Analysis of banks' systemic risk contribution and contagion determinants trough the leave-one-out approach

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Abstract

In this paper we develop an in-depth analysis of the systemic risk and contagion determinants, trough the differential effects on the banking system of excluding one bank.

The splitting of risk contributions as the sum of two components, namely the stand-alone bank risk and the contagion risk, allow measuring the role of assets riskiness, capitalization, and interconnectedness. We find that the stand-alone and contagion components are not strictly linked each other, so one bank that is relatively safe as a single can turn out to be an important contagion vehicle as part of a network, and that capital is more effective in reducing the contagion component than the stand-alone one.

The different behavior of the systems in different crises severity, and the capability of this method to assess the macro effects of micro variations, allow for a more accurate targeting of specific supervisory interventions, resulting in a relevant contribute to macroprudential regulation.

Keywords: Leave-One-Out, Macroprudential regulation, Banking, Systemic risk contribution.

JEL codes: C63, G01, G21

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1. Introduction

As witnessed by the ruinous outcomes of many financial institutions' defaults during the last financial crisis, the default of a single bank may produce effects that extend far beyond the institution itself, possibly hitting large shares of the banking system and of the real economy. In this context, the scientific debate has focused on what systemic risk is and how to measure it.

Systemic crises can stem from a single huge default event or from many smaller defaults and contagion effects. While the first case is evidently driven by the dimension of the failing institution, in the second case, and anyway when contagion spreads out, it is not simple to assess the contribution of each single institution to the crisis, even in theoretical terms. It is evident that the same initial default (or defaults) can turn on or not a systemic crisis depending on the importance of financial linkages, on the strength/weakness of the other banks, on the strength/weakness of the real economy, etc. As suggested by Brunnermeier et al (2009), a systemic risk measure should identify both the risk posed by individually systemic institutions which are so large to cause negative risk spillover effects on other institutions via their linkages, as well as the risk stemming from smaller institutions which can turn to be systemic as part of a herd.

The importance of this issue has also been acknowledged by supervisors and regulators, which have moved from a micro-prudential perspective (the Basel I and Basel II approaches), seeking to enhance the safety and soundness of individual financial institutions, to a macro-prudential approach (such as the one introduced in the Basel III framework) which pursues the stability of the financial system as a whole.

However, this complexity is still not entirely tackled and the debate is open on how to charge each of the participants to their responsibility share (risk contribution) to the crisis (or to a possible crisis).

A vast literature focusing on all these issues proposes market-based measures of systemic importance. Still, a fundamental open question is: how is it possible to quantify the role of assets riskiness, capitalization, and interconnectdedness of single banks in determining the system riskiness? Or, in other terms, is there any clear effect of single bank (micro) variables affecting the system (macro) riskiness?

This paper aims to contribute to the scientific debate by answering these questions on the determinants of each financial institution contribution to systemic risk by means of a Leave-One-Out approach (LOO). The basic idea behind the LOO approach is that the contribution of each bank to systemic risk can be obtained comparing the performance of the banking system including all banks to the performance of the same banking system when excluding the considered bank.

This approach allows estimating the effect on the system of including or not one specific bank, but also to split this systemic risk contribution in two components, the stand-alone and the contagion risk, and to quantify the effect of each of the considered balance sheet variables to each of the two components.

The method is tested[3] on a sample of 116 European banking groups included in the last stress test performed by the EBA (European Banking Authority, 2014) as of end 2013.

A regression analysis is then conducted to measure how the balance sheet variables are related to each of the LOO contribution two components, the stand-alone and the contagion risk. Results show that size matters but is not sufficient as a proxy for the contribution of a bank to systemic risk, since other variables play a crucial role. Capital reduces the stand-alone risk, as expected, but the reduction of contagion risk is remarkably higher. The stand-alone component significantly depends also on the level of risk-weighted assets while the contagion risk component is also driven by the value of interbank positions.

Moreover, we explore how the dimension of the crisis impacts on the bank-specific Leave-One-Out contributions, computing the expected losses conditional on different thresholds. Indeed, we find that the dimension of the crisis relevantly affect results, so that some banks can have a barrier effect in small crises while having a positive contribution in larger crises. Details are in Appendix one.

