Liquidity and equity short-term fragility: stress tests for the European banking system

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Abstract

This paper assesses the resilience of Eurozone banks' equity and liquidity against large shocks to financial markets. Our analysis refers to 35 banks in the Eurozone from 2005 to 2015. We adopt a new type of model that combines copulas and non-linear factorial structures in order to treat the case of large sets of multiclass assets exposed to extreme risks. Our contribution is fourfold. First, we employ a model that accounts for teh senistivity of the Asset as well Liability sides. Second, we measure the impact of different sources of shocks (stock, bond, sovereign bond markets,...) not only on banks' solvency but also on their liquidity positions, third, we take into account second round and spillover effects between different financial markets and countries, illustrating potential contagion cases. Fourth, we assess the role of diversification in improving banks' resilience by examining the particular situation where stock and bond returns become positively dependent, as recently observed. Our main findings are: taking into account interdependency between items of the balance sheets indeed matters; liquidity shortfalls are substantial compared to capital ones and banks' fragility remains still high in 2015. Contagion risks remain high. Finally, losing diversification opportunities when stock and bond returns become slightly positively related, increase capital and mainly liquidity shortfalls with an increase around 20% for some Italian banks in the atter case and above 80% for Greek banks and around 70% for a French bank, in the former case.

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JEL classification: F32, G17, G21

1. Introduction

As the recent global financial crisis has shown, one main issue is to examine systemic risk and, accordingly, to give a macroprudential dimension to stress tests,[1] especially when assessing the impact of extreme shocks to financial markets, as pointed out by the BoE (Bank of England, 2013) or Greenlaw et al. (2012). A first dimension is to examine both sides of the balance sheet, and explicitly consider fire sales, runs by

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[1] Today stress tests conducted by central banks are not macroprudential (Arnould and Dehmej, 2016).

wholesale creditors, common exposures and credit crunch risks. Second, liquidity ratios, in addition to capital requirements, should be part of the overall framework of a macroprudential stress test. Eurozone banks rely heavily on wholesale funding which accounts for 61% of their liabilities (IMF, 2013). This funding is particularly prone to runs and plays a central role in transmitting shocks from financial markets to banks (Babihuga and Spaltro, 2014). As shown by the Northern Rock bankruptcy, wholesale funding, particularly short-term wholesale funding is a major source of fragility (Chen et al., 2014). López-Espinosa et al. (2013) even claim that unstable funding is the most significant factor driving systemic risk. Finally, second round effects, spillovers or network contagion must be accounted for in a stress test framework, otherwise losses and shortfalls can be greatly underestimated (BCBS, 2015).

In this paper, we aim at improving macroprudential stress tests along different directions. First, we build a top-down stress test[2] to assess not only the solvency of the banks depending on their capital, as usually done, but also, simultaneously, their liquidity resilience, when they are exposed to severe shock to financial markets. Second, these shocks can hit not only stock markets as in the the SRISK approach proposed by Acharya et al. (2012) but also bond, commodity or currency markets, for which banks must report their exposures, third we take into account second round effects and spillovers between different financial markets including markets of different countries. Finally we examine a critical scenario which is plausible today, where bond returns may be positively linked with stock returns.The latter circumstances are indeed worth examining because the usual diversification benefits may thus be significantly reduced.

Our results show that failing to account for these different directions may lead to significant underestimation of banks' fragility in the European banking system if one refers to what has been observed over the ten last years.

More precisely, we examine a panel of 35 listed European banks over the period 2005-15. For each bank, using market data and banks' reports, we build a solvency ratio and a liquidity ratio. The solvency ratio corresponds to the ratio of shareholders' equity to assets, which is broadly used as in (Brownlees and Engle, 2017). The liquidity ratio is obtained by dividing short-term assets by short-term liabilities as in Pierret (2015).[3] As announced before we focus on four major sources of extreme shocks (Stock market, Rate, Commodity and Currency). We capture the corresponding risks from representative market indices that are assigned, as Kahlert and Wagner (2015), to the different items of the short-term assets and liabilities of the

[2]Top-down stress tests refer to stress tests where banks only provide balance sheet data and the regulator uses its model to estimate the losses, unlike bottom-up stress tests where banks estimate their losses using their own risk model.

[3]Note that the ratios we retain to assess banks' resilience were not imposed on the banks over the whole period of study, which may appear unfair. However, by focusing on ratios that are not imposed before 2015, we offer two measures that are consistent over time. This allows us to compare the situations of the banks ex post, as they have evolved over time and we can see which banks spontaneously obey the related constraints today.

banks' balance sheet. In this regard, our analysis is connected with the literature that focuses on bank risk exposures, as in Begenau et al. (2015) who document the exposure of U.S. banks to rate and credit risks or Benoit et al. (2015) who obtain an implied measure of U.S. banks' exposures to equity, interest rate, foreign exchange and commodity risks. We do not take into account direct links between banks as in Allen and Gale (2000). However, we include the interrelationships resulting from the common exposures of their balance sheets to adverse events in the different financial markets, which are themselves interrelated.

A main point is thus to take into account the links between the different market indices and assets under extreme circumstances, which is a priori a challenging task once the number of markets and assets is large (53 in our case). We achieve this using a Canonical Vine Risk Factor (CVRF) model, which combines copulas and factors to characterize the links (including tail dependencies) of large sets of multi-class assets, as proposed in Bruneau et al. (2015). Using copulas is important, as ignoring tail dependencies can lead to a severe underestimation of systemic risk, as pointed out by López-Espinosa et al. (2015). Over the period 2005-15, we indeed find that tail dependencies between the returns of the assets of our datatbase are recognized in 40% of the cases. We could have referred to multivariate distributions like the multivariate Student one to allow for tail dependencies. However beyond the estimation difficulties encountered when the dimension is high, such a modelling is too constrained as it imposes that any couple of returns should be distributed as a bidimensional Student[4], which is not the case as shown later. Likewise, we could have adopted the GARCH-DCC approach, with a copula based characterization of the residuals, as promoted in the SRISK related analysis proposed by Engle et al., (2012), which has the advantage to provide a dynamic characterization of the dependence structure. However this modelling is not without some drawbacks and especially, it is easily implemented in the SRISK approach thanks to the limited dimension of the problem but its generalization to high dimensions is far from being obvious.

The factorial structure interestingly reduces the dimension of the problem as in the linear case of the APT models used in Ross (1976) and Chamberlain and Rothschild (1983) and, like these models, it allows to capture the exposition of assets to different sources of common risks, but, what is new in CVRF models, in case of extreme risks. In our case, six factors account for "market", rate, sovereign, credit, currency and commodity risks and summarize well the links between the different markets. Moreover, to illustrate potential contagion effects, we highlight the propagation of shocks to particular country based stock indices.

We choose to characterize the dependence structure as it emerges from the observation of the whole period 2005-2015. However, occasionally, we compare the findings over different subperiods; thus, we account for

[4]Any affine transformation of a vector whose distribution is a multivariate Student is also distributed as a multivariate Student.

changes in the dependence structure by using a two-year rolling window, with a one-year overlap when estimating the parameters of the CVRF model.[5] Dependencies between assets have indeed notably changed over the sample period, especially the tail dependency between bond and stock returns, which was very negative after the crisis and is close to being positive today.

Our paper relates to different strands of the literature.

First, it relates to the literature on the fragility of banks' liquidity. Vasquez and Federico (2015) link banks' fragility to their structural liquidity as well as leverage and show that weaker structural liquidity and higher leverage in the pre-crisis period were more likely to involve default. Pierret (2015) uses a panel VAR model to show that short-term liquidity and solvency indeed (asymmetrically) interact - a higher solvency risk limits the access of a bank to short term funding and a firm with more short-term funding has a higher risk of insolvency during a crisis. Finally, Distinguin et al. (2013) use a simultaneous equation methodology to explicitly account for endogeneity issues and show that banks with lower capital ratios have a higher level of short-term liquidity and that banks with a higher liquidity transformation also have lower regulatory capital levels.

Second, we build on the literature investigating banks' portfolio structure and related asset diversification issues. For example, Rustam and Walden (2007) analyze the limitations of diversification for heavy-tailed risks, while Rustam et al. (2011) examine diversification disasters due to the interconnectedness of financial intermediaries' risk portfolios during critical events. Our work relates more specifically to Koliai (2016), who also analyzes a dependency structure between different classes of assets using a Canonical Vine (C-Vine) model to stress test a simple bank's portfolio and examine the impact of the stress on the bank's capital. We extend his analysis to develop macroprudential stress tests that explicitly account for banks' liquidity positions, their interaction with capital situations and spillover effects on banks' shortfalls.

Our paper may also contribute to theoretical analyses, like, for example Greenwood et al. (2015), who models spillovers between banks through their common exposures but does not explicitly account for evolving dependency structure between asset classes.

The paper continues as follows. In section 2 we explain the computational methodology and the construction of liquidity and solvency ratios from short-term balance sheets. In Section 3 we present the data. Section 4 documents the results of the stress test exercises we implement and, in particular, it addresses the issue of potential contagion effects and of the impact of diversification on banks' resilience. Section 5 concludes.

[5] Over each sub-period, the model we use is static, which doesn't substantially limit our analysis, as we only examine effects of shocks one period (week) ahead and we don't consider banks' reactions to shocks to financial markets.

2. Methodology

In this section, we briefly describe modeling principles,[6] namely how to build a CVRF model and how to run simulations for stress test exercises. Finally we turn to measures of the equity and liquidity ratios computed from banks' balance sheets.

2.1. Computation Methodology

2.1.1. CVRF Model

Let us condider a set of n returns $R = (R_1, ..., R_n)$

According to Sklar's theorem (Sklar, 1959) the multivariate cumulated distribution function (cdf) F of R can be defined as:

$$\forall r_1, r_2, ..., r_n, F(r_1, ..., r_n) = C(F_1(r_1), ..., F_n(r_n)),$$

where F_i denotes the marginal cumulated distribution functions of return R_i and C is an appropriate n-dimensional copula, that is, a cdf with uniformly distributed marginals $U_i = F_i(R_i)$ on [0,1].[7]

Accordingly, the modeling of margins and dependence of the different returns R_i can be separated.

Moreover, for an absolutely continuous F with strictly increasing (absolutely) continuous functions F_i, the joint density function f of $\mathbf{R}$ is obtained by differentiating (2.1.1) as

$$\forall r_1, r_2, ..., r_n, f(r_1, ..., r_n) = c(F_1(r_1), ..., F_n(r_n)) \cdot f_1(r_1) \cdots f_n(r_n),$$

which is the product of the C-copula's density, c, and the marginal densities f_i.

An important point is that the density c can be decomposed as a product of bivariate non-conditional and conditional copulas.

$$\forall (r_1, ..., r_n), c(F_1(r_1), ..., F_n(r_n)) = \prod_{j=1}^{n-1} \prod_{i=1}^{n-j} c_{j,i+1|1,...,j-1} \left(F(r_j \mid r_1, ..., r_{j-1}), F(r_{i+j} \mid r_1, ..., r_{j-1})\right) \qquad (1)$$

where $c_{j,i+1|1,...,j-1}$ is the density of the bivariate conditional copula that characterizes the dependence of j^{th} and $(i+1)^{th}$ assets' returns given the returns of assets $1, ..., j-1$. For $j = 1$ the bivariate copula just characterizes the non-conditional dependence of the first assets' return and the one of the $(i+1)^{th}$ asset.

[6]See Bruneau et al. (2015) for a more detailed description.

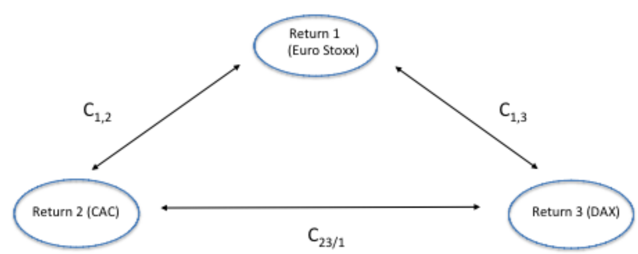
[7]As usual, we make the distinction between R_i and r_i, which denote respectively the return of asset i, that is a random variable, and a particuar value of this return. Thus It is well known that, under regularity conditions, $U_i = F_i(R_i)$ is uniformly distributed on [0,1]; in other words, for any value r_i of R_i, $u_i = F_i(r_i)$ is a draw from a uniform random variable U_i on [0,1].

For example, for three returns, one can write

$$\forall(r_1, r_2, r_3), c(F_1(r_1), F_2(r_2), F_3(r_3)) = c_{1,2}(F_1(r_1), F_2(r_2)) \cdot c_{1,3}(F_1(r_1), F_3(r_3)) \cdot c_{2,3|1}(F(r_2|r_1), F(r_3|r_1))$$

It is noteworthy that this decomposition is not unique. To help organize the possible factorization of the joint density, Bedford and Cooke (2001) and Bedford and Cooke (2002) have introduced a graphical model called a regular vine. A special case of regular vines is the Canonical Vine (C-Vine) where certain variables play a leading role. To give a simple example, we can consider the European stock index (Euro Stoxx), the French stock index (CAC 40) and the German stock index (DAX), the first playing a leading role and chosen as the first index (Figure 1).

Figure 1: A example of a Canonical Vine tree with three variables



Thus, the joint distribution of the three indexes is known, once given three bivariate copulas, first the ones with density $c_{1,2} = c_{EuroStoxx,CAC}$ and $c_{1,3} = c_{EuroStoxx,DAX}$, which account for the links between the return of the leading Eurostoxx index and the returns of the two other indexes, and, second, the conditional copula with density $c_{2,3|1} = c_{CAC,DAX|EuroStoxx}$, which captures the "residual" links between the CAC and DAX indexes that do not transit through the Eurostoxx. However, a complete n-dimensional C-Vine has to be decomposed into $n(n-1)/2$ bivariate copulas, each of them depending on parameters. This means that the numbers of parameters to estimate grows rapidly with the number of returns. To reduce the number of parameters to estimate, some conditional independence assumptions are useful to simplify the structure. It is thus worth recalling that conditional independence of two variables Y, Z, given a third one X, just means that the density $c_{Y,Z|X}$ of the conditional copula is equal to 1 [8].

In the previous example, one can suppose that there no links between the DAX and CAC returns, which do no transit through the Eurostoxx, according to the CAPM, with the Eurostoxx as market index. In that case, $c_{2,3|1} = c_{CAC,DAX|EuroStoxx} = 1$ and the dependence structure of the three indexes are characterized according to:

$$c_{EuroStoxx,CAC,DAX} = c_{EuroStoxx,CAC} \cdot c_{EuroStoxx,DAX}$$

According to the same principles, Heinen and Valdesogo (2009) build a Canonical Vine Market Sector (CVMS) model, a non-linear version of an extended CAPM where the return of each asset depends on a global market's return and on the return of a sector-based index but is independent from the return of any asset belonging to another sector, once taken conditionally on the returns of the global market and the sectoral index.

The main point is that the CVMS model allows to capture non-linear dependence between risk factors (market risk and sectorial risk factors captured by the returns of the corresponding indexes) and asset returns, beyond the linear ones which are measured trough the usual beta coefficients. These coefficients are sufficient link measures in the only Gaussian world. In particular, the beta coefficients are not well adapted to capture the exposition of the assets to extreme common risks, when there are tail dependencies. In the CVMS model, the contribution of a risk factor to a return is captured by a bivariate copula. In the previous example, $c_{EuroStoxx,CAC}$ (resp.$c_{EuroStoxx,DAX}$) replace the beta to assess the sensitivity of CAC return (resp. DAX return) to movements in the market index $EuroStoxx$.

In what follows, we use a Canonical Vine Risk Factor (CVRF) model (Bruneau et al., 2015), which is build according to the same principles of the CVMS model but refer to different types risk factors; for example, in addition to stock indexes, a German bond index such as the Bobl[9] is introduced to capture the rate risk in the Eurozone as explained in the example given previously. The dependence structure of the asset returns is thus characterized by a well chosen C-Vine including relevant conditional independence constraints.

