDP)	0.04	0.12	0.16	0.16	0.14	0.02	0.05	0.08	0.08	0.07

Note: Results are presented in level deviations from the no-shock baseline.
Source: QUEST model simulations.

Activity in REA, to the contrary, remains almost unchanged, because there is no contagion to sovereign or private sector financing costs in REA in the scenario. By consequence, GDP spillover to REA derives mainly from the trade channel; less import demand in IT, ES and PT implies less demand for REA exports. IT (ES+PT) government debt increases by 5% (3%) of GDP within five years in the absence of stabilising budgetary measures, as shown in Graph 3.20, despite the limited duration (two years) of the risk premium shock and the gradual pass-through to financing costs in light of the 7-year average maturity of outstanding sovereign debt in the simulation.

The absolute size of real economic effects in Graph 3.20 and Table 3.8 depends crucially on the size of the spillover from sovereign to private sector financing costs (½) , and the size of the contraction of activity in ES and PT relative to IT depends on the intensity (above, ½) of the cross-border transmission of sovereign risk shocks. Both values are rather upper bounds in the literature. The strength of co-movement of sovereign risk spreads in the EA "periphery" during 2011-2014 has been rather in the range of up to one third (e.g. European Commission 2015), and the exposure of banks in ES and PT to IT sovereign debt is around ten times smaller than the exposure of domestic IT banks (see Table 3.8 above). Concerning sovereign-to-corporate spillover, Augustin et al. (2018) find values of around 0.1 for a sample of companies from 15 EA countries in 2010. Compatible with this finding of more moderate sovereign-to-corporate spillover, Bevilaqua (2019) document the link between corporate and sovereign funding costs to weaken in periods of sovereign stress.

Graph 3.21. **QUEST simulations on macroeconomic effects of moderate financial contagion**



Source: QUEST model simulations.

Table 3.9. **QUEST simulations on macroeconomic effects of moderate financial contagion**

	IT					ES and PT				
Year	1	2	3	4	5	1	2	3	4	5
Real GDP (%)	-0.06	-0.08	-0.07	-0.05	-0.04	-0.02	-0.02	-0.02	-0.02	-0.01
Employment (%)	-0.04	-0.04	-0.02	0.00	0.01	-0.01	-0.01	-0.01	0.00	0.01
Consumption (%)	0.02	0.04	0.05	0.05	0.05	0.01	0.02	0.02	0.02	0.02
Corporate investment (%)	-0.70	-1.04	-0.91	-0.70	-0.51	-0.26	-0.39	-0.35	-0.28	-0.21
Housing investment (%)	-0.48	-0.70	-0.58	-0.40	-0.25	-0.12	-0.17	-0.15	-0.11	-0.07
Exports (%)	0.01	0.01	0.00	-0.02	-0.03	0.00	-0.01	-0.01	-0.02	-0.02
Imports (%)	-0.03	-0.09	-0.12	-0.12	-0.10	-0.01	-0.03	-0.04	-0.05	-0.04
Real wage (%)	-0.03	-0.05	-0.05	-0.03	-0.03	-0.01	-0.01	-0.01	-0.01	-0.01
GDP delator (%)	-0.01	-0.01	0.00	0.02	0.04	0.00	0.00	0.00	0.00	0.01
Government debt (% of GDP)	0.81	2.12	3.31	4.16	4.78	0.27	0.70	1.08	1.35	1.55
Government balance (% of GDP)	-1.09	-1.19	-1.03	-0.79	-0.64	-0.32	-0.35	-0.30	-0.23	-0.18
Trade balance (% of GDP)	0.01	0.02	0.03	0.03	0.03	0.00	0.01	0.01	0.01	0.01

Note: Results are presented in level deviations from the no-shock baseline.

Source: QUEST model simulations.

Less pronounced sovereign-to-private contagion dampens the macroeconomic costs of sovereign risk shocks in terms of contraction of economic activity. To illustrate this point, we rerun the scenario from Graph 3.20 and Table 3.8 with alternative, more moderate assumptions on spillover. In particular, we reduce sovereign-to-sovereign spillover from IT to ES and PT from one-half to one-third and the spillover from sovereign to private sector funding costs from 50% to 10%, in line with Augustin et al. (2018). Results are reported in Graph 3.21 and Table 3.9, and they display a substantial weakening of the adverse GDP effects. In particular, IT real GDP declines by up to -0.1% in this milder scenario, as opposed to -0.4% in year 2 in the strong-transmission case, and real GDP in ES and PT remains stable compared to the -0.2% decline before. In sum, in light of the strong uncertainty attached to the size of financial (funding costs/asset prices) contagion, macroeconomic effects are also highly uncertain.