In order to analyze the evolution of the European banking system riskiness, we also computed LOO contributions for the same sample of banks included in the 2014 EU-wide stress test for three more years, namely 2007, 2009 and 2011 and compared it with some market-based measures, i.e. SRISK and MES. Results show that, differently from the market based measures, LOO registers high risks values already in 2007, and an important risk reduction after the recapitalization experienced from 2011.

Finally, since our approach is somehow related to the Shapley value (proposed in Drehmann and Tarashev, 2013), we also compared its results with the LOO risk contributions. The test conducted on three small samples (for which the Shapley value is feasible), for four years and four different thresholds, on the one side proofed that the LOO method clearly outperforms the Shapley values in terms of computation complexity, on the other side resulted in a very high correlation between the two measures, even when considered in its value per assets unit, so excluding the size effect. Details are in Appendix two.

The rest of the paper is organized as follows. In Section 2 we report the analysis of the recent literature on systemic risk contributions and simulation models. Section 3 presents the methodology for computing the LOO contributions to systemic risk. Section 4 presents and discusses results of the model empirical application. Section 5 concludes.

2. Related Literature

The related literature analysis refers to two different topics: the systemic risk measurement and the simulation models.

[3] In order to show the methodological steps in practice we first apply the LOO method to a small sample of nine French banks, reported in appendix 1.

The literature on financial systemic risk has advanced significantly in recent years, from both a theoretical and an empirical perspective, developing different approaches for measuring systemic risk contributions.

The initial approach, focused on the identification of financial institutions able to pose a systemic threat (the so-called 'too big to fail' institutions, also known as systemically important financial institution, SIFIs), has subsequently evolved to a smoother approach, aimed at quantifying the risk contribution in a systemic perspective.

In this aim, Acharya et al. (2010) proposed to measure the exposure to systemic risk of an individual bank by means of its propensity to be undercapitalized (in terms of expected equity loss) when the system as a whole is undercapitalized. The measure is called Marginal Expected Shortfall (MES).

The authors based their analysis on daily stock market returns, defining as systemic event the worst *q* percentage market outcomes at a daily frequency as R_q^{worst}. They then define the 'Marginal Expected Shortfall' (MES) as the expected net equity return of bank *i* during the preset fixed-percentage market worst days:

$$MES_{it}^{q} = E(r_{it} \mid R_q^{worst})$$

In this way the systemic crisis threshold is set in terms of 'value at risk' (VaR), and MES refers to that part of systemic risk that is reflected on each bank.

As this measure is based on firstly identifying the system crisis, then verifying its relationship with the undercapitalization of the considered bank, its aim is in quantifying how the bank is undergoing the crisis.

While this quantification is fundamental for proxying the risk of that bank to be involved in a forthcoming crisis, it can not distinguish the correlation effects, so the exposure of the considered bank to a common factor affecting the whole system, from causality, so the effect of the rest of the system distress to the considered bank, by means of contagion.

Huang et al (2009, 2010 and 2011) proposed to measure the systemic risk of the banking sector, using credit default swap spreads and equity prices of individual institutions, to derive their risk neutral probability of default, and the asset return correlations. These inputs are employed to construct a bank-specific indicator of the systemic risk posed to the financial system, called distress insurance premium (DIP).

The DIP of a bank represents a hypothetical insurance premium that the considered institution should pay against systemic financial distress.

The systemic risk of the banking sector is the risk-neutral expectation[4] of the total loss in the system L exceeding a certain threshold level $L_{\min}$

[4] For CoVar and for MES the expectation is based on the objective measure.

$$DIP = E^{Q}(L \mid L > L_{\min})$$

where $L = \sum_{i=1}^{N} L_i$ is the sum of the losses of all the N banks in the system.

Individual risk contributions are obtained as:

$$\frac{\partial DIP}{\partial L_i} = E^{Q}(L_i \mid L \geq L_{\min})$$

DIP is a risk measure closely related to MES, but referring to a predefined threshold in terms of its amount, differently from VaR, which refers to the threshold as a percentage.

Adrian and Brunnermeier (2011) proposed a different approach called CoVaR. It accounts for the value-at-risk (VaR) of the financial system, (as measured by capital market losses) conditional on the distress of the considered financial institutions.

In more formal terms, it is the value at risk of the financial system (denoted by j) conditional on some event $\mathbb{C}(X_i)$ of institution i. CoVar is implicitly defined as:

$$Pr\left(X_j \leq CoVar_q^{j|\mathbb{C}(X_i)} \mid \mathbb{C}(X_i)\right) = q$$

where q is the selected probability level. CoVaR is a risk measure that estimates the risk contribution of a single institution to the system risk as the VaR of the total financial sector conditional upon an event (distress) of that institution.