To get a simplified idea of a CVRF model, let us consider the example where we are interested in capturing the dependence structure of EuroStoxx, Bobl, CAC and DAX indexes, two stocks and two bonds

[8] Indeed, according to the definition of the copula, one has:

$$f_{Y,Z|X} = c_{Y,Z|X} \cdot f_{Y|X} \cdot f_{Z|X}$$

as well as the independence condition:

$$f_{Y,Z|X} = f_{Y|X} \cdot f_{Z|X}$$

[9] The Bobl is a rolling basket of German bonds with five years' remaining maturity.

of respectively a French bank, and a German one, S_G and S_F and B_G and B_F.

Thus, we can suppose, for example, that:

- all returns are related to the return $R_{Eurostoxx}$ of Eurostoxx from which one identifies the first risk factor $F^{(1)} = F_{market-risk}$ such that the exposure of any asset $i; i = 2, ..., 8$ to $F^{(1)}$ is measured though the bivariate copula $c_{Asset_i,Eurostoxx} = c_{i,1}$

- all returns are related to the one of the Bobl, conditionally on $R_{Eurostoxx}$; the rate risk is thus captured by a second risk factor, $F^{(2)} = F_{rate-risk}$ whose contribution to return of any asset i is captured through conditional copula $c_{Asset_i,Bobl|Eurostoxx} = c_{i,2|1}; i = 3, ..., 8$

- the returns of the CAC and DAX indexes are independent, conditionally on $F^{(1)}, F^{(2)}$, which means that $c_{CAC,DAX|Eurostoxx,Bobl} = c_{3,4|1,2} = 1$; thus one can identify two additional risk factors, a France specific risk factor $F^{(3)} = F_{France}$(resp. a German one,$F^{(4)} = F_{Germany}$); more precisely, the return of the French bank' s stock (resp. of the German one) is just exposed to $F^{(1)}, F^{(2)}, F^{(3)}$ (resp. $F^{(1)}, F^{(2)}, F^{(4)}$) and its expostion to $F^{(3)}$ (resp. $F^{(4)}$) is given by the conditional copula $c_{5,3|1,2}$ (resp.$c_{6,4|1,2}$)

- the returns of the bonds are just related to $R_{Eurostoxx}$ and R_{Bobl} which means that all copula densities $c_{7,k|1,2}$ (resp. $c_{8,k|1,2}$) is equal to 1 (conditional independence) for $k \geq 3$ and $k \neq 7$ (resp. for $k \geq 3$ and $k \neq 8$).

To build the corresponding CVRF model one has just to specify a dependence matrix M^s with elements equal to 0, in the case of (unconditional or conditional) independence, and 1 otherwise, as in Table 1. It is thus worth noting that when the element (i, j) of matrix M^s is equal to 0 (resp. 1) it means independence (resp. dependence) of i^{th} and j^{th} assets returns conditionally on the returns associated with columns k of M^s for $k < j$.

Table 1: Dependence matrix

	$R_{Eurostoxx}$	R_{Bobl}	R_{CAC}	R_{DAX}	R_{S_F}	R_{S_G}	R_{B_F}	R_{B_G}
$R_{Eurostoxx}$	1							
R_{Bobl}	1	1						
R_{CAC}	1	1	1					
R_{DAX}	1	1	0	1				
R_{S_F}	1	1	1	0	1			
R_{S_G}	1	1	0	1	0	1		
R_{B_G}	1	1	0	0	0	0	1	
R_{B_G}	1	1	0	0	0	0	0	1

According to the previous table, the density of the conditional bivariate copulas associated with a cell whose value is zero is equal to 1, indicating a conditional independence condition.

Once the dependence matrix has been specified, we proceed to the estimation of the model in two steps. First we estimate the marginal distribution of the return of each asset. Different approaches are possible :

adopting a parametric approach, for example by specifying an ARMA-GARCH with a residual distributed as a t-Student or a GED (Fernandez and Steel, 1998) or a non-parametric approach by estimating the empirical distribution as (Meucci, 2007). In the following, we adopt the latter approach.

According to

$$U_i = F_i(R_i)$$

each observed value $r_{i,t}$ of return R_i, for $i = 1, ..., n$, is transformed into a uniform residual u_i, t by using the corresponding empirical cumulative distribution function:

$$u_{i,t} = F_i^{emp}(r_{i,t})$$

Using algorithm 3 given in Aas et al. (2009) we also recursively deduce samples of conditional distributions:

$$u_{i|1,...,i-1,t} = F_{i|1,...,i-1}^{emp}(r_{i,t} \mid r_{1,t}, ..., r_{i-1,t})$$

from the sample of historical values $(r_{i,t}; i = 1, ...n, t = 1, ..., T)$.

Then, referring to the Cvine decomposition like the one given in equation (1), for all couples (i, j) for which the corresponding returns are supposed to be dependent according to matrix M^s, we choose the (unconditional, resp. conditional) bivariate copulas which fits best the corresponding (unconditional, resp. conditional) sample according the BIC criterium; thus the copula is chosen among a set of copula families (Gaussian, Student t, Clayton and Frank).

2.1.2. Simulation of shocks from the CVRF model

To simulate an extreme shock to the return of a factor F_{k_0}, we constrain the corresponding uniform residual $\hat{u}_{s_0}$ to an extreme zone, for example $\hat{u}_{k_0} \leq 0.01$. Then, by using the algorithm proposed by Brechmann and Schepsmeier (2013), we can draw N samples of $(u_i, \forall i \neq k_0)$ from the C copula constrained by matrix M^s, conditionally on $\hat{u}_{k_0} \leq 0.01$.

The inverse empirical cumulative (conditional) distribution functions $(F_{i/k}^{-1})$ thus provide N samples of the corresponding rates of return, $\hat{r}_i^{(j)} = F_i^{-1}(\hat{u}_i^{(j)}); i = 1, ..., n; j = 1, ..., N$. These samples are representtaive of the responses of all assets to the shock to factor F_{k_0}.

An extreme shock to a factor's return not only affects the returns of the other assets that are directly related to the stressed factor, according to matrix M^s, but also the returns of the assets that are indirectly linked through other factors.

In the previous example, a shock to F_1, corresponding to an extreme value of Euro Stoxx return will spread out directly to the rest of the returns as all assets are linked with F_1 . But the return of the German bank, R_6 (rep. the one of the French bank, R_5), will also be exposed to an indirect effect relayed by the DAX index (resp. the CAC index). The CVRF model can therefore account for spillover effects induced by interrelationships between the financial markets. In what follows we will examine how shocks to particular country based stock indices can induce contagion effects on the banking system.

The CVRF model used in the rest of this paper can be viewed as an extension of previous example (see Table 16 in Appendix 5.5, where the indicated values of the Kendall's tau coefficients give the position of the cells 1 in matrix M^s).

2.2. Banks' short-term portfolios

Extreme shocks to financial markets may affect banks' solvency, impair the market value of their short-term assets and reduce their ability to serve their short-term debt. As in Kahlert and Wagner (2015), we identify four market indices, namely: Stocks (S), Bonds (B), Currencies (C) and Commodities (Co), which are representative of the four major sources of risk (Stock market, Rate, Currencies and Commodity) for which banks have to report their exposures. Then we assess the impact of extreme shocks to one of theses indexes on the balance sheet of the banks.

We split a bank's balance sheet into short-term assets STA, long-term assets LTA, short-term liabilities STD, long-term liabilities LTD and equity W.

Moreover, for each bank i, we decompose short-term assets $STA_{i,t}$ and short-term liabilities $STD_{i,t}$ into items that are either non-trading (NT) or linked to one of the four indices listed above. Accordingly, for short-term assets (resp. short-term debt), we define the vector of the different items as:

$$STA_{i,t} = \begin{bmatrix} sta_{i,t}^{NT} & sta_{i,t}^{S} & sta_{i,t}^{B} & sta_{i,t}^{C} & sta_{i,t}^{Co} \end{bmatrix}^T \; STD_{i,t} = \begin{bmatrix} std_{i,t}^{NT} & std_{i,t}^{S} & std_{i,t}^{B} & std_{i,t}^{C} & std_{i,t}^{Co} \end{bmatrix}^T \quad (2)$$

where T denotes the transposed vector.

To investigate the resilience against one shock to one of the four retained market indexes, we consider both a solvency and a liquidity ratio, respectively Eq and Liq .

We define Eq as the leverage ratio that characterizes the solvency of a bank, i.e. its ability to withstand losses on its operations, and Liq as the ratio of short-term resources to short-term liabilities that evaluates the ability of a bank to fulfil its short-term commitments. At date t, these ratios are defined as:

$$Eq_{i,t} = \frac{W_{i,t}}{e^T \cdot STA_{i,t} + LTA_{i,t}}$$

and

$$Liq_{i,t} = \frac{e^T \cdot STA_{i,t}}{e^T \cdot STD_{i,t}} \tag{3}$$

where e is a 5×1 vector whose components are all equal to 1 and $W_{i,t}$ stands for the market value of bank's i equity at date t.

We rely on Basel III requirements (BCBS , 2011) to set the prudential thresholds with which banks have to comply. For the solvency ratio, contrary to Brownlees and Engle (2017), we retain a 3% threshold as required for leverage by Basel III, since our solvency ratio does not refer to risk-weighted assets. Of course it would have been interesting to refer to the weighted capital ratio which is widely used in stress tests. However, due to the lack of detailed data, we could not use risk-weighted assets without deciding, quite arbitrarily, which risk to assign to the different items of the banks' balance sheets, whose composition is notably simplified in our analysis. Moreover, capital requirements based on risk-weighted assets may be not sufficient as there is "risk that risk will change" (Engle (2009)) and should be supplemented by requirements based on total assets as recommended by Acharya et al. (2014).

For the liquidity ratio, which refers to short-term and market trading items, the most exposed to critical events in the financial markets, we set a 100% threshold.[10] This means that a liquidity ratio under 100% implies a lack of short-term assets to cover short-term debt commitments and a potential need for the bank to sell or pledge non-liquid assets in the short-term, with a high haircut, leading to potential losses for the bank.

Suppose that there is an extreme shock to one financial maket, for example to the European stock market, which means that the rate of return $r^S_{t+1} = R^S_{t+1} - 1$ of the stock index S (Eurostoxx) between t and $t+1$ takes a large negative value, for example -20%.

Thus the returns of the bond, currency and commodity markets, denoted R^B_{t+1}, R^C_{t+1}, R^{Co}_{t+1} are impacted as well as the returns of the stocks of the different banks $R^{W_i}; i = 1, ...35$.

To assess the resilience of a bank against the shock - denoted hereafter *shock*-, we have to consider short term asset, short term debt and equity at date $t+1$, all these items being random variables conditionally on the shock:

$$\begin{aligned} STA^{|shock}_{i,t+1} &= STA^T_{i,t} \cdot R^{|shock}_{t+1} \\ STD^{|shock}_{i,t+1} &= STD^T_{i,t} \cdot R^{|shock}_{t+1} \\ W^{|shock}_{i,t+1} &= W_{i,t} \cdot R^{W_i|shock}_{t+1} \end{aligned}$$

[10] Our ratio is close to the new Liquidity Coverage Ratio gradually introduced by Basel III (BCBS , 2011), with a 60% threshold since January 2015.

with $R_{t+1}^{|shock}$ denoting the 5×1 random vector of the returns of the different markets:

$$R_{t+1}^{|shock} = \begin{bmatrix} 1 & R_t^{S|shock} & R_{t+1}^{B|shock} & R_{t+1}^{C|shock} & R_{t+1}^{Co|shock} \end{bmatrix}^T$$

The notations $R_{t+1}^{W|shock}$ and $R_{t+1}^{W_i|shock}$ mean that the distribution of these random variables is taken conditionally on the shock *shock*. Note that the first component of $R_{t+1}^{|shock}$ is equals to 1 because it corresponds to the return of non-trading items (such as Cash and Balances with Central Banks). Those items (see Appendix 5.4 for the detailed list) are very liquid and do not lose value in the case of an extreme shock to the market. Moreover, $R_t^{S|shock}$ is equal to a given value once conditioned on the shock, when this shock is on the stock market ($1 - 0.2 = 0.8$ in the previous example).

Thus, we can compute the expected values of Capital and Liquidity shortfalls, given the shock, according to:

$$E(CS_{i,t+1} \mid shock) = E\left[\min(0^-, R_{t+1}^{W_i|shock} W_{i,t} - 0.03 * (STA_{i,t}^T \cdot R_{t+1}^{|shock} + LTA_{i,t}))\right]$$

$$E(LS_{i,t+1} \mid shock) = E\left[\min(0^-, (STA_{i,t} - STD_{i,t})^T \cdot R_{t+1}^{|shock})\right]$$

with $\min(0^-, X)$ denoting a strictly negative value.

Since long-term assets, $LTA_{i,t}$ (mostly composed of loans and securities held to maturity) and long-term liabilities, $LTD_{i,t}$ (mostly composed of long-term bonds and insured customers' deposits) are not exposed to extreme market shocks in the short term, and because their value is not marked to market, they are assumed to be stable between weeks t and $t+1$ ($LTA_{i,t+1} = LTA_{i,t}$ and $LTD_{i,t+1} = LTD_{i,t}$).

To compute the expected capital and liquidity shortfalls, conditionally on the shock, we run simulations. Thus we have to simulate not only the vector of the returns of the market indices representative of the four sources of risk between t and $t+1$, $(R_{t+1}^S, R_{t+1}^B, R_{t+1}^C, R_{t+1}^{Co})$[11], but also the returns of the stocks of the banks, $R_{i,t+1}^{(W)}, i = 1, ..., 35$, conditionally on the shock, that is conditionally on an highly negative value of $r_{t+1}^{Stock} = R_{t+1}^{Stock} - 1$. Of course, this type of calculations can be performed for a shock to any other market (Bonds, Currencies...). We thus employ the methodology described in Section 2.1.2. In all cases, the main point is that simulations are thus performed by taking *into account the interdependence structure between all returns*, as summarized by the corresponding dependence matrix M^s which has been retained.

[11] More precisely, the set of simulated returns also includes the returns of national stock indices, one for each country of our panel as well as the returns of a sovereign bond index and a corporate bond index, as explained later.

3. Data

The sample period for our data ranges from January 2005 to December 2015. It covers two crises (the Great Recession and the Eurozone sovereign debt crisis) but also less volatile periods such as 2005-6 or 2013-5. We use 52 financial market series all extracted from Bloomberg and balance sheet data of 35 banks from 11 countries extracted from SNL Financial. The availability of data from SNL Financial explains our choice of the period. To be more precise, we use the whole observation period to fit the CVRF model, but we focus mainly on the most recent period (2014-2015) to assess the fragility of the banks, even if some comparisons are proposed with previous periods through rolling windows of two years.

3.1. Market data

To construct the dependency matrix M^s, we identify six sources of risk, i.e. six risk factors, which we believe allow us to summarize the common risks underlying the different financial markets. Each source of risk is associated with a market index, as summarized in Table 2.

Table 2: Risk indices

Market indices	**Sources of risk**
Euro Stoxx	Stock market
Bobl	Rate
iBboxx euro Sov	*Sovereign*
iBoxx euro Corp	*Corporate*
EUR-USD exchange rate	Currency
DJUBS Commodity	Commodity

Due to a lack of data on the exposures of the banks to sovereign and corporate risks, the market indices shown in italic are not directly linked to banks' short-term portfolios, unlike the other four. Nevertheless, we retain them in the CVRF model because omitting them in the dependency matrix might lead to a wrong set of dependencies, since banks are indeed exposed to these risks. We choose the Euro Stoxx index[12] to identify the first source of risk (F_1 of Table 1), considering that stock markets are primary drivers of risks contagion through agents' expectations (Cappiello et al., 2006). The second source of risk, representative of the rate risk, is captured by the return of the Bobl index.[13] In the same way, sovereign, corporate, currency and commodity risks are identified from the returns of the corresponding indices (iBoxx Euro Sovereign, iBoxx

[12] Banks' weights are around 15% of the index and only 8 of our 35 banks are represented in this index. Despite this significant but not overwhelming weight, we believe that using this index depicts the fact that banks have other banks' shares in their portfolio.