Besides the strength of direct financial contagion, overall spillover to the real economy also depends on the macroeconomic context, i.e. it may be state-dependent. An example is the presence of the zero lower bound (ZLB) on monetary policy rates. A binding ZLB, which implies the absence of standard monetary expansion in response to below-target inflation and negative output gaps, amplifies the negative impact of financial shocks on the real economy, unless compensated by fiscal policy or "unconventional" monetary policy measures. In particular, re-running the previous scenarios with a temporarily binding ZLB amplifies the GDP loss in IT as the originating country, in ES and PT (although the ratio of ES+PT relative to IT output losses remains at the same order of magnitude), and notably also in the REA. While active monetary policy stabilises the EA aggregate in the scenarios above, it does no stabilise short-term dynamics at the ZLB, so that lower domestic demand in IT, ES and PT also affects REA activity negatively through lower demand for REA exports, a temporary increase in the real interest rate and real effective exchange rate appreciation. Slowing activity in REA also feeds back to IT, ES and PT via lower demand for the latter's exports, in turn.

4. CONCLUSIONS

This paper explores empirically different transmission channels of financial spillovers and contagion risk within the EU and, in particular, the euro area. The spread of financial market disturbances within and between countries, even in the absence of direct economic and financial linkages, is a salient feature of the modern financial system and has been amply witnessed during the 2008-2009 global financial crisis. A deeper understanding of possible cross-country financial interactions can better inform the economic policy debate in Europe and the design of macroeconomic and financial policy reforms in the EMU.

The value added of the present analysis, compared to existing literature on spillovers and contagion, is twofold. First, we focus on the euro area using the latest available data (in some cases, up to 2019), whereas most of the existing literature only looks at previous episodes, notably the global financial crisis and the euro area debt crisis. Focusing on these more recent episodes allows better tailoring the conclusions of our empirical analysis to the current policy environment, given that several important regulatory reforms have been implemented meanwhile. Second, rather than adopting one empirical methodology, the paper relies on different analytical tools and models to quantify feedback loops and the macroeconomic relevance of financial spillover and contagion risk. These tools include correlation analysis and exposure heatmaps, analysis of bank balance sheets, reduced-form models that infer the interconnectedness among agents from market data, and simulated structural models. Given the specific features of financial markets in the largest EU Member States in terms of size, financial interconnectedness, systemic relevance, and the level of sovereign exposure of bank balance sheets, the analysis looks at three main transmission channels: the sovereign-bank nexus, the bank-to-bank channel, and inter-sovereign spillovers within the euro area.

The first part of the analysis exploits data on sovereign bonds and CDS as well as data on bank valuation (equity, CDS, and bonds) to infer cross-asset price correlations across the euro area. In particular, real-time heatmaps are presented as a simple screening tool to get a first indication of potential financial spillovers/contagion risks and detect the sources of short-term vulnerabilities, while keeping in mind that cross-asset correlation is a necessary, but not a sufficient condition for contagion. The results confirm that banks in the euro area remain strongly exposed to the debt of their respective sovereigns (and to the respective private sectors). The correlation analysis also suggests that redenomination risk, i.e. the risk of one or more countries abandoning the monetary union, has declined in importance as an additional transmission channel at the euro area level since 2012. This risk has gradually become more idiosyncratic and "country-specific", i.e. related to possible concerns of a unilateral exit of specific Member States, as opposed to an outright break-up of the euro. The drivers of this change are difficult to test but may relate (beyond the asset purchasing programmes of the ECB) to evolving market perceptions in response to the strengthening of the banking supervisory framework, with the creation of the Single Supervisory Mechanism, the reform of the European Stability Mechanism, and the successful implementation of difficult country adjustment programmes.