More precisely, ΔCoVaR of institution i is the difference between the VaR of the financial system when institution i is in distress and the VaR of the financial system in case of normal (median) state of the considered institution.

In this framework, the contribution of institution i to the system j, denoted by ΔCoVar, can be computed as the difference between the CoVaR of the financial system conditional upon the distress of an individual bank i and the CoVaR of the financial system when the same considered bank is in its 'normal' state, where a proxy for the normal state is the median:

$$\Delta CoVar_q^{j|i} = CoVar_q^{j|X_i = VaR_i^q} - CoVar_q^{j|X_i = median_i}$$

In this way ΔCoVar quantifies which effects the distress of an institution can have on the whole system, so focusing on the active role of a bank possibly inducing a crisis. Here also is worth noticing that when the system is exposed to a common risk factor, the correlation between the considered bank distress and the whole system distress can be driven by the common factor (correlation), or by the consequences induced on the system by the considered bank distress (contagion). As MES, ΔCoVar do not distinguish these two determinants.

Lopez-Espinosa et al. (2012) proposed a variant of ΔCoVaR, which captures risk-spillovers from a financial institution to the rest of the financial system. In a recent work, Castro and Ferrari (2014) develop a test of significance on Delta CoVaR.

The SRISK indicator proposed by Brownlees and Engle (2012) and further developed by Acharya, Engle, and Richardson (2012) measures the capital shortfall of a firm conditional on a severe market decline; such measure is a function of accounting information, namely the size and the leverage of the institution, and of a market-based measure, i.e. the expected equity loss of the institution conditional on the market decline, also called Long Run Marginal Expected Shortfall (LRMES). LRMES estimation is based on equity returns by means of a GARCH-DCC time series model.

Apart from SRISK, which also includes accounting variables, the cited models only rely on capital markets data.

Even though the market is often considered to be the best reference for assessing the actual state of the economy, the backtesting exercise on the performances of market-based measures highlighted some limits in its added value for regulators. Zhang et al (2015), analyzing the performances of some market-based measures, verified that only DeltaCoVaR "*consistently adds predictive power to conventional early warning models. However, the additional predictive power remains small and it is not normally confirmed for the Asian and the 1998 crises*". They also proof that, among the non-market based indicators, size is the most consistent proxy of systemic importance.

Another interesting study is developed by Gauthier et al. (2012), which, for computing incremental VaR, Shapley values, ΔCoVar, and MES, used an approach similar to the one used here, in the aim of verifying if a capital allocation based on these measures will lead to a safer banking system. Their simulation model is based on macro stress scenarios in which each industry sector suffer of default rates based on historical values, and each bank suffer from these default rates based on its exposure to the specific sector. Then, contagion is considered both via fire sales and direct interbank exposures. In their analysis, only some limited correlation between macroprudential capital ratios based on the different metrics, and bank characteristics, is found, and no deeper analysis is performed on their determinants.

Besides the fact that the exposures riskiness is derived from historical values, so backward looking and not able to incorporate the effects of possibly approaching economic crises, or of the different risk profiles chosen by each bank, their results give important insights on the possible effects of a different regulation, where the minimum capital requirement is computed not only for preserving the single bank safety, but also for preserving the whole system safety.

Another important approach is the one developed in Drehmann and Tarashev (2013), based on the Shapley value for assessing the contribution to systemic risk of interconnected institutions.[5] The Shapley value concept (see Shapley, 1953) is one of the most important references in cooperative

[5] The implementation of this methodology requires a simulation model to derive a distribution of losses in each identified subsystem.