[13] The Bobl is a rolling basket of German bonds with five years' remaining maturity, which is well representative of the maturity of the bonds banks have in their trading portfolio, as indicated by Begenau et al. (2015)

Euro Corp, EUR-USD exchange rate and DJUBS Commodity). We also introduce 11 series of national stock indices to control for country-specific risks (see Appendix 5.1). In all we retain 17 market indices.[14]

We use the weekly returns of these indices (as of Fridays). We report some descriptive statistics for the six main market indices in Table 3. We observe that the returns of the stock and commodity market indices are more volatile than those of the other market indices. Positive kurtosis indicates that the distribution of the returns of the six market indices have fat tails. The distributions of Euro Stoxx, Euro Corporate bonds, EUR-USD exchange rate and DJUBS Commodity indices are asymmetric, as indicated by the negative skewness, and have longer left tails than the normal distribution, as indicated by the values of the minimal return and the excess kurtosis, which means that extreme negative returns are relatively frequent. It shows that accounting for tail dependency is crucial.

Table 3: Descriptive statistics (weekly returns, 2005-2015)

	Euro Stoxx	Bobl	iBoxx Euro Sov	iBoxx Euro Corp	EUR-USD exchange rate	DJUBS Commodity
Min	-22.22%	-1.60%	-2.20%	-3.36%	-5.87%	-13.57%
Max	12.21%	1.62%	3.02%	1.45%	5.12%	6.48%
Mean	0.07%	0.05%	0.09%	0.08%	-0.03%	-0.08%
Median	0.40%	0.06%	0.12%	0.11%	-0.02%	0.02%
Std. Dev.	3.07%	0.46%	0.56%	0.46%	1.41%	2.46%
Skewness	-0.83	-0.02	0.06	-1.08	-0.25	-0.80
Excess Kurtosis	5.91	0.85	2.55	6.46	1.30	2.92

We also collect weekly returns of each bank's stock over the same period (January 2005-December 2015).[15]

3.2. Balance sheet data

The listed banks in our panel are those that took part to the AQR and stress test conducted by the ECB in 2014. We have identified 38 such banks as in Acharya and Steffen (2014), but continuous data are available for only 35 of them[16] (see Appendix 5.2). Our sample covers 40% of all the assets of the Eurozone Monetary and Financial Institutions (MFI) and our sample is quite well representative of the relative weights of the different countries in the European banking system (See Table 13 in Appendix 5.3).

Using the SNL Financial data base, we extract detailed balance sheet information for the 35 banks in the panel, from 2005 to 2015, but we mainly focus on the most recent period (2014-2015) as announced before. We build truncated balance sheets, focusing on assets and liabilities with a short-term maturity as

[14]We tried alternative series such as "World MSCI Index" to characterize the stock market risk or "Citi Germany GBI 3-7 Yr Index" to account for the rate risk and we obtain quite similar results concerning the dependency structure between assets and extreme shocks.

[15]Market value of a bank is not a perfect substitute for the book value of its capital, as pointed out by Tavolaro and Visnovsky (2014), but it is widely used as an imperfect substitute.

[16]We did not include the banks BP, VBPS and LBK because of a lack of continuous data on their balance sheet or share.

Pierret (2015) but adapted for Eurozone banks[17] (Appendix 5.4). We consider that an asset can be labeled as short-term if it is highly liquid or can at least be related to a financial market where it can be sold quickly. On the liability side, we take all items that have a maturity lower than one year and those that are linked to wholesale funding, which is considered to be highly unstable (Babihuga and Spaltro, 2014). We link each short-term balance sheet item either to the non-trading assets class or to one of the four market indices (Table 4). In the non-trading short-term assets we include those that are the most liquid (such as cash and balances with central banks). Concerning the trading assets, we only take into account those that are available for sale or held for trading. We also add all the derivatives, since the vast majority of them are labeled as trading securities. Loans are not taken into account as they are not sufficiently liquid to be part of short-term assets.

On the liability side, using data from SNL Financial we suppose that an average of 10% of senior and subordinated debt matures each year and as a consequence can be considered as short-term debt. All trading liabilities are negative positions in derivatives, which are treated as short-term debt as they are commitments that can become harder to fulfil in the case of a critical event (Table 4).

Table 4: Short-term balance sheet

Short-term Assets	**Short-term Liabilities**
Non-trading short-term assets	Non-trading short-term liabilities
- Cash and Balances with Central Banks	- Deposits Maturing in less than 3 months
- Net Loans to Banks	- Total Deposits from Banks
Stock market risk related trading assets	- Repurchase agreements not in Deposits
Rate risk related trading assets	- Wholesale Debt maturing less than 1 year
Commodity risk related trading assets	- Securities Sold not yet repurchased
Currency risk related trading assets	Stock risk related trading liabilities
	Rate risk related trading liabilities
	Commodity risk related trading liabilities
	Currency risk related trading liabilities

We then compose a portfolio of the five asset classes for each bank. We find that non-trading items are larger on the liability side than on the asset side, and, conversely, trading items are more important on the asset side. Moreover, we observe that a clear change is the reduction in the part of stock market risk-related trading items, on both asset and liability sides, and a slight increase in rate risk-related instruments, particularly on the asset side. This portfolio rebalancing towards rate risk-related instruments and non-trading items can be explained by a flight to quality or liquidity (Beber et al., 2009), due to the crises in 2007 and 2010. Banks rebalanced their portfolios to reduce their exposures to the most risky assets, which are strongly linked with the stock index, during the crises to diversify risks. Banks have also slightly

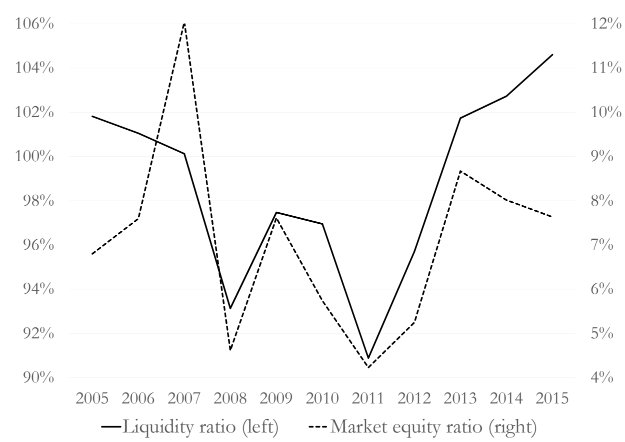
[17] For example, we have no information about commercial paper for Eurozone banks.

increased the proportion of non-trading short-term assets. The latter fact can be explained by the liquidity injection from the ECB. See Figure **??** in Appendix **??** which displays the decomposition of the aggregate short-term portfolio of the whole panel of banks into the five asset classes, and its variation over time.

Following the methodology already presented, we calculate the liquidity and solvency ratios for each bank of our panel as well as the aggregate ratios of our sample of banks for each year from 2005 to 2015. The evolution of the aggregate ratios over time is displayed in Figure 2. We observe that the ratios started to decline in 2007, the year the crisis started for the banking sector, then went up in 2009 before going down again when the European debt crisis started in 2011. Today liquidity and solvency ratios seems to have recovered and liquidity ratio reached its highest point in 2015.

Figure 2 shows the large effort the banking sector made after the crisis to deal with its short-term funding issues and restore its liquidity. However, this figure provides an aggregate perspective, hiding very disparate situations. In our sample, the liquidity ratio has a standard deviation of 46%,[18] and the solvency ratio, a standard deviation of 6%.[19]

Figure 2: Solvency and Liquidity aggregate ratios for the set of 35 banks



4. Stress tests

The stress tests we implement are designed to answer three types of question :

1) How the dependencies between the different items of the bank's balance sheet affect banks' resilience?

2) What are the effects of shocks from different sources and can one highlight spillover and contagion effects?

[18]With a maximum of 400% for CRG in 2009 and a minimum of 7% for TPEIR in 2013.
[19]With a minimum of 0.02% for Dexia in 2014 and a maximum of 50% for ALBK in 2013.

3) What is the impact of the dependency structure between assets of different classes on the fragility of the banks (benefits of diversification for the resilience of banks) ?

1) Concerning the first point, capital and liquidity are indeed related as the corresponding ratios involve common items of the balance sheet, on the Asset as well as Liability sizes. Moreover, a same shock may induce losses which jointly affect capital and liquidity. The point thus is to check that both capital and liquidity represent two joint pillars of resilience. In that sense, we are interested in the ranking of the banks in both directions. ???

2) About the second point, we will consider the effects of shocks to different financial markets on the solvency and liquidity ratios and the related shortfalls of the banks of our panel; in particular, we will examine the effects of shocks which only affects certain classes of assets, for example the European Sovereign bond index, so as to show spillover effects and eventually shocks to specific country stock indices or to a particular bank to highlight potential contagion effects.

3) Finally to treat the last issue 3), we will build a particular scenario where stock and bond returns are positively correlated (See Appendix 5.8) according to an extrapolation of what has been observed over the laste period.

In all investigations, we choose to focus on the most recent period (2014-2015), with banks chracterized by their balance sheets on this period.

However, in order to capture a wide range of extreme risks, we will refer to a CVRF model estimated over the whole observation period, as it is presented in next section.

4.1. Dependency analysis between assets over the whole period

We look for the factorial structure of the CVRF model by referring first to the Kendall's tau coefficients. Indeed, for any couple of random variables, this coefficient is related to the corresponding copula and, notably, it is equal to 0 in case of independence.[20]

Accordingly, we estimate the unconditional and conditional Kendall's tau coefficients for all couples of our set of 52 series; when we find a low value of the coefficient (under 0.2) we suspect a low dependence for the concerned couple, which can justify an independence condition.

Let us consider different tables of Kendall's tau coefficients as given in Appendix 5.5.

[20] If $(X,Y)^T$ is a vector of continuous random variables with copula C, the Kendall's tau for $(X,Y)^T$ is given by:

$$\tau(X,Y) = 4\int_0^1\int_0^1 C(u,v)c(u,v)dudv - 1$$

with c denoting the density of the copula.

First, Table 14 reports the unconditional Kendall's tau coefficients with red cells in the case of absolute values of coefficients greater than 0.2. According to this table, we observe that banks' returns are significantly linked with each other as well as with the returns of country-based stock market indices.

Second, Table 15 displays the conditional Kendall's tau coefficients reflecting the CVine structure. Indeed, the Kendall's taux reported in each column thus correspond to the distributions of the couple of returns taken conditionally on the returns of the previous columns, with red cells in the case of absolute values of Kendall's tau coefficients greater than 0.2. With the exception of the first column, which remains unconditional (see Section 2.1.1), the number of Kendall's tau coefficients greater than 0.2 drops significantly. The remaining Kendall's tau coefficients greater than 0.2 are between returns of stocks of banks from the same country (as between BNP-Parisbas and Société Générale) or between returns of stocks of banks and their national stock market index (as between the Italian banks UCG, ISP, BMPS, UBI, MB, PME, BPSO and CE and the Italian stock market index, IT).

Accordingly, we impose conditional independence in three cases: first, for banks' stock returns belonging to different countries; second, for the returns of the different country-based stock market indices taken conditionally on the Euro Stoxx; third,by assuming the stock return of each bank is dependent on its own national stock market index but independent of those of others countries. We report 0 in the corresponding cells, which gives us the M^s dependence matrix of the CVRF model. The conditional Kendall's tau coefficients obtained when imposing these independence constraints are given in Table 16.

We observe that the latter constraints do not change the value of the Kendall tau coefficients reported in Table 15 very much. Some links between returns of stock indices and individual stocks belonging to different countries are lost but only in five cases,[21] and these links are weak, with a Kendall tau around 0.2. Moreover, some links appear to be reinforced when the independence constraints are added, but again in very few cases and with a final Kendall tau around 0.2. Accordingly, we trust in the CVRF model we retain as it allows us to capture well all the dependencies between the different asset returns in our data base while limiting the number of parameters to estimate. Accordingly, the matrix M^s we retain to characterize the dependency structure is the one with cells equal to 1 and 0, as deduced from (Table 16), with 1 associated with cells containing numerical values and 0 with the others.

Note that choosing to give the first place to the Euro Stoxx or the Bobl index does not change anyting to the characterization of the dependency structure, as their dependency is unconditional. The ordering of the subsequent indexes (sovereign, currency, etc) matters in choosing the final dependence matrix M^s, but all the dependencies are taken into account regardless of their order, which is important to capture the

[21] More precisely for the following pairs: (CY, EL), (DE, IT), (DE, ES), (KBC, BNP) and (BNP, DBK)

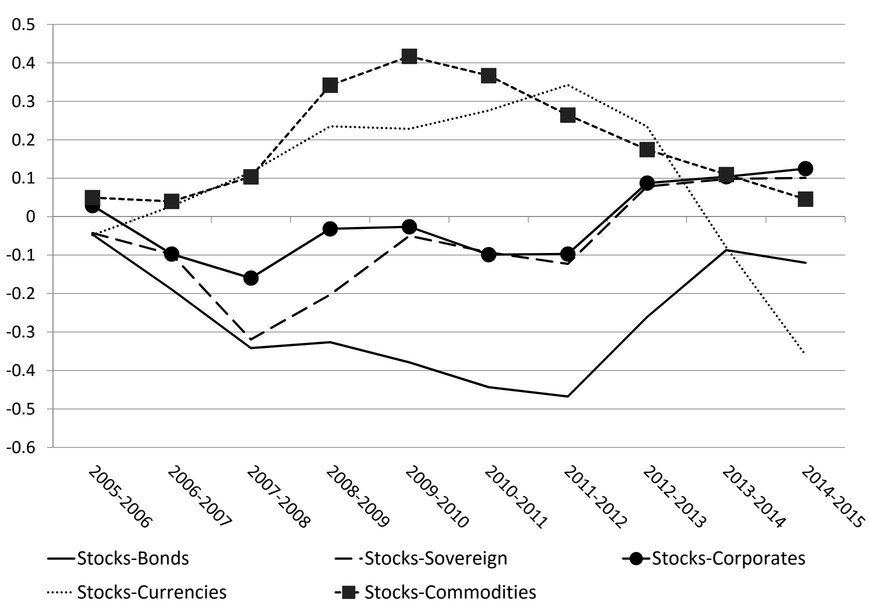
spillover or contagion effects. Moreover, it is worth noting that the banks in our panel have low exposures to ”specific” risks like sovereign, currrency, ... and may also be affected by shocks to foreign countries through the stock indexes.

Table 5: Estimation: Copula families

Copula name	Tail dependence	Frequency
Student-t	Yes	31%
Clayton	Yes	9%
Gaussian	No	31%
Frank	No	29%

When two returns are supposed to be interrelated, the best bivariate copula is chosen from among the Gaussian, Student-t, Clayton and Frank copulas to account for this interrelationship, using the BIC criterion. It is worth noting that the Gaussian and Frank copulas do not allow for tail dependency, while the Student-t and Clayton copulas allow for symmetric and lower tail dependencies, respectively. We report aggregate results about the estimations of the bivariate copulas for the different assets in Table 5. These results give evidence of frequent tail dependency between our series since copula specifications with tail dependence (Student-t and Clayton) are retained as the best fit for about 40% (=31%+ 9%) of the total of 397 bivariate copulas.

Figure 3: Evolution of the Kendall’s tau coefficients



It is woth noting that dependencies have varied over time and are likely to evolve in the near future (See Figure 3 which shows the evolution of the Kendall’s tau coefficients). Thus, we can distinguish between two groups of assets, those that are positively linked with the global stock market index (commodities and currencies) and those that are negatively related to this index (bonds, sovereign and corporate). For example, the dependency between stock market and bond indices becomes even more negative in periods of turmoil, most likely due to investors' heightened risk aversion.