The second part of the analysis quantifies potential losses in the financial sector that are due to the interconnectedness within the banking system, using the CIMDO model. Over the period 2015-2019, against the context of continuous deleveraging and despite some short-term spikes, the overall level of risk to stability in the EU banking system declined and remained far below the peaks reached during the 2008 Lehman crisis or the 2016 Brexit referendum. The analysis suggests that a plausible scenario with a loss given default of 20% would entail a 50% probability that losses in the EA banking system exceed 190 billion EUR (ca. 2% of euro area GDP). We also find that the marginal contribution of individual financial institutions to EU systemic risk, which depends on their interlinkages with other institutions, is often not proportional to the institution's relative size. Finally, the analysis highlights which financial institutions are most prone to generate systemic effects and losses, most interconnected to the EU banking system, and most exposed to stress.

The third part analyses sovereign-bank feedback loops and bank-to-bank channels with the SYMBOL model to quantify spillovers and contagion risks. Heatmaps with bank-level data provide a first picture of banks' cross-border exposures and existing linkages between banks and sovereigns in the euro area and highlight the high degree of home bias in bank lending to private and government sectors. The SYMBOL model provides an underlying structure and is calibrated on those bank-level data. We use the model to assess the impact of a large rise in the riskiness of periphery banks and sovereigns, with origin in Italy, purely as an illustrative scenario. The analysis emphasises the potential for significant loop-induced losses across the euro area, and the importance of limiting cross-border contagion risks.

In the final part of the analysis, simulations with the Commission's structural macroeconomic model QUEST illustrate the possible macroeconomic ("real economy") impact of elevated financial stress. Specifically, we consider an upper-bound scenario that combines a rise in Italian sovereign spreads by 200 basis points, together with inter- (to Spain and Portugal) and intra-country (from sovereign to private sector) financing cost spillover of 50% each. The simulations suggest a real output contraction in Italy of up to 0.4% (cumulated to 1.6% over 5 years), and GDP spillovers to Spain and Portugal that are proportional to the spillover in financing costs, i.e. peaking at 0.2% in our example. Accordingly, less pronounced spillover of financing costs is associated with less adverse macroeconomic effects.

Overall, the main findings of the paper can be summarised as follows: (i) negative spillover risks from sovereigns to banks appears to be currently smaller than in previous episodes; (ii) the bank-to-bank transmission channel appears to remain the most relevant in terms of financial spillovers, where a shock can still lead to severe losses; (iii) redenomination risk appear to play a smaller and more country-specific role in terms of contagion risks across sovereigns; and (iv) financial shocks can generate quantitatively relevant losses in terms of economic activity, potentially spilling over across borders.

The empirical results can also be related to post-crisis changes in the institutional and regulatory environment. The original regulatory framework did not target questions of interconnectedness and contagion risks, despite the recommendation of the Basel Committee on Banking Supervision (BCBS, 1991) to take action against large and concentrated exposures in banking portfolios. This happened only later with the introduction of large exposure limits (BCBS, 2014) and capital surcharges for systemically important financial institutions (G-SIB, D-SIB). Post-crisis advances in financial regulation can be expected to affect interconnectedness and contagion risk within the banking sector (and beyond). Unintended effects that can give rise to increased interconnectedness through the implementation of the Bank Recovery and Resolution Directive (BRRD), which requires banks to prepare recovery plans to overcome financial distress and grants national authorities powers to ensure an orderly resolution of failing banks with minimal costs for taxpayers, deserve special attention. Other requirements affect non-banks or the interconnectedness of banks and non-banks. The new reporting requirements also imply that authorities will have access to more granular data, which will allow better measurement of exposures and their differentiation according to the risk they pose to the financial system as a whole in the future. Namely, data on large exposures are now complemented by more granular data on banks' largest liability counterparty exposure.

Future work could develop and extend the present analysis in four main directions. First, the analysis could be broadened to off-balance sheet positions, which may affect the results and illustrate the potential importance of additional channels of interconnectedness and contagion (e.g. step-in risk, derivatives positions, involvement in collateral chains). Second, other financial sub-sectors (e.g. insurance, pension funds, and investment funds) could be included alongside banks. Non-bank financial institutions have markedly grown in relative size, partly because of the deleveraging in the banking sector, as banking regulation has become tighter. Third, the analysis could be extended to financial linkages of the euro area with other regions to draw a more global picture of exposure and associated risks. Finally, the analysis has been undertaken before the COVID-19 crisis. Further research could reflect on the impact of the pandemic on financial spillover and contagion risks and on the functioning of the aforementioned transmission channels. The "real economy" origination of the pandemic crisis suggests a stronger focus on non-financial corporations in general and sectoral specialisation of individual Member States in particular in the analysis of spillover and contagion.

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