games, i.e. in contexts where the competition is between coalitions of players, rather than between single players (e.g. voting games). The Shapley value for a player in a game can be defined as the average of that player's marginal contributions to every possible coalition. On the one hand, the Shapley value has many desirable properties: symmetry, zero player, efficiency and additivity. On the other hand, this approach carries a strong limitation due to its computational complexity, so that its computation is feasible only for small samples.
The approach used here is somehow related to the Shapley value, but while the Shapley value accounts for the difference of including or not a bank into all possible subgroups, the LOO method only evaluates the effects of excluding one bank from the full system. From this point of view the LOO can be considered as a first order approximation of the Shapley value. A detailed discussion of the two approaches is presented in appendix two.
With reference to the second topic of this literature review, banking systems simulation models have had an important development in the recent literature (for a detailed and in-depth analysis see Zedda, 2017). With specific reference to Monte Carlo simulations, the main references in literature are the models developed by Elsinger et al (2006), De Lisa et al (2011), and Drehmann and Tarashev (2013). These models have important differences both on how to estimate the banks' assets portfolio riskiness, and on the simulation process.
The Elsinger et al (2006) model bases its estimation of the banks' assets riskiness on the market value of listed banks, and then inverting the European call option pricing formula, with maturity fixed to one year. They then simulate the system performances, assuming that the banks' asset portfolio returns are normally distributed, by drawing the same quantile of the default frequency distribution of each bank, so to include correlation effects. The unknown bank-to-bank exposure values of the interbank matrix are estimated by coupling the information on the total exposures of each bank, and the maximum entropy hypothesis.

This model, as the other models based on market values, on the one side carries all the information implicitly included in market values, so up-to-date and forward looking, on the other side this source is only available for the banks whose shares are traded in stock exchanges, so typically it cannot not be applied to small banks. This is a relevant limit as simulations are always system dependent. Another limit of this model is that correlation cannot be tuned, so its value is the one deriving form the specific process (drawing the same quantile for all banks) and cannot be differentiated among banks.

The Drehmann and Tarashev (2013) model, for evaluating the systemic risk contribution of banks developed a Monte Carlo based approach, based on a mixture of idiosyncratic and common shocks, tuned by setting the idiosyncratic and common shocks variance (and covariance matrix) so to have an *a posteriori* default rate coherent with the estimates of the banks probability of default as published by rating agencies.

Simulations are performed on the base of the following formula:

$$L_{is}(m_s, z_{is}, \rho_i) = \rho_i \, m_s + \sqrt{1 - \rho_i^2} \, z_{is}$$

where $\rho_i \in [0,1]$ is the common factor loading, m_s is the randomly generated value for the common factor and z_{is} is the randomly generated idiosyncratic factor for each of the i banks.

Note that if the probability of default estimated by the rating agencies also include contagion risks, as contagion risks are system dependent, the estimation of losses variance, derived from it, results to be system dependent. So, in this case, the approach can be directly applied only when simulations refer to the same system considered by the rating agencies for estimating its contagion risks. For different (or hypothetical) systems, or when including banks with no rating, the parameters are to be adequately calibrated. Here also, the interbank matrix is estimated based on the total bank exposures and on the maximum entropy. The limits of this approach, being based on ratings, are similar to the ones of market-based measures.

In this paper we use the model proposed in De Lisa et al (2011), known as Systemic Model for Banking Originated Losses (SYMBOL). This model was initially developed for Deposit Guarantee Schemes dimensioning, and since then has been repeatedly applied for the ex-ante impact assessment of several European Commission legislative proposals (see for instance Marchesi et al. 2012, European Commission, 2014) and for estimating the impact of financial crises on public finances (see European Commission, 2011a, 2011b, Zedda et al., 2012, Galliani and Zedda, 2015).

The starting point of the SYMBOL model is the estimation of the assets riskiness of each bank credit portfolio, quantified as the weighted average of the assets probability of default, and obtained by inverting the Basel Internal Ratings Based (FIRB) function (see Basel Committee on Banking Supervision, 2005, 2006, 2010 rev. 2011 and 2013), given the level of minimum capital requirements and total assets values[6], setting the other variables, i.e. loss given default (LGD), maturity (M) and size (S), to their standard values:

$$\hat{PD}_i : K\left(\hat{PD}_i \mid LGD = 0.45 \; M = 2.5 \; S = 50\right) = K_i$$

where $$K_i\left(PD_{ik}, LGD_{ik}, M_{ik}, S_{ik}\right) = \sum_i C_{ki}\left(PD_{ki}, LGD_{ki}, M_{ki}, S_{ki}\right) \times A_{ki} \quad k = 1, \ldots, K$$

is the sum of the capital allocation parameter (C_{ij}) of each exposure k of bank i multiplied by its amount A_{ki} .[7]

[6] Other parameters contained in the Basel IRB function (loss given default, maturity of the credit positions, and the size of the obligor) are set at their standard values.