Similarly, the commodity and currency indices appear to be more tightly related to the stock index during theses periods, which means that the diversification benefits from these assets are likely to be reduced under tail events. Investors seem to have considered Euro sovereign bonds as safe-haven assets during the 2007-8 crisis, but it is worth observing that their negative links with the stock market index tend to weaken significantly after the Eurozone debt crisis and even become positive after 2011-12. This observation let us imagine a particular scenario where stock and bond returns are positively correlated.

4.2. Results of different stress tests

We have estimated the CVRF model by using the whole set of observations. However, we refer to the balance sheets of the banks over the most recent period to assess their resilience against the different types of shocks for the near future. Before turning to the impact of the shocks on the banks, it is worth noting that financial markets are also impacted. See, in Appendix last columns of 18 and which report the responses of these markets to different shocks over the most recent period.

In what follows, we first assess the impact of large shocks to each of the first two indexes (Euro Stoxx and Bobl), since stock and bonds represent the major sources of risk and directly affect 75% of banks' short-term assets (see Figure **??**). In a second step, we examine the effects of a large shock to the sovereign bond index to show how spillover effects may appear. Then we turn to the contagion effects by focusing on shocks to a specific country based stock indices. In the last step, we examine how fragility of the banks changes in the scenario where stock and bond returns become (weaky) positively linked.

Let us note that the magnitude of the shocks is deduced from what has been observed during the worth events in particular financial markets, between 2005 and 2015; for example a shock to the European stock index means a drop of the corresponding return by 22%, as it has been observed in 2008.

In next subsection, we comment the results of different stress tests which are formatted to answer the three questions adressed at the beginning of this section.

4.2.1. Joint examination of liquidity and capital shortfalls

In this exercise, we aim at assessing the expected capital and liquidity shortfalls over 2014-2015 by considering successively shocks to the Eurostoxx and to the Bobble indices.

Before looking at the ranking of the banks, we examine the global expected shortfalls for the European banking system, then we focus on th country level and we also group together banks with a similar fragility contribution (G-sib, D-Sib ans others).

Table 6 shows the global expected capital and liquidity shortfalls over a week in 2015, given the balance sheets of 2015 and the dependence structure estimated over the whole period. Each type of shocks has a magnitude corresponding to the 1% worse observation over this period

Table 6: Total shortfalls (billions of dollars)

Shocks to	*Equity*	*Rate*	*Sovereign*	*Corporate*	*Forex*	*Commodities*
Capital Shortfall	-77,28	-57	-62,79	-63,49	-66,40	-67,51
Liquidity Shortfall	-550,85	-548,27	-549,29	-539,50	-544,05	-549,16

Comments The liquidity shortfalls appear to be higher than the capital ones, which can be explained by the fact that the banks had not yet obligation to hedge their activity against liquity risks in 2015. Moreover, for the different types of shock, the responses in terms of shortfall are rather close. Inded, in each case, the estimated shortfalls include the shortfalls before the shock which are due to an insufficient level of capital. Then the slight differences account for the pure effects of the shocks, which are the reactions of the banks within just a week. More generally speaking, the magnitude of the shorfalls, in particular the liquidity ones highly depends on the definition of the cpital ratio or liquidity ratio which is retained. We should also refer to shortfalls obtained by using RWA, even if such a measure can be discussed (Engle, 2009).

Anyway, it is interesting to observe that the shocks have all effects, whatever their origin. Moreover, the previous finding may be related to indirect effects. Indeed, the links between the different financial markets may explain that an extreme shock to one of them, by affecting the other ones, induces similar responses of the banks.

Next, we examine the expected capital and liquidity shortfall per country after two main shocks, respectively, to the stock and bond markets, still over the most recent period 2014-2015. For sake of place, the results are not presented here but they are available upon request.

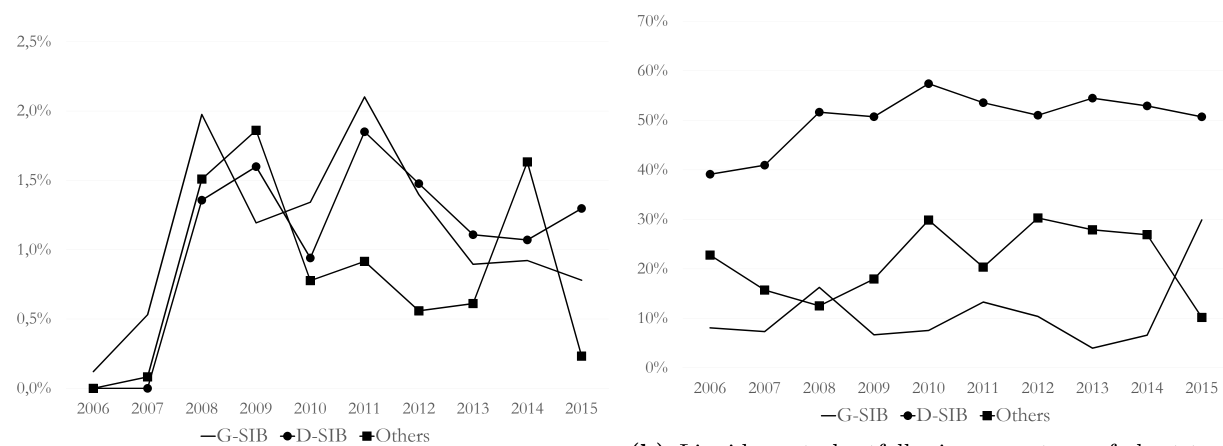
Not surprisingly, for both types of shocks, the greatest shortfalls, for capital as well as liquidity, are observed in countries that have a reputation for fragility, namely, Greece, Ireland, Italy, Portugal and Spain (Malta is excluded), reflecting the lasting effects of the past difficult situations their banking systems have been through. Belgium appears to be also particulraly fragile but also France. A precise examination shows that these fragilities are explained by the one of the banks Dexia and Société Générale respectively.

It is noteworthy that contrary to the results of the ECB stress test in 2014 (ECB, 2014), we do not find major shortfalls for the Italian banking system. Nonetheless, when we focus on the banks separately, we do identify massive shortfalls for three of the four banks[22] that did not pass the ECB stress test in 2014. Banca Monte dei Paschi in particular displays major capital shortfalls. If capital shortfalls have receded for all countries and today are quite moderate, liquid asset shortfalls are still large for Greek banks (Figure **??**). Additionally, in recent years, French banks display high liquid asset shortfalls, solely due to Société Générale, as seen later.

Finally, to follow a usual classification of the banks, whe have also sorted them into the Global Systemically Important Banks (G-SIBs) as defined by the Financial Stability Board [23], the D-SIBs as they are denominated by the European Banking Authority (EBA)[24] and the Others, including the eight remaining banks (see Appendix 5.2).

Here we just present the results for a shock to the stocks, but with a dynamic component and by presenting the shortfalls in percentage of the total assets or debt.

Figure 4: Average shortfalls of a bank according to bank size, in percentage of its total assets



(a) Capital shortfalls, in percentage of total assets

(b) Liquid asset shortfalls, in percentage of short-term debt

We observe that, before and after the crisis of 2007, the three groups have similar capital shortfalls (Figure 4a). Moreover, the Great Recession seems to have affected all banks in a similar manner. Recently, equity shortfalls have decreased but the D-SIB remains the most fragile group, probably because banking regulations enforced after the crisis targeted the largest banks and not domestic systemic banks. Note that the origin of the shock (equity or bond index) brings only difference in magnitude, especially for D-SIBs.

[22]Namely: Banca Monte dei Paschi, Banca Carige and Banca Popolare di Milano. We do not identify shortfalls for Banca Popolare di Vinceza since it does not belong in our panel.

[23]It includes nine banks in the period 2005-11 and seven in the period 2012-15. Dexia (DEXB) and Commerzbank (CBK) were removed from the list in 2012.

[24]The institutions have been identified as Other Systemically Important Banks (O-SIBs) by relevant authorities across the Union according to harmonized criteria provided by the EBA at the beginning of 2016. There are 17such banks in the period 2005-11 and 19 in the period 2012-15. We include Dexia (DEXB) and Commerzbank (CBK) after their removal from the G-SIB list in 2012.

Concerning liquidity troubles, they are heavily concentrated in the D-SIB group (Figure 4b). This is mainly due to Greek banks that lack short-term assets to cover their massive short-term debt (in non-trading liabilities, but also in rate risk-related derivatives). The other group displays low liquid asset shortfalls throughout the whole period and the G-SIB group only displays a surge in 2015, likely because of Dexia and Société Générale. Anyway, accounting for liquidity fragility gives a very different picture compared to capital shortfalls.

Eventually, we have calculated the ranking of the banks in both directions, for the two types of shocks. Resuts are reported in Tables 10 and 8.

Table 7: Banks' capital and liquidity fragility ranking in 2015
(shortfalls in millions of Euros and respectively in percentages of the total assets, and the total debt after the worse shock to the stock market (-22%))

	Capital fragility		Liquidity fragility
DBK (Germany)	-21,3	GLE (France)	-270,0
ACA (France)	-20,6	DEXB (Belgium)	-63,9
GLE (France)	-10,9	ETE (Greece)	-53,4
DEXB (Belgium)	-6,8	EUROB (Greece)	-48,6
CBK (Germany)	-5,4	TPPEIR (Greece)	-41,8

Table 8: Banks' capital and liquidity fragility ranking **in 2015**
(shortfalls in millions of Euros after the worse shock to the bond market (-1.4%))

	Capital fragility		Liquidity fragility
DBK (Germany)	-15,6	GLE (France)	-265,8
ACA (France)	-15,2	DEXB (Belgium)	-63,9
DEXB (Belgium)	-6,8	ETE (Greece)	-53,4
GLE (France)	-4,6	EUROB (Greece)	-48,7
BNP (France)	-4,0	TPPEIR (Greece)	-42,2
CBK (Germany)	-3,3	ALPHA (Greece)	-27,4

Observations Two banks appear to reveal both types of fragility: Société Générale, Dexia, whatever the type of shock. Moreover, some banks may be relatively resilient in terms of capital solvency while exposed to high liquid asset shortfalls; this is the case for three banks in Greece (National Bank of Greece, Eurobank Ergasias and Piraeus Bank) which are the most fragile in terms of liquidity in teh panel of banks but have all a good capitalization.

Note that the ranking of the banks according to their capital shortfalls as obtained with our methodology is quite similar to the one based on the SRISK measure (Acharya et al., 2012). In 2015, after a shock to stocks, both rankings are very closed, with three French banks, Crédit Agricole, BNP Pariba s andSociété Générale and the Deutsche Bank appearing as the most fragile banks as shown in Table 9.

To summarize, our methodology is trustworthy with the additional interest to offer a ranking of the banks according to two fragility directions. Focusing on the only SRISK measure and omitting considering liquidity fragility obviously leads to underestimating the fragility of the banking sytem.

Table 9: Comparison between our measure and the SRISK in 2015, billion of Euros

	Our ranking	SRISK ranking
ACA (France)	1	3
DBK (Germany)	2	2
GLE (France)	3	4
BNP (France)	4	1
DEXB (Belgium)	5	11

4.2.2. Example of spillover effects

Here we focus on the effects of a large shock to the Sovereign bond index, which cannot directly affects banks' balance sheets, given our data about the balance sheets. Indeed we have no information about the investments of the banks in such bonds. Nevertheless, we observe capital and liquidity shortfalls as shown by the shortfalls of the 5 most fragile banks.

Table 10: Banks' capital and liquidity higher shortfalls in 2015 after a shock to the sovereign bonds (shortfalls in millions of Euros and and respectively in percentages of the total assets, and the total debtafter the worse shock to the sovereign bonds)

	Capital fragility		Liquidity fragility
DBK (Germany)	-18,0	GLE (France)	-267,2
ACA (France)	-16,8	DEXB (Belgium)	-63,9
DEXB (Belgium)	-6,8	ETE (Greece)	-53,4
GLE (France)	-6,0	EUROB(Greece)	-48,7
CBK (Germany)	-3,8	TPPEIR (Greece)	-42,1

4.2.3. Potential contagion effects

Here, we examine whether local shocks may spread over the whole banking system. Local shocks are thus shocks to particular banks' equities. According to Table 20 and **??** in Appendix which show the responses of different banks and countries to a shock to equity of Société Générale (GLE) and to the equity of the central bank of Portugal (BCP) (stilll in 2015) respectively, one indeed observes contagion effects as both local shocks spread out to other banks and other countries.

4.2.4. Benefits of diversification for banks' resilience

To assess the benefit of diversification for banks' resilience in cases of extreme financial shock, we focus on a scenario where stocks and bonds returns are supposed to move in the same direction. Rankin and Shah Idil (2014) show that it is common for the correlation between bond and stock returns to be negative.

Accordingly, bonds have largely been used as hedge for stock market risk. However, this negative link can reverse and turn positive. A study at the Bank of England shows that, in the past 250 years, the correlation between bonds and equity prices can vary between 0.8 and -0.2 (Roberts-Sklar, 2016). Before 2000, the correlation between stock and bonds prices is positive, growth or the prospect of growth prompts an increase in equity price, as well as an increase in bonds price because of anticipated inflation. Campbell et al. (2013) show that inflation risk can prompt positive links between stock and (nominal) bond returns during periods of high unexpected inflation. But since prolonged period of low inflation and more credible central banks in the mid-2000s, inflation anticipation has been anchored and the likelihood of high inflation risks lowered; bonds have become a hedge for equity risks.

Central banks have poured billions into the financial system and growth is slowly picking up. In the medium term, inflation will return and the dependency between stock and bond price may reverse. In the short term, the quantitative easing policy of the ECB is creating a shortage of liquid bonds, which may put bonds prices under pressure, while encouraging investors to turn to stocks. The negative dependency between stock and bonds may then reverse before the return of inflation.

Indeed, we find that the dependence between European sovereign bond and stock indices has reversed in Europe since the end of 2013 (Figure 3) and the dependence between the bond and stock indices seems to follow a similar trend.

To assess how banks benefit from the diversification between stocks and bonds, we focus on a scenario where the returns of Euro Stoxx and bond indices (Global, Corporate and Sovereign) become slightly positively related. More precisely, we suppose that the corresponding Kendall's tau are equal to 0.10. This is indeed the case for the (Euro Stoxx, Sovereign bond index) couple in 2013-14, and almost the case for the couple (Euro Stoxx, Corporate bond index) with a Kendall's tau about 0.06 in 2013-14. Finally a Kendall's tau of 0.10 for Euro Stoxx and Bobl returns is obtained by extrapolating the trend observed since 2011 (Figure 3). It is worth noting that a Kendall's tau of 0.10 corresponds to a standard correlation coefficient equal to 0.16.[25] For the sake of consistency, we also take the opposite of the estimated conditional Kendall's tau coefficients for pairwise dependencies comprising the Bobl index and a country-based stock index as well as for pairwise dependencies comprising the Bobl index and a bank stock. See Appendix 5.8 to see all the Kendall's tau coefficients for the scenario, with the altered ones in grey.

To assess the diversification benefits in extreme circumstances, we compute liquid assets and capital

[25]For the Gaussian and Student's-t copulas and all other elliptical copulas, the relationship between the linear correlation coefficient (ρ) and Kendall's tau (τ) is given by:

$$\rho = sin\left(\frac{\pi}{2}\tau\right)$$

shortfalls of each bank by focusing on t2015, as described in Section 2.1, successively with the CVRF structure estimated for the whole period, denoted by “negative dependency”, and the modified CVRF structure corresponding to the scenario described above (“positive dependency”).

In both cases, we examine two extreme cases corresponding to the worst return observed respectively for Euro Stoxx and the Bobl over the whole period (see Table 3). When the return of the Euro Stoxx is equal to -22.2%, the worst value observed over 2005 for the rate of return of the Bobl is equal to 0.8%, according to the estimated CVRF structure and it is equal to -0.2% when the CVRF structure is modified. In the case of a shock to the bond index, i.e. a rate of return of the Bobl equal to -1.36%, the rate of return of the Euro Stoxx is equal to 4.8% (respectively -2.26%) according to the estimated (resp. modified) CVRF structure.

In Tables 11 and 12 we compute the relative changes according to:

$((shortfall_{Scenario} - shortfall_{Reference})/shortfall_{Reference})$.

Table 11: Diversification effects: strongest relative changes in capital and liquidity shortfalls in 2015 after a shock to the stocks (in %, after the worse shock to the stocks (-22%))

	Capital fragility		Liquidity fragility
ETE(Greece)	-0,06 %	MB(Italy)	29,9 %
ALPHA(Greece)	-0,08 %	GLE(France)	1,7 %
DEXB(Belgium)	- 0,2 %	ETE (Greece)	0,9
EUROB(Greece)	-0,3 %	ALBK(Ireland)	0,9%
BMPS(Italy)	-0,4 %	TPEIR(Greece)	0,6%
Average	-1,0 %		3,7 %
Maximum	-0,06 %		26,7%
Minimum	- 5,2 %		0 %

Table 12: Diversification effects: strongest relative changes in capital and liquidity shortfalls in 2015 after a shock to the stocks (in %, after the worse shock to the rates(-1,36%)

	Capital fragility		Liquidity fragility
ETE(Greece)	86,9 %	MB(Italy)	26,7 %
TPEIR(Greece)	84,3 %	BRE(Italy)	15,7 %
GLE(France)	67,0 %	ALBK (Ireland)	2,6 %
EUROB(Greece)	39,5 %	ALPHA(Greece)	0,2%
ACA(France)	27,2 %	EUROB(Greece)	0,06%
Average	26,8 %		1,38 %
Maximum	86,9 %		29,9%
Minimum	-7,4 % %		-14,7 %

As expected, changing the dependency structure does not change much the size of capital shortfalls after a shock to the stock market index. Indeed if a shock to stock market has a great impact on capital shortfalls, potential spillover effects through the bond index can only affect it marginally. Moreover the effects are globally favorable, even if very limited.

Conversely, the change in the dependency structureand, accordingly, the loss of diversification oppportunities, leads to a striking rise of capital shortfalls after a shock to the bond index, with an average increase by about 30%,increases above 80% for some Greek banks, as well as a one of almost 70% for the French Bank Société Générale.

As for liquidity shortfalls, the average rise induced by the change in the dependency structure is generally rather limited. Nonetheless, the increase is substancial, about 30% for some Italian banks for both types of shocks.

Our results show that removing the hedging opportunity between bonds and equity indices, reducing diversification benefits as a results, induces a significant increase in capital shortfalls, and a moderate increase in liquid asset shortfalls, although the increase may be significant for some banks. It shows that the structure of tail dependencies plays a crucial role in determining banks' shortfalls during a stress test.

5. Conclusion

In this paper we have introduced a methodology combining copulas and non-linear factor models, which enables us to assess the short-term resilience of the Eurozone banking system against extreme shocks to financial markets. We have shown that this methodology is useful for macroprudential stress tests 1) because it jointly takes into account not only capital but also liquidity fragilities 2) it accounts for spillover effects between different markets 3) it allows to capture contagion effects and, finally 4) it makes easy to confront the banking system to well imagined stress scenarios.

This is of particular importance as our results show that not accounting for liquidity leads to be missing some problematic situations. For example, ignoring the liquidity risks leads to hide the fragility of Italian banks. We also find that spillovers effects have to be taken into account, as they involve effects that are of similar magnitude to the one of direct effects. Large contagion effects can also be expected, notably, from one particular bank to the others. A shock to the equity of the French bank Société Générale for example weakens the liquidity situation of Greek banks. Finally, observing that asset dependencies - and particularly tail ones between stocks and bonds- have changed greatly over the sample period, we have build a plausible scenario where bond and stock returns become positively (however weakly) interelated. Thus, we find that the fragility of some banks may be significantly increased, up to 80% for Greek banks and 30% for Italian banks for capital and liquidity directions respectively. The French bank Crédit Agricole would also clearly suffer in terms of solvency, in case of a shock to the bonds, with an increase in its shortfall by about 30%.

According to these results, it appears to be worth controlling for both capital and liquidity positions of banks when assessing their fragility by implementing stress tests. Thus it is crucial to take into account the tail dependencies between the returns of all asset classes which enter in the banks' balance sheets, on the Asset as well as on the Liability sizes. Special attention has also to be paid to spillovers and potential fire sales which depend on how the shock spreads through the financial system according to the complex links between banks' balance sheets and financial markets. Moreover, contagion effects have to be kept in mind which leads to continue working on a reinforced supervision of the banking sytem. Finally, taking into account possible changes in the dependence structure between asset returns should inspire stress scenarii.

5.1. Country stock market indices

Country name	Country code	Stock market index
Austria	AT	ATX Index
Belgium	BE	BEL20 Index
Cyprus	CY	CYSMMAPA Index
France	FR	CAC Index
Germany	DE	DAX Index
Greece	EL	ASE Index
Ireland	IE	ISEQ Index
Italy	IT	FTSEMIB Index
Malta	MT	MALTEX Index
Portugal	PT	PSI20 Index
Spain	ES	IBEX Index

5.2. Global systemic and Domestic systemic banks of the panel

Country	Bank Ticker	Name	Total Assets (2015, billion Eur)
Austria	EBS	Erste Group Bank AG	200
Belgium	KBC	KBC	252
	DEXB	Dexia SA	230
Cyprus	HB	Hellenic Bank Public Company Limited	7
France	BNP	BNP Paribas SA	1994
	ACA	Crédit Agricole SA	1529
	GLE	Société Générale SA	1334
Germany	DBK	Deutsche Bank AG	1629
	CBK	Commerzbank AG	533
	ARL	Aareal Bank AG	52
Greece	ETE	National Bank of Greece SA	111
	TPEIR	Piraeus Bank SA	88
	ALPHA	Alpha Bank AE	69
	EUROB	Eurobank Ergasias SA	74
Ireland	BKIR	Bank of Ireland	131
	ALBK	Allied Irish Banks PLC	103
Italy	UCG	UniCredit SpA	860
	ISP	Intesa Sanpaolo SpA	676
	BMPS	Banca Monte dei Paschi di Siena SpA	169
	UBI	Unione di Banche Italiane SCpA	117
	MB	Mediobanca - Banca di Credito Finanziario SpA	71
	BPE	Banca popolare dell'Emilia Romagna SC	61
	PMI	Banca Popolare di Milano Scarl	50
	CRG	Banca Carige SpA - Cassa di Risparmio di Genova e Imperia	30
	BPSO	Banca Popolare di Sondrio SCpA	36
	CE	Credito Emiliano SpA	37
Malta	BOV	Bank of Valletta Plc	10
	HSB	HSBC Bank Malta Plc	7
Portugal	BCP	Banco Comercial Português SA	75
	BPI	Banco BPI SA	41
Spain	SAN	Banco Santander SA	1340
	BBVA	Banco Bilbao Vizcaya Argentaria, SA	750
	SAB	Banco de Sabadell, SA	209
	POP	Banco Popular Espanol SA	159
	BKT	Bankinter SA	59

Note: G-SIBs are in dark grey, D-SIBs in pale grey and other banks are in white. In 2012, Dexia and Commerzbank were removed of the G-SIB list by the FSB.

5.3. Representativeness of the banks' sample

Table 13: Representativeness of our sample of banks

	Whole Sample (35 banks)	Austria (1 bank)	Belgium (2 banks)	Cyprus (1 bank)	France (3 banks)	Germany (3 banks)
Panel	100%	2%	6%	0.1%	36%	20%
Eurozone	41%	3%	4%	0.4%	28%	29%
	Greece (4 banks)	Ireland (2 banks)	Italy (10 banks)	Malta (2 banks)	Portugal (2 banks)	Spain (5 banks)
Panel	2%	2%	16%	0.1%	1%	15%
Eurozone	2%	5%	14%	0.2%	2%	12%

Note: We make the average of the ratio of total assets for each country compare to the total for all coutries. For the Eurozone we use data from the ECB statistical data warehouse for MFI in the Eurozone. Cyprus and Malta entered the Eurozone in 2008; we made the calculations accordingly.

5.4. Balance sheet items and SNL Financial keys

Balance sheet item	SNL Financial Keys	Bank portfolio
ASSETS		
Cash and Balances with Central Banks	246025	Non trading items
Net Loans to Banks	224934	
Total Gross Loans	132210	
Debt Instruments Held for Trading	224995	Rate risk related
Debt Instruments Held at Fair Value	225004	
Debt Instruments Available for Sale	225012	
Interest Rate Derivative Assets	225293	
Positive Replacement: Credit Derivative	225294	
Equity Instruments Held for Trading	224996	Stock risk related
Equity Instruments Held at Fair Value	225005	
Equity Instruments Available for Sale	225013	
Positive Replacement: Equity Derivative	225295	
Positive Replacement: Foreign Exchange Derivative	225296	Currency risk related
Positive Replacement: Commodity Derivative	225297	Commodity risk related
Total Assets	132264	
LIABILITIES		
Deposits from Customers Held at Amortized Cost	224952	Non trading items
Total Deposits from Banks	224953	
Senior Debt	132311	
Total Subordinated Debt	132314	
Securities Sold, not yet Purchased	132321	
Memo: Repurchase Agreements Not in Deposits	224969	
Memo: Deposits from Central Banks	224970	
Memo: Deposits from non-Central Banks	224971	
Deposits Maturing in less than 3 months	225134	
Negative Replacement: Interest Rate Derivative	225300	Rate risk related
Negative Replacement: Credit Derivative	225301	
Negative Replacement: Equity Derivative	225302	Stock risk related
Negative Replacement: Foreign Exchange Derivative	225303	Currency risk related
Negative Replacement: Commodity Derivative	225304	Commodity risk related
Total Equity	132385	
Total Liabilities	132367	

5.5. *Kendall's tau coefficients under different structures*

Table 14: Unconditional Kendall's tau coefficients (without factorial structure)

	Eq	Rate	Sov	Corp	Fx	Com	AT	BE	CY	FR	DE	EL	IE	IT	MT	PT	ES
Eq	1																
Rate	-0.27	1															
Corp	-0.08	0.53	1														
Sov	-0.02	0.55	0.51	1													
Fx	0.07	-0.14	-0.05	-0.07	1												
Com	0.18	-0.15	-0.13	-0.04	0.3	1											
AT	0.59	-0.27	-0.1	-0.02	0.11	0.23	1										
BE	0.71	-0.25	-0.05	-0.01	0.05	0.15	0.56	1									
CY	0.29	-0.2	-0.06	-0.01	0.11	0.09	0.28	0.28	1								
FR	0.87	-0.27	-0.09	-0.03	0.07	0.19	0.6	0.72	0.29	1							
DE	0.81	-0.25	-0.1	-0.01	0.04	0.18	0.55	0.66	0.26	0.77	1						
EL	0.41	-0.22	-0.05	0.02	0.11	0.14	0.4	0.39	0.39	0.4	0.37	1					
IE	0.55	-0.18	-0.05	0.02	-0.02	0.1	0.5	0.54	0.22	0.56	0.53	0.36	1				
IT	0.75	-0.28	-0.05	-0.02	0.09	0.16	0.58	0.64	0.3	0.72	0.63	0.44	0.5	1			
MT	0.02	-0.02	-0.02	0.01	-0.02	0.03	0.04	0	0.03	0.03	0.01	0	0.04	0.03	1		
PT	0.53	-0.23	-0.03	0.01	0.07	0.15	0.46	0.51	0.28	0.51	0.47	0.43	0.42	0.55	0.04	1	
ES	0.73	-0.27	-0.03	-0.03	0.11	0.16	0.54	0.6	0.29	0.66	0.6	0.42	0.46	0.7	0	0.55	1
EBS	0.49	-0.25	-0.08	-0.05	0.11	0.16	0.64	0.46	0.24	0.48	0.45	0.35	0.41	0.51	0.01	0.36	0.47
KBC	0.54	-0.23	-0.02	-0.01	0.07	0.1	0.47	0.55	0.24	0.51	0.47	0.37	0.44	0.55	0.01	0.42	0.53
DEXB	0.3	-0.17	-0.01	-0.02	0.03	0.07	0.29	0.36	0.23	0.31	0.27	0.22	0.24	0.3	0	0.24	0.28
HB	0.24	-0.16	-0.06	-0.01	0.07	0.08	0.26	0.24	0.57	0.25	0.23	0.31	0.2	0.24	0.02	0.24	0.23
BNP	0.6	-0.29	-0.08	-0.06	0.07	0.14	0.47	0.52	0.26	0.61	0.51	0.37	0.45	0.58	0.01	0.42	0.56
ACA	0.54	-0.23	-0.02	-0.01	0.07	0.13	0.45	0.5	0.23	0.54	0.46	0.36	0.43	0.56	0.01	0.44	0.54
GLE	0.61	-0.23	-0.04	-0.01	0.09	0.13	0.49	0.54	0.24	0.6	0.51	0.36	0.46	0.62	0.03	0.43	0.58
DBK	0.61	-0.25	-0.06	-0.02	0.08	0.12	0.48	0.52	0.25	0.59	0.57	0.37	0.43	0.59	0.02	0.43	0.55
CBK	0.49	-0.23	-0.05	-0.02	0.08	0.13	0.47	0.45	0.25	0.47	0.46	0.35	0.37	0.5	0.02	0.41	0.46
ARL	0.46	-0.15	0	0.06	0.06	0.14	0.45	0.45	0.21	0.45	0.43	0.33	0.39	0.48	0.05	0.39	0.43
ETE	0.34	-0.17	-0.04	0	0.09	0.11	0.35	0.31	0.35	0.32	0.3	0.62	0.29	0.37	0.02	0.34	0.34
TPEIR	0.33	-0.16	-0.04	0	0.09	0.11	0.34	0.31	0.35	0.32	0.29	0.58	0.3	0.34	0	0.32	0.33
ALPHA	0.3	-0.17	-0.04	-0.02	0.07	0.1	0.27	0.26	0.34	0.28	0.26	0.57	0.26	0.32	-0.02	0.27	0.29
EUROB	0.27	-0.2	-0.08	-0.04	0.1	0.11	0.29	0.25	0.32	0.26	0.24	0.54	0.24	0.29	-0.02	0.27	0.28
BKIR	0.39	-0.18	-0.01	-0.01	0.09	0.11	0.38	0.36	0.18	0.38	0.35	0.28	0.5	0.39	0.03	0.32	0.37
ALBK	0.34	-0.18	-0.04	-0.02	0.05	0.08	0.32	0.31	0.21	0.33	0.3	0.29	0.41	0.34	0.05	0.29	0.33
UCG	0.56	-0.28	-0.06	-0.05	0.08	0.11	0.47	0.5	0.27	0.53	0.47	0.4	0.39	0.69	0.01	0.46	0.56
ISP	0.56	-0.23	0	-0.04	0.08	0.12	0.43	0.48	0.22	0.52	0.46	0.36	0.37	0.68	0.01	0.42	0.56
BMPS	0.38	-0.18	-0.01	0	0.08	0.12	0.35	0.35	0.24	0.37	0.32	0.3	0.28	0.46	0.01	0.36	0.41
UBI	0.45	-0.24	-0.03	-0.05	0.06	0.08	0.38	0.4	0.22	0.43	0.38	0.36	0.34	0.56	0.04	0.38	0.48
MB	0.46	-0.17	0.04	0.03	0.07	0.09	0.4	0.42	0.21	0.44	0.39	0.36	0.35	0.57	0.04	0.39	0.49
BPE	0.38	-0.16	0.02	0	0.07	0.08	0.34	0.36	0.23	0.36	0.32	0.33	0.31	0.47	0.03	0.39	0.41
PMI	0.4	-0.17	0.04	0	0.08	0.08	0.35	0.38	0.24	0.38	0.32	0.3	0.31	0.51	0.02	0.37	0.41
CRG	0.33	-0.18	-0.02	-0.03	0.08	0.12	0.32	0.31	0.22	0.31	0.27	0.32	0.26	0.38	0.02	0.32	0.36
BPSO	0.35	-0.18	0	-0.02	0.07	0.1	0.31	0.32	0.21	0.33	0.28	0.29	0.27	0.43	0.08	0.36	0.38
CE	0.44	-0.21	-0.02	-0.01	0.09	0.08	0.38	0.43	0.23	0.42	0.38	0.33	0.37	0.5	0.04	0.38	0.46
BOV	0	-0.01	-0.01	0	0	0.03	0.04	-0.02	0.01	0	-0.02	0.01	0.01	0.02	0.45	0.04	0.01
HSB	0.03	-0.01	-0.02	0.03	-0.01	0.03	0.04	0.02	0.03	0.04	0.03	0.02	0.05	0.03	0.54	0.04	0.02
BCP	0.34	-0.21	-0.03	-0.02	0.06	0.07	0.32	0.32	0.21	0.32	0.29	0.32	0.26	0.37	0.04	0.51	0.37
BPI	0.36	-0.2	-0.01	-0.02	0.08	0.09	0.34	0.34	0.22	0.34	0.3	0.31	0.28	0.4	0.06	0.51	0.39
SAN	0.62	-0.25	-0.02	-0.03	0.11	0.13	0.46	0.5	0.27	0.56	0.51	0.39	0.4	0.61	0	0.46	0.75
BBVA	0.63	-0.25	-0.03	-0.03	0.11	0.12	0.49	0.53	0.27	0.58	0.52	0.39	0.44	0.64	0.01	0.48	0.75
SAB	0.41	-0.21	-0.03	-0.05	0.1	0.08	0.37	0.37	0.21	0.39	0.32	0.33	0.32	0.46	0.01	0.39	0.52
POP	0.45	-0.25	-0.06	-0.09	0.11	0.1	0.4	0.4	0.22	0.42	0.36	0.33	0.34	0.5	0	0.4	0.57
BKT	0.45	-0.22	-0.03	-0.07	0.09	0.06	0.34	0.38	0.2	0.42	0.36	0.3	0.33	0.49	0	0.39	0.56

Unconditional Kendall's tau coefficients (without factorial structure), continuation of the table

	EBS	KBC	DEXB	HB	BNP	ACA	GLE	DBK	CBK	ARL	ETE	TPEIR	ALPHA	EUROB	BKIR	ALBK	UCG	ISP
EBS	1																	
KBC	0.49	1																
DEXB	0.27	0.31	1															
HB	0.22	0.2	0.18	1														
BNP	0.46	0.52	0.28	0.21	1													
ACA	0.44	0.53	0.31	0.19	0.6	1												
GLE	0.47	0.51	0.29	0.21	0.65	0.61	1											
DBK	0.43	0.47	0.29	0.19	0.55	0.53	0.56	1										
CBK	0.44	0.42	0.29	0.19	0.44	0.47	0.47	0.51	1									
ARL	0.4	0.38	0.23	0.16	0.39	0.41	0.41	0.44	0.39	1								
ETE	0.32	0.29	0.23	0.27	0.32	0.32	0.31	0.34	0.32	0.29	1							
TPEIR	0.31	0.28	0.22	0.28	0.31	0.29	0.31	0.31	0.29	0.26	0.58	1						
ALPHA	0.26	0.28	0.19	0.28	0.3	0.29	0.28	0.28	0.28	0.25	0.56	0.57	1					
EUROB	0.3	0.26	0.19	0.24	0.27	0.26	0.26	0.29	0.27	0.22	0.53	0.55	0.55	1				
BKIR	0.35	0.38	0.22	0.13	0.34	0.37	0.38	0.35	0.31	0.31	0.24	0.26	0.22	0.19	1			
ALBK	0.28	0.33	0.22	0.16	0.33	0.33	0.34	0.29	0.28	0.25	0.25	0.27	0.24	0.25	0.42	1		
UCG	0.47	0.5	0.28	0.21	0.53	0.51	0.57	0.51	0.46	0.4	0.35	0.3	0.3	0.27	0.34	0.3	1	
ISP	0.44	0.48	0.27	0.18	0.51	0.5	0.55	0.51	0.44	0.4	0.31	0.3	0.3	0.24	0.35	0.28	0.61	1
BMPS	0.33	0.37	0.26	0.19	0.38	0.38	0.4	0.36	0.36	0.3	0.3	0.27	0.24	0.24	0.26	0.27	0.44	0.43
UBI	0.4	0.43	0.22	0.17	0.44	0.44	0.47	0.44	0.4	0.31	0.33	0.31	0.28	0.26	0.33	0.27	0.53	0.55
MB	0.39	0.42	0.24	0.17	0.44	0.43	0.45	0.44	0.38	0.37	0.31	0.28	0.28	0.24	0.31	0.26	0.49	0.51
BPE	0.32	0.38	0.19	0.19	0.35	0.36	0.38	0.36	0.37	0.31	0.33	0.3	0.26	0.24	0.29	0.26	0.44	0.43
PMI	0.35	0.41	0.26	0.21	0.37	0.4	0.4	0.39	0.4	0.31	0.29	0.27	0.26	0.23	0.3	0.24	0.48	0.49
CRG	0.3	0.29	0.16	0.19	0.32	0.31	0.32	0.32	0.3	0.29	0.29	0.27	0.23	0.25	0.23	0.19	0.36	0.34
BPSO	0.3	0.35	0.17	0.16	0.33	0.33	0.38	0.35	0.34	0.29	0.27	0.27	0.21	0.22	0.26	0.21	0.39	0.41
CE	0.37	0.43	0.23	0.17	0.42	0.43	0.44	0.41	0.38	0.36	0.29	0.28	0.26	0.23	0.32	0.26	0.44	0.47
BOV	0.03	0.01	0.01	0.02	0	0.03	0.01	0.01	0.03	0.05	0.05	0.01	-0.01	-0.01	0.02	0.04	0.04	0.02
HSB	0.02	0.03	0.02	0.02	0.01	0.01	0.04	0.02	0.01	0.06	0.05	0.03	-0.01	0.01	0.01	0.02	0.03	0.02
BCP	0.29	0.34	0.23	0.18	0.34	0.36	0.34	0.31	0.33	0.27	0.27	0.27	0.26	0.25	0.26	0.23	0.36	0.32
BPI	0.3	0.35	0.2	0.17	0.34	0.36	0.35	0.34	0.35	0.29	0.25	0.25	0.23	0.21	0.25	0.23	0.39	0.33
SAN	0.43	0.5	0.25	0.2	0.54	0.51	0.54	0.51	0.43	0.38	0.33	0.33	0.31	0.29	0.36	0.32	0.54	0.53
BBVA	0.44	0.51	0.28	0.2	0.56	0.54	0.57	0.53	0.45	0.41	0.32	0.32	0.29	0.27	0.38	0.35	0.56	0.56
SAB	0.35	0.42	0.25	0.17	0.41	0.43	0.43	0.39	0.37	0.3	0.29	0.3	0.26	0.24	0.31	0.28	0.43	0.44
POP	0.39	0.44	0.27	0.18	0.44	0.44	0.45	0.4	0.38	0.31	0.3	0.27	0.26	0.24	0.34	0.32	0.45	0.45
BKT	0.34	0.41	0.24	0.15	0.46	0.45	0.46	0.42	0.34	0.31	0.25	0.23	0.23	0.21	0.31	0.28	0.45	0.47

	BMPS	UBI	MB	BPE	PMI	CRG	BPSO	CE	BOV	HSB	BCP	BPI	SAN	BBVA	SAB	POP	BKT
BMPS	1																
UBI	0.46	1															
MB	0.36	0.47	1														
BPE	0.36	0.45	0.4	1													
PMI	0.41	0.47	0.46	0.47	1												
CRG	0.39	0.36	0.33	0.3	0.32	1											
BPSO	0.36	0.42	0.39	0.45	0.4	0.34	1										
CE	0.38	0.46	0.42	0.38	0.4	0.34	0.39	1									
BOV	0	0.03	0.07	0.02	0.02	0.03	0.05	0.02	1								
HSB	0.03	0.02	0.03	0.04	0.01	0.01	0.08	0.05	0.25	1							
BCP	0.33	0.35	0.28	0.31	0.29	0.26	0.31	0.32	0.01	0.02	1						
BPI	0.28	0.35	0.3	0.33	0.31	0.27	0.3	0.32	0.04	0.05	0.46	1					
SAN	0.39	0.46	0.44	0.38	0.39	0.35	0.36	0.44	0.01	0.02	0.36	0.36	1				
BBVA	0.43	0.48	0.47	0.4	0.43	0.37	0.39	0.47	0.01	0.01	0.36	0.37	0.71	1			
SAB	0.37	0.43	0.41	0.38	0.38	0.3	0.38	0.4	0.03	0.02	0.33	0.34	0.49	0.5	1		
POP	0.39	0.42	0.43	0.38	0.38	0.34	0.38	0.41	0.03	0.01	0.34	0.35	0.55	0.56	0.56	1	
BKT	0.37	0.43	0.44	0.37	0.38	0.28	0.36	0.39	0.02	0	0.33	0.33	0.51	0.55	0.5	0.55	1

Table 15: Conditional Kendall's tau coefficients (with factorial structure)

	Eq	Rate	Sov	Corp	Fx	Com	AT	BE	CY	FR	DE	EL	IE	IT	MT	PT	ES
Eq	1																
Rate	-0.28	1															
Corp	-0.08	0.53	1														
Sov	-0.02	0.57	0.31	1													
Fx	0.07	-0.13	0.05	0.04	1												
Com	0.18	-0.08	-0.08	0.08	0.28	1											
AT	0.59	-0.09	0.03	0.14	0.07	0.11	1										
BE	0.71	-0.02	0.05	0.06	-0.06	-0.02	0.14	1									
CY	0.29	-0.11	0.08	0.11	0.07	-0.03	0.06	0.04	1								
FR	0.87	-0.05	-0.06	0.04	-0.03	0.09	0.09	0.15	0.02	1							
DE	0.81	0.05	-0.16	0.05	-0.04	0.03	0.02	0.06	-0.02	-0.07	1						
EL	0.41	-0.08	0.09	0.13	0.07	-0.02	0.12	0.03	0.24	-0.07	-0.06	1					
IE	0.54	0.04	-0.01	0.06	-0.1	-0.03	0.2	0.11	0.01	0.09	0.02	0.09	1				
IT	0.75	-0.06	0.15	0.07	0.06	-0.04	0.1	0.02	0.04	-0.06	-0.25	0.07	0	1			
MT	0.05	0	-0.02	0.04	-0.02	0.04	0.01	-0.05	0.02	0.04	-0.05	-0.03	0.06	0.04	1		
PT	0.53	-0.05	0.1	0.1	0.01	0.03	0.11	0.09	0.06	-0.04	-0.09	0.17	0.01	0.11	0.03	1	
ES	0.72	-0.05	0.15	0.02	0.1	-0.05	0.05	-0.07	0.04	-0.18	-0.31	0.05	-0.04	0.05	-0.03	0.15	1
EBS	0.49	-0.09	0.07	0.05	0.07	0.01	0.46	-0.02	-0.02	-0.08	-0.07	0.02	0.01	0.12	-0.03	-0.09	-0.02
KBC	0.54	-0.05	0.16	0.06	0.04	-0.07	0.15	0.19	0.01	-0.1	-0.13	0.06	0.04	0.12	0.01	-0.03	0.02
DEXB	0.3	-0.06	0.09	0.02	-0.04	0.02	0.09	0.2	0.09	0	-0.05	-0.03	-0.04	-0.04	-0.01	-0.03	0.01
HB	0.24	-0.07	0.02	0.09	0.03	-0.02	0.09	0.04	0.5	0.03	0.01	-0.03	-0.02	0	0.01	0.04	-0.02
BNP	0.61	-0.12	0.08	0.01	0.04	-0.06	0.06	-0.02	0.06	0.14	-0.18	0.06	0.02	0.05	-0.04	-0.04	0.04
ACA	0.54	-0.07	0.1	0.08	0.04	-0.06	0.09	0.04	0.01	0.04	-0.17	0.09	0.05	0.12	-0.02	0.03	0.05
GLE	0.61	-0.05	0.09	0.07	0.07	-0.07	0.09	0.01	0	0.07	-0.17	0.03	0.06	0.13	0.01	-0.03	0.03
DBK	0.61	-0.04	0.06	0.04	0.03	-0.06	0.09	-0.02	0.03	-0.03	0.04	0.05	0	0.11	-0.01	0	0.05
CBK	0.49	-0.08	0.09	0.07	0.04	-0.01	0.16	0.03	0.02	-0.07	0.03	0.07	0.01	0.12	-0.01	0.02	0.02
ARL	0.47	0.03	0.04	0.1	0.04	0.02	0.18	0.06	0.03	-0.03	-0.02	0.07	0.04	0.13	0.04	0.02	-0.02
ETE	0.35	-0.04	0.04	0.07	0.06	0.01	0.11	-0.03	0.19	-0.05	-0.05	0.46	0.02	0.03	0.02	-0.01	-0.02
TPEIR	0.33	-0.04	0.05	0.07	0.05	0.02	0.13	0.01	0.21	-0.03	-0.06	0.44	0.01	-0.02	-0.02	0.01	-0.01
ALPHA	0.3	-0.06	0.05	0.08	0.03	0.02	0.05	-0.03	0.21	-0.02	-0.07	0.44	-0.02	0	-0.04	-0.09	-0.07
EUROB	0.28	-0.1	0.05	0.08	0.07	0.02	0.1	-0.02	0.18	-0.04	-0.05	0.41	-0.02	-0.04	-0.03	-0.05	-0.02
BKIR	0.39	-0.04	0.11	0.04	0.06	-0.01	0.13	0.01	-0.01	-0.02	-0.05	0.05	0.33	0.06	0.02	0.01	-0.03
ALBK	0.33	-0.07	0.08	0.07	0.01	-0.02	0.09	-0.02	0.06	0.03	-0.06	0.07	0.25	0.02	0.04	-0.02	0.03
UCG	0.56	-0.11	0.13	0.02	0.05	-0.08	0.1	-0.03	0.04	-0.09	-0.21	0.08	-0.01	0.42	-0.03	-0.03	-0.02
ISP	0.56	-0.03	0.15	-0.05	0.04	-0.05	0.02	-0.01	-0.01	-0.14	-0.23	0.08	0	0.42	-0.04	-0.1	-0.03
BMPS	0.38	-0.04	0.09	0.08	0.04	0	0.06	-0.01	0.06	-0.05	-0.13	0.05	-0.03	0.24	-0.02	0.06	0.09
UBI	0.45	-0.08	0.13	-0.01	0	-0.07	0.06	-0.04	0.03	-0.06	-0.15	0.13	0.03	0.35	0.02	-0.01	0.12
MB	0.47	-0.02	0.18	0.06	0.04	-0.04	0.07	-0.02	0.01	-0.06	-0.14	0.12	0.03	0.34	0.05	0.01	0.11
BPE	0.37	-0.03	0.14	0	0.04	-0.05	0.09	0.02	0.07	-0.05	-0.15	0.13	0.05	0.26	0.02	0.08	0.06
PMI	0.4	-0.04	0.2	0.03	0.03	-0.06	0.06	0.04	0.07	-0.03	-0.17	0.04	0.04	0.3	-0.02	0.02	0.03
CRG	0.32	-0.06	0.09	0.02	0.03	0.01	0.08	-0.02	0.07	-0.04	-0.11	0.1	0.01	0.15	0.01	0.05	0.07
BPSO	0.35	-0.05	0.14	0.02	0.03	-0.02	0.05	-0.04	0.06	-0.06	-0.17	0.08	0.02	0.23	0.05	0.1	0.06
CE	0.45	-0.05	0.13	0.05	0.04	-0.07	0.05	0.09	0.02	-0.06	-0.12	0.05	0.05	0.21	0.03	0.02	0.07
BOV	0.05	0	0.01	0.02	0.01	0.04	0.04	-0.06	0	-0.02	-0.09	-0.03	0.06	0.02	0.44	0.01	-0.01
HSB	0.05	0.01	-0.04	0.08	-0.01	0.03	-0.01	-0.02	0.02	0.01	-0.03	-0.01	0.04	0.02	0.54	0.01	0.01
BCP	0.3	-0.09	0.11	0.06	0.01	-0.04	0.06	0.01	0.06	-0.05	-0.09	0.13	-0.02	0.05	0.02	0.32	0.01
BPI	0.36	-0.08	0.13	0.04	0.04	-0.04	0.09	0.02	0.05	-0.06	-0.12	0.09	0.01	0.13	0.05	0.32	0.01
SAN	0.62	-0.05	0.16	0.02	0.09	-0.06	0.02	-0.14	0.03	-0.18	-0.29	0.07	-0.01	-0.01	-0.02	0.03	0.42
BBVA	0.63	-0.06	0.16	0.01	0.09	-0.09	0.08	-0.06	0.04	-0.13	-0.27	0.05	0.03	0.08	-0.03	0.04	0.39
SAB	0.41	-0.06	0.1	-0.01	0.06	-0.08	0.09	-0.03	0.04	-0.06	-0.21	0.1	0.02	0.13	-0.01	0.1	0.27
POP	0.45	-0.1	0.12	-0.03	0.07	-0.07	0.09	-0.05	0.04	-0.11	-0.2	0.1	0.03	0.13	-0.02	0.06	0.3
BKT	0.44	-0.08	0.12	-0.05	0.04	-0.11	0.04	-0.05	0.03	-0.04	-0.2	0.06	0.04	0.13	-0.03	0.08	0.3

Conditional Kendall's tau coefficients with factorial structure (continuation of previous table)

	EBS	KBC	DEXB	HB	BNP	ACA	GLE	DBK	CBK	ARL	ETE	TPEIR	ALPHA	EUROB	BKIR	ALBK	UCG	ISP
EBS	1																	
KBC	0.16	1																
DEXB	0.03	0.03	1															
HB	0.02	0.02	-0.01	1														
BNP	0.14	0.2	0.04	-0.02	1													
ACA	0.1	0.19	0.12	0.01	0.22	1												
GLE	0.12	0.15	0.11	0.02	0.28	0.18	1											
DBK	0.06	0.11	0.1	-0.05	0.22	0.15	0.08	1										
CBK	0.08	0.08	0.06	-0.04	0.12	0.12	0.06	0.16	1									
ARL	0.07	-0.01	-0.02	-0.03	0.06	0.07	0.03	0.1	0.02	1								
ETE	0.04	-0.06	0.07	0.01	0.04	0.03	-0.06	0.05	0.03	0.02	1							
TPEIR	0.06	-0.04	0.02	0.02	0.04	0	0.03	0.04	0.02	-0.02	0.28	1						
ALPHA	0.02	0.03	0.04	0.05	0.05	0.04	-0.05	0.04	0.05	0.04	0.26	0.21	1					
EUROB	0.06	-0.02	0.05	-0.03	0.02	0.03	-0.03	0.09	0.03	-0.01	0.23	0.21	0.19	1				
BKIR	0.08	0.08	0.08	-0.02	0.01	0.03	0.04	0.06	-0.02	0.03	-0.02	0.05	0.03	-0.05	1			
ALBK	0.03	0.08	0.06	-0.01	0.07	0.03	0.07	0.01	0.02	-0.01	0.04	0.06	0	0.06	0.19	1		
UCG	0.11	0.11	0.06	-0.01	0.11	0.04	0.12	0.01	0.03	0.03	0.04	-0.03	0	-0.01	0.03	0.02	1	
ISP	0.09	0.03	0.07	0.02	0.14	0.09	0.09	0.08	0.03	0.04	0.04	0.03	0.03	-0.04	0.05	-0.02	0	1
BMPS	0.03	0.07	0.1	0.04	0.08	0.07	0.02	-0.01	0.04	0.03	0.08	0.03	-0.02	0.03	0.03	0.05	0	0.03
UBI	0.09	0.03	0.04	0	0.06	0.06	0.08	0.03	0.07	-0.07	0.06	0.04	0	-0.02	0.09	-0.01	0.04	0.09
MB	0.05	0.01	0.05	0.01	0.07	0.04	0.01	0.03	0.01	0.02	0.02	0.03	0.03	-0.05	-0.02	-0.03	-0.07	0.02
BPE	0.05	0.07	-0.02	0	0.02	-0.01	0.03	0.02	0.07	-0.01	0.09	0.03	-0.03	-0.06	0.05	0	0.02	0.04
PMI	0.07	0.07	0.06	0.02	0.01	0.08	0.04	0.03	0.11	0.02	0	0.04	0.04	-0.04	0.03	-0.03	0.02	0.1
CRG	-0.01	-0.02	-0.03	0.07	0.07	0.05	0.01	0.04	0.04	0.07	0.03	-0.01	-0.02	0.04	0.02	-0.05	0.02	-0.01
BPSO	0.04	0.05	-0.02	-0.03	0.04	0.02	0.11	0.06	0.07	0.03	0.03	0.04	-0.02	0.01	0	-0.02	-0.05	0.04
CE	0.03	0.06	0.03	-0.05	0.07	0.05	0.04	0.04	0.04	0.06	0.05	0.02	0.04	0.03	0.02	-0.02	-0.01	0.06
BOV	0.03	-0.02	0.03	0.01	-0.05	0.05	-0.06	0.01	0.01	0.05	0.07	-0.04	-0.04	-0.01	-0.01	0.04	0.04	-0.03
HSB	0.02	-0.03	0.04	0.01	0.03	-0.03	0	-0.01	-0.03	-0.02	0.05	0.02	-0.06	0.03	-0.04	-0.03	0.06	0.03
BCP	0.04	0.07	0.07	0.01	0.06	0.06	0.03	-0.05	0.04	-0.01	-0.02	0.04	0.03	0.04	0.01	0.01	0.04	0.03
BPI	0.05	0.1	0.03	-0.03	0.07	0.05	0.01	0.01	0.04	0.01	-0.03	0	0.02	-0.04	0.03	0.02	0.03	-0.02
SAN	0.02	0.09	0.04	-0.02	0.06	0.03	-0.01	0.05	0.02	0.02	-0.01	0.03	0.03	0.01	0.03	0.04	0.11	0.05
BBVA	0.05	0.12	0.07	-0.05	0.13	0.09	0.06	0.01	0.03	0.04	0.01	0.02	0.05	-0.01	0.06	0.06	0.09	0.09
SAB	0.05	0.12	0.11	0.01	0.05	0.06	0.03	-0.01	0.06	-0.02	0.03	0.03	0.03	-0.05	0.01	0.02	-0.01	0.03
POP	0.1	0.09	0.09	0.03	0.06	0.09	0	0.02	0.03	-0.01	-0.01	-0.07	0.01	-0.02	0.09	0.07	0.02	0.01
BKT	0.06	0.11	0.08	-0.02	0.12	0.09	0.06	0.01	-0.02	0.01	-0.05	-0.05	0.03	0	0.01	0	-0.04	0.09

	BMPS	UBI	MB	BPE	PMI	CRG	BPSO	CE	BOV	HSB	BCP	BPI	SAN	BBVA	SAB	POP	BKT
BMPS	1																
UBI	0.15	1															
MB	0.02	0.05	1														
BPE	0.03	0.15	0.03	1													
PMI	0.06	0.1	0.11	0.13	1												
CRG	0.18	0.09	0.03	0.01	0.02	1											
BPSO	0.06	0.09	0.07	0.19	0.05	0.07	1										
CE	0.07	0.09	0.04	0.05	0.04	0.04	0.08	1									
BOV	-0.03	0.01	0.06	-0.03	-0.03	-0.01	0	-0.01	1								
HSB	0.02	-0.04	-0.02	0.06	-0.01	-0.04	0.03	-0.02	-0.15	1							
BCP	0.05	0.05	-0.04	0.02	-0.03	0.03	0.03	0.04	-0.04	-0.02	1						
BPI	-0.01	0.06	-0.05	0.04	-0.01	0.05	-0.01	0.01	-0.01	0.02	0.15	1					
SAN	0.05	0.02	-0.04	0.05	0.01	0.05	0.03	0.03	-0.04	-0.03	0.05	-0.01	1				
BBVA	0.06	0	-0.01	0.01	0.07	0.07	0.02	0.03	-0.04	-0.04	0.02	-0.01	0.12	1			
SAB	0.07	0.05	0.04	0.07	0	-0.01	0.04	0.05	-0.01	0.01	0.05	0.02	0.02	-0.01	1		
POP	0.1	-0.01	0.05	0.1	-0.01	0.05	0.06	0.02	0.02	-0.01	0.04	0.05	0.07	0.05	0.23	1	
BKT	0.06	0.02	0.07	0.05	0.01	0.03	0.02	0.01	0.03	-0.02	0.02	0.05	-0.01	0.04	0.09	0.17	1

Table 16: Conditional Kendall's tau coefficients for the CVRF model
Nota: This table is similar to the previous one but we implemented independence hypothesis.

	Eq	Rate	Sov	Corp	Fx	Com	AT	BE	CY	FR	DE	EL	IE	IT	MT	PT	ES
Eq	1																
Rate	-0.28	1															
Corp	-0.08	0.53	1														
Sov	-0.02	0.57	0.31	1													
Fx	0.07	-0.13	0.05	0.04	1												
Com	0.18	-0.08	-0.08	0.08	0.28	1											
AT	0.59	-0.09	0.03	0.14	0.07	0.11	1										
BE	0.71	-0.02	0.05	0.06	-0.06	-0.02	-	1									
CY	0.29	-0.11	0.08	0.11	0.07	-0.03	-	-	1								
FR	0.87	-0.05	-0.06	0.04	-0.03	0.09	-	-	-	1							
DE	0.81	0.05	-0.16	0.05	-0.04	0.03	-	-	-	-	1						
EL	0.41	-0.08	0.09	0.13	0.07	-0.02	-	-	-	-	-	1					
IE	0.54	0.04	-0.01	0.06	-0.1	-0.03	-	-	-	-	-	-	1				
IT	0.75	-0.06	0.15	0.07	0.06	-0.04	-	-	-	-	-	-	-	1			
MT	0.05	0	-0.02	0.04	-0.02	0.04	-	-	-	-	-	-	-	-	1		
PT	0.53	-0.05	0.1	0.1	0.01	0.03	-	-	-	-	-	-	-	-	-	1	
ES	0.72	-0.05	0.15	0.02	0.1	-0.05	-	-	-	-	-	-	-	-	-	-	1
EBS	0.49	-0.09	0.07	0.05	0.07	0.01	0.46	-	-	-	-	-	-	-	-	-	
KBC	0.54	-0.05	0.16	0.06	0.04	-0.07	-	0.21	-	-	-	-	-	-	-	-	
DEXB	0.3	-0.06	0.09	0.02	-0.04	0.02	-	0.21	-	-	-	-	-	-	-	-	
HB	0.24	-0.07	0.02	0.09	0.03	-0.02	-	-	0.5	-	-	-	-	-	-	-	
BNP	0.61	-0.12	0.08	0.01	0.04	-0.06	-	-	-	0.14	-	-	-	-	-	-	
ACA	0.54	-0.07	0.1	0.08	0.04	-0.06	-	-	-	0.06	-	-	-	-	-	-	
GLE	0.61	-0.05	0.09	0.07	0.07	-0.07	-	-	-	0.07	-	-	-	-	-	-	
DBK	0.61	-0.04	0.06	0.04	0.03	-0.06	-	-	-	-	0.04	-	-	-	-	-	
CBK	0.49	-0.08	0.09	0.07	0.04	-0.01	-	-	-	-	0.03	-	-	-	-	-	
ARL	0.47	0.03	0.04	0.1	0.04	0.02	-	-	-	-	-0.01	-	-	-	-	-	
ETE	0.35	-0.04	0.04	0.07	0.06	0.01	-	-	-	-	-	0.51	-	-	-	-	
TPEIR	0.33	-0.04	0.05	0.07	0.05	0.02	-	-	-	-	-	0.49	-	-	-	-	
ALPHA	0.3	-0.06	0.05	0.08	0.03	0.02	-	-	-	-	-	0.48	-	-	-	-	
EUROB	0.28	-0.1	0.05	0.08	0.07	0.02	-	-	-	-	-	0.45	-	-	-	-	
BKIR	0.39	-0.04	0.11	0.04	0.06	-0.01	-	-	-	-	-	-	0.35	-	-	-	
ALBK	0.33	-0.07	0.08	0.07	0.01	-0.02	-	-	-	-	-	-	0.26	-	-	-	
UCG	0.56	-0.11	0.13	0.02	0.05	-0.08	-	-	-	-	-	-	-	0.47	-	-	
ISP	0.56	-0.03	0.15	-0.05	0.04	-0.05	-	-	-	-	-	-	-	0.47	-	-	
BMPS	0.38	-0.04	0.09	0.08	0.04	0	-	-	-	-	-	-	-	0.27	-	-	
UBI	0.45	-0.08	0.13	-0.01	0	-0.07	-	-	-	-	-	-	-	0.39	-	-	
MB	0.47	-0.02	0.18	0.06	0.04	-0.04	-	-	-	-	-	-	-	0.37	-	-	
BPE	0.37	-0.03	0.14	0	0.04	-0.05	-	-	-	-	-	-	-	0.31	-	-	
PMI	0.4	-0.04	0.2	0.03	0.03	-0.06	-	-	-	-	-	-	-	0.35	-	-	
CRG	0.32	-0.06	0.09	0.02	0.03	0.01	-	-	-	-	-	-	-	0.19	-	-	
BPSO	0.35	-0.05	0.14	0.02	0.03	-0.02	-	-	-	-	-	-	-	0.29	-	-	
CE	0.45	-0.05	0.13	0.05	0.04	-0.07	-	-	-	-	-	-	-	0.24	-	-	
BOV	0.05	0	0.01	0.02	0.01	0.04	-	-	-	-	-	-	-	-	0.45	-	
HSB	0.05	0.01	-0.04	0.08	-0.01	0.03	-	-	-	-	-	-	-	-	0.54	-	
BCP	0.3	-0.09	0.11	0.06	0.01	-0.04	-	-	-	-	-	-	-	-	-	0.36	
BPI	0.36	-0.08	0.13	0.04	0.04	-0.04	-	-	-	-	-	-	-	-	-	0.36	
SAN	0.62	-0.05	0.16	0.02	0.09	-0.06	-	-	-	-	-	-	-	-	-	-	0.49
BBVA	0.63	-0.06	0.16	0.01	0.09	-0.09	-	-	-	-	-	-	-	-	-	-	0.48
SAB	0.41	-0.06	0.1	-0.01	0.06	-0.08	-	-	-	-	-	-	-	-	-	-	0.35
POP	0.45	-0.1	0.12	-0.03	0.07	-0.07	-	-	-	-	-	-	-	-	-	-	0.39
BKT	0.44	-0.08	0.12	-0.05	0.04	-0.11	-	-	-	-	-	-	-	-	-	-	0.35

Conditional Kendall's tau coefficients for the CVRF model (continuation of previous table)

	EBS	KBC	DEXB	HB	BNP	ACA	GLE	DBK	CBK	ARL	ETE	TPEIR	ALPHA	EUROB	BKIR	ALBK	UCG	ISP
EBS	1																	
KBC	-	1																
DEXB	-	0.04	1															
HB	-	-	-	1														
BNP	-	-	-	-	1													
ACA	-	-	-	-	0.31	1												
GLE	-	-	-	-	0.37	0.23	1											
DBK	-	-	-	-	-	-	-	1										
CBK	-	-	-	-	-	-	-	0.27	1									
ARL	-	-	-	-	-	-	-	0.16	0.09	1								
ETE	-	-	-	-	-	-	-	-	-	-	1							
TPEIR	-	-	-	-	-	-	-	-	-	-	0.3	1						
ALPHA	-	-	-	-	-	-	-	-	-	-	0.26	0.22	1					
EUROB	-	-	-	-	-	-	-	-	-	-	0.24	0.24	0.21	1				
BKIR	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1			
ALBK	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.23	1		
UCG	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	
ISP	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.11	1
BMPS	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.07	0.05
UBI	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.1	0.13
MB	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.02	0.06
BPE	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.04	0.03
PMI	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.05	0.12
CRG	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.03	0.01
BPSO	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.02	0.05
CE	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.04	0.1
BOV	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
HSB	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BCP	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BPI	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SAN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BBVA	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SAB	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
POP	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BKT	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

	BMPS	UBI	MB	BPE	PMI	CRG	BPSO	CE	BOV	HSB	BCP	BPI	SAN	BBVA	SAB	POP	BKT
BMPS	1																
UBI	0.19	1															
MB	0.05	0.09	1														
BPE	0.09	0.18	0.04	1													
PMI	0.09	0.12	0.11	0.15	1												
CRG	0.18	0.09	0.04	0.04	0.01	1											
BPSO	0.12	0.12	0.09	0.23	0.04	0.09	1										
CE	0.11	0.1	0.06	0.07	0.04	0.07	0.08	1									
BOV	-	-	-	-	-	-	-	-	1								
HSB	-	-	-	-	-	-	-	-	-0.15	1							
BCP	-	-	-	-	-	-	-	-	-	-	1						
BPI	-	-	-	-	-	-	-	-	-	-	0.19	1					
SAN	-	-	-	-	-	-	-	-	-	-	-	-	1				
BBVA	-	-	-	-	-	-	-	-	-	-	-	-	0.2	1			
SAB	-	-	-	-	-	-	-	-	-	-	-	-	0.06	0.06	1		
POP	-	-	-	-	-	-	-	-	-	-	-	-	0.11	0.09	0.29	1	
BKT	-	-	-	-	-	-	-	-	-	-	-	-	0.02	0.11	0.21	0.19	1

5.6. Shocks to indices

Table 17: Returns after a shock at the 1% tail distribution of the Equity index

	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2012 - 2013	2013 - 2014	2014 - 2015
Equity index	-3,3%	-4,5%	-11,8%	-11,8%	-9,7%	-11,1%	-6,9%	-4,8%	-4,5%	-6,4%
Bond index	0,0%	0,2%	0,5%	0,6%	0,5%	1,0%	1,0%	0,3%	0,1%	0,2%
Sovereign index	0,1%	0,1%	0,8%	0,4%	0,1%	0,4%	0,3%	-0,2%	-0,2%	-0,1%
Corporate index	0,0%	0,1%	0,2%	0,2%	0,2%	0,1%	0,3%	-0,1%	0,0%	-0,1%
Foreign exchange index	0,1%	0,1%	-1,3%	-1,5%	-2,4%	-2,9%	-1,8%	-0,9%	0,1%	1,4%
Commodity index	-0,6%	-0,5%	-3,0%	-5,1%	-4,8%	-3,5%	-2,3%	-1,0%	-0,7%	-0,9%
Austrian index	-3,7%	-5,2%	-19,3%	-15,3%	-6,2%	-10,5%	-9,6%	-3,1%	-5,8%	-4,6%
Belgian index	-3,2%	-5,0%	-8,1%	-8,3%	-8,7%	-9,3%	-7,3%	-4,0%	-4,3%	-4,5%
Cyprus index	-2,8%	-5,5%	-12,1%	-8,1%	-6,2%	-16,7%	-8,4%	-3,1%	0,4%	-0,6%
French index	-3,8%	-5,0%	-15,6%	-15,8%	-9,5%	-10,3%	-8,5%	-4,3%	-5,4%	-6,5%
German index	-4,1%	-5,3%	-15,3%	-15,3%	-8,1%	-9,3%	-9,3%	-4,3%	-4,5%	-6,1%
Greek index	-4,1%	-6,1%	-11,7%	-7,3%	-7,9%	-7,9%	-4,7%	-3,0%	-11,8%	-8,2%
Irish index	-3,2%	-5,0%	-12,9%	-7,8%	-11,2%	-7,6%	-5,7%	-2,7%	-3,4%	-4,0%
Italian index	-3,0%	-4,2%	-14,3%	-10,9%	-8,5%	-11,5%	-9,8%	-5,8%	-5,6%	-6,1%
Maltese index	0,9%	-0,6%	-1,7%	-1,4%	-0,8%	-0,9%	-0,5%	0,4%	0,1%	0,1%
Portuguese	-0,9%	-3,9%	-9,6%	-9,3%	-6,0%	-7,2%	-7,7%	-5,6%	-8,9%	-7,0%
Spanish index	-3,1%	-4,3%	-14,2%	-15,3%	-6,9%	-9,9%	-7,7%	-4,7%	-4,3%	-4,6%

Table 18: Returns after a shock at the 1% tail distribution of the Bond index

	2005 - 2006	2006 - 2007	2007 - 2008	2008 - 2009	2009 - 2010	2010 - 2011	2011 - 2012	2012 - 2013	2013 - 2014	2014 - 2015
Equity index	0,6%	1,5%	2,4%	3,1%	3,2%	5,5%	5,5%	1,7%	0,8%	1,2%
Bond index	-0,8%	-0,6%	-1,2%	-1,4%	-0,9%	-1,0%	-1,3%	-1,1%	-1,0%	-0,8%
Sovereign index	-0,9%	-0,6%	-1,0%	-1,5%	-0,8%	-0,6%	-0,5%	-0,8%	-0,8%	-1,0%
Corporate index	-0,7%	-0,6%	-1,7%	-0,8%	-0,8%	-0,8%	-0,7%	-0,5%	-0,6%	-0,6%
Foreign exchange index	0,4%	-0,1%	0,3%	1,2%	0,2%	1,0%	1,8%	0,9%	0,3%	0,1%
Commodity index	0,4%	0,5%	0,0%	2,5%	1,7%	1,6%	1,3%	0,5%	0,0%	0,3%
Austrian index	1,6%	2,6%	3,5%	4,8%	4,5%	4,0%	4,1%	1,4%	0,5%	1,5%
Belgian index	0,8%	1,8%	1,3%	2,2%	3,2%	3,3%	3,6%	1,3%	0,8%	1,0%
Cyprus index	2,1%	3,1%	2,3%	3,4%	4,7%	3,7%	5,6%	1,3%	-0,5%	0,1%
French index	0,7%	1,6%	2,6%	3,3%	3,2%	4,8%	4,9%	1,5%	0,7%	1,3%
German index	0,8%	1,9%	2,8%	3,6%	3,1%	4,7%	4,5%	1,4%	0,6%	1,2%
Greek index	1,1%	1,5%	2,5%	3,3%	3,5%	4,2%	3,5%	1,4%	1,2%	2,1%
Irish index	0,8%	1,7%	0,0%	0,5%	3,4%	3,4%	2,8%	0,8%	0,7%	0,3%
Italian index	0,5%	1,4%	1,6%	2,3%	3,4%	5,9%	6,3%	2,7%	1,3%	1,1%
Maltese index	0,8%	0,7%	-0,3%	-1,3%	-0,3%	0,4%	-0,1%	0,0%	0,2%	0,4%
Portuguese	0,9%	1,2%	1,1%	1,8%	2,8%	3,7%	2,0%	1,4%	1,5%	1,5%
Spanish index	0,7%	1,6%	2,2%	2,8%	2,8%	6,0%	6,1%	2,5%	1,2%	1,1%

5.7. Examples of contagion effects

Table 19: Contagion effects - Shortfalls of banks and countries after a shock to equity of Société Générale (GLE) (in billions of euros)

BELGIUM	Solvency shortfall	Liquity shortfall
	-6,8	-63,9
DEXB	-6,8	-63,9
FRANCE	Solvency shortfall	Liquity shortfall
	-38,0	-269,5
GLE	- 12,85	-269,5
GLE	-12,85	
BNP	-4,30	
GERMANY	Solvency shortfall	Liquity shortfall
	-26,0	
DBK	-20,7	
CBK	-5,2	
ARL	-0,15	
IRELAND	Solvency shortfall	Liquity shortfall
		-5,6
ALBK		-5,6
ITALY	Solvency shortfall	Liquity shortfall
	-4,6	-0,13
UCG	-2,80	
BMPS	-1,70	
CRG	-0,07	
MB		-0,10
BPE		-0,03
GREECE	Solvency shortfall	Liquity shortfall
	-3,3	-171,2
ALPHA	-2,07	-27,32
ETE	-0,50	-53,38
TPEIR	-0,44	-41,87
EUROB	-0,25	-48,60
PORTUGAL	Solvency shortfall	Liquity shortfall
	-0,07	-8,7
BCP	-0,07	-8,7
SPAIN	Solvency shortfall	Liquity shortfall
		-22,3
SAB		-5,4
POP		-16,9

Table 20: Contagion effects - Shortfalls of banks and countries after a shock to equity of the central bank of Portugal (BCP) (In billions of euros)

BELGIUM	Solvency shortfall	Liquity shortfall
	-6,8	$-63,9$
DEXB	-6,8	-63,9
FRANCE	Solvency shortfall	Liquity shortfall
	-33,7	-269,1
ACA	-19,79	
GLE	-9,56	-269,1
BNP	-4,42	
GERMANY	Solvency shortfall	Liquity shortfall
	-25,6	
DBK	-20,7	
CBK	-5,07	
ARL	-0,15	
IRELAND	Solvency shortfall	Liquity shortfall
		-5,6
ALBK		-5,59
ITALY	Solvency shortfall	Liquityshortfall
	-4,6	-0,15
UCG	-2,84	
BMPS	-1,66	
CRG	-0,07	
MBP		-0,11
BPE		-0,04
GREECE	Solvency shortfall	Liquityshortfall
	-3,3	-171,2
ETE	-0,48	-53,38
TPEIR	-0,43	-41,86
ALPHA	-2,08	-27,32
EUROB	-0,25	-48,59
SPAIN	Solvency shortfall	Liquityshortfall
	0	-24,5
SAB		-5,43
POP		-16,86
BKT		-2,20
PORTUGAL	Solvency shortfall	Liquityshortfall
	0	-8,7
BCP		-8,71

5.8. *Kendall's taus under the scenario of positive tail dependency between stocks and bonds*

	Euro Stoxx	Bobl	Euro Sov.	Euro Corp.	EUR-USD	Commo.	AT	BE	CY	FR	DE	EL	IE	IT	MT	PT	ES
Euro Stoxx	1																
Bobl	0.10	1															
Euro Sov.	0.10	0.53	1														
Euro Corp.	0.10	0.57	0.31	1													
EUR-USD	0.07	-0.13	0.05	0.04	1												
Commo.	0.18	-0.08	-0.08	0.08	0.28	1											
AT	0.59	0.09	0.03	0.14	0.07	0.11	1										
BE	0.71	0.02	0.05	0.06	-0.06	-0.02	-	1									
CY	0.29	0.11	0.08	0.11	0.07	-0.03	-	-	1								
FR	0.87	0.05	-0.06	0.04	-0.03	0.09	-	-	-	1							
DE	0.81	0.05	-0.16	0.05	-0.04	0.03	-	-	-	-	1						
EL	0.41	0.08	0.09	0.13	0.07	-0.02	-	-	-	-	-	1					
IE	0.54	0.04	-0.01	0.06	-0.10	-0.03	-	-	-	-	-	-	1				
IT	0.75	0.06	0.15	0.07	0.06	-0.04	-	-	-	-	-	-	-	1			
MT	0.05	0.00	-0.02	0.04	-0.02	0.04	-	-	-	-	-	-	-	-	1		
PT	0.53	0.05	0.10	0.10	0.01	0.03	-	-	-	-	-	-	-	-	-	1	
ES	0.72	0.05	0.15	0.02	0.10	-0.05	-	-	-	-	-	-	-	-	-	-	1
EBS	0.49	0.09	0.07	0.05	0.07	0.01	0.46	-	-	-	-	-	-	-	-	-	-
KBC	0.54	0.05	0.16	0.06	0.04	-0.07	-	0.21	-	-	-	-	-	-	-	-	-
DEXB	0.30	0.06	0.09	0.02	-0.04	0.02	-	0.21	-	-	-	-	-	-	-	-	-
HB	0.24	0.07	0.02	0.09	0.03	-0.02	-	-	0.50	-	-	-	-	-	-	-	-
BNP	0.61	0.12	0.08	0.01	0.04	-0.06	-	-	-	0.14	-	-	-	-	-	-	-
ACA	0.54	0.07	0.10	0.08	0.04	-0.06	-	-	-	0.06	-	-	-	-	-	-	-
GLE	0.61	0.05	0.09	0.07	0.07	-0.07	-	-	-	0.07	-	-	-	-	-	-	-
DBK	0.61	0.04	0.06	0.04	0.03	-0.06	-	-	-	-	0.04	-	-	-	-	-	-
CBK	0.49	0.08	0.09	0.07	0.04	-0.01	-	-	-	-	0.03	-	-	-	-	-	-
ARL	0.47	0.03	0.04	0.10	0.04	0.02	-	-	-	-	-0.01	-	-	-	-	-	-
ETE	0.35	0.04	0.04	0.07	0.06	0.01	-	-	-	-	-	0.51	-	-	-	-	-
TPEIR	0.33	0.04	0.05	0.07	0.05	0.02	-	-	-	-	-	0.49	-	-	-	-	-
ALPHA	0.30	0.06	0.05	0.08	0.03	0.02	-	-	-	-	-	0.48	-	-	-	-	-
EUROB	0.28	0.10	0.05	0.08	0.07	0.02	-	-	-	-	-	0.45	-	-	-	-	-
BKIR	0.39	0.04	0.11	0.04	0.06	-0.01	-	-	-	-	-	-	0.35	-	-	-	-
ALBK	0.33	0.07	0.08	0.07	0.01	-0.02	-	-	-	-	-	-	0.26	-	-	-	-
UCG	0.56	0.11	0.13	0.02	0.05	-0.08	-	-	-	-	-	-	-	0.47	-	-	-
ISP	0.56	0.03	0.15	-0.05	0.04	-0.05	-	-	-	-	-	-	-	0.47	-	-	-
BMPS	0.38	0.04	0.09	0.08	0.04	0.00	-	-	-	-	-	-	-	0.27	-	-	-
UBI	0.45	0.08	0.13	-0.01	0.00	-0.07	-	-	-	-	-	-	-	0.39	-	-	-
MB	0.47	0.02	0.18	0.06	0.04	-0.04	-	-	-	-	-	-	-	0.37	-	-	-
BPE	0.37	0.03	0.14	0.00	0.04	-0.05	-	-	-	-	-	-	-	0.31	-	-	-
PMI	0.40	0.04	0.20	0.03	0.03	-0.06	-	-	-	-	-	-	-	0.35	-	-	-
CRG	0.32	0.06	0.09	0.02	0.03	0.01	-	-	-	-	-	-	-	0.19	-	-	-
BPSO	0.35	0.05	0.14	0.02	0.03	-0.02	-	-	-	-	-	-	-	0.29	-	-	-
CE	0.45	0.05	0.13	0.05	0.04	-0.07	-	-	-	-	-	-	-	0.24	-	-	-
BOV	0.05	0.00	0.01	0.02	0.01	0.04	-	-	-	-	-	-	-	-	0.45	-	-
HSB	0.05	0.01	-0.04	0.08	-0.01	0.03	-	-	-	-	-	-	-	-	0.54	-	-
BCP	0.30	0.09	0.11	0.06	0.01	-0.04	-	-	-	-	-	-	-	-	-	0.36	-
BPI	0.36	0.08	0.13	0.04	0.04	-0.04	-	-	-	-	-	-	-	-	-	0.36	-
SAN	0.62	0.05	0.16	0.02	0.09	-0.06	-	-	-	-	-	-	-	-	-	-	0.49
BBVA	0.63	0.06	0.16	0.01	0.09	-0.09	-	-	-	-	-	-	-	-	-	-	0.48
SAB	0.41	0.06	0.10	-0.01	0.06	-0.08	-	-	-	-	-	-	-	-	-	-	0.35
POP	0.45	0.10	0.12	-0.03	0.07	-0.07	-	-	-	-	-	-	-	-	-	-	0.39
BKT	0.44	0.08	0.12	-0.05	0.04	-0.11	-	-	-	-	-	-	-	-	-	-	0.35

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