[7] see De Lisa et al., (2010) for a detailed explanation of all terms in this representation of the FIRB approach

$$C_{ik}\left(PD_{ik}, LGD_{ik}, M_{ik}, S_{ik}\right) = \left[LGD_{ik} \times \left[\sqrt{\frac{1}{1-R\left(PD_{ik}, S_{ik}\right)}}N^{-1}\left(PD_{ik}\right) + \sqrt{\frac{R\left(PD_{ik}, S_{ik}\right)}{1-R\left(PD_{ik}, S_{ik}\right)}}N^{-1}\left(0.999\right)\right] - PD_{ik} \times LGD_{ik}\right] \times$$
$$\times\left[1+\left(M_{ik}-2.5\right)B\left(PD_{ik}\right)\right]\times\left(1-1.5\times B\left(PD_{ik}\right)\right)^{-1}\times 1.06$$

where:

$$B_{ik}\left(PD_{ik}\right) = \left[0.11852 - 0.05478\ln\left(PD_{ik}\right)\right]^{2}$$

and

$$R_{ik}\left(PD_{ik}, S_{ik}\right) = 0.12\frac{1-e^{-50PD_{ik}}}{1-e^{-50}} + 0.24\left[1-\frac{1-e^{-50PD_{ik}}}{1-e^{-50}}\right] - 0.04\left[\frac{S_{ik}-5}{45}\right]$$

The calibrated $\hat{PD}_i$ are then used to generate a set of correlated losses across all banks in the system. For each simulation *j*, calculate bank *i*'s losses L_{ij} performing a Monte Carlo simulation based on the following representation of the FIRB formula:

$$L_{ij}\left(z_{ij}, \hat{PD}_i\right) = \left[0.45\, N\left[\sqrt{\frac{1}{1-R\left(\hat{PD}_i, 50\right)}}N^{-1}\left(\hat{PD}_i\right) + \sqrt{\frac{R\left(\hat{PD}_i, 50\right)}{1-R\left(\hat{PD}_i, 50\right)}}N^{-1}\left(z_{ij}\right)\right] - 0.45\, \hat{PD}_i\right] \times$$
$$\left(1-1.5\, B\left(\hat{PD}_i\right)\right)^{-1} \times 1.06$$

Where

$i = 1, ..., H$ are for banks

$j = 1, ..., J$ refer to simulations

$z_{ij} \sim N\left(0,1\right)\forall i, j$

$\mathrm{cov}\left(z_{ij}, z_{lj}\right) = 0.5\ \forall i \neq l$ (where *i, l* are bank indexes)

Simulated losses of each bank are then compared with their capital: whenever the losses of a bank exceed its capital, the bank is considered to default:

$$\mathrm{L_{ij}}\left(\mathrm{z_{ij}}, \widehat{\mathrm{PD}}_{\mathrm{i}}\right) \geq \mathrm{CAP_i}$$

Then, the simulated losses of each bank are compared with the regulatory capital available to absorb shocks: banks are considered to fail whenever simulated losses exceed capital. The correlation among banks' assets portfolios captures the exposure to common factors, i.e. common borrowers, macro variables, or, more in general, the business cycle.[8]

[8] The assets correlation parameter is set at 50%.

The contagion mechanism is based on the actual interbank exposures, assuming that whenever a bank fails, 40% of its interbank debts are passed on as losses to its creditor banks (see James, 1991) and distributed among them proportionally to each creditor bank exposure share. [9] Following the Furfine sequential algorithm (see Furfine, 2003), whenever this additional contagion loss makes bank's losses to exceed its capital, that bank is also considered to fail, and so on, until one more bank fails.

Systemic losses are then computed as the sum of excess losses over the entire bank sample.

3. Methodology

The basic idea behind the LOO approach is that the contribution of each bank to systemic risk can be obtained comparing the performance of the banking system including all banks to the performance of the same banking system when excluding the considered bank.

A fundamental feature of the LOO approach, which can provide an insight of great relevance for banking supervision and regulation, is that it allows splitting the systemic risk contribution of each bank into two components, namely the stand-alone risk contribution of the bank, which is the loss of the considered bank as a single, not connected to the system (as in a Basel I/Basel II approach), plus the contagion risk contribution of the bank to the system, which accounts for the losses transmission role of the bank (as in macroprudential perspective). While the stand-alone contribution is always positive, as the risk that a bank may default is always present, the contagion risk contribution, though generally positive, can be also negative, signaling a barrier effect to defaults propagation.

Another advantage of this approach is that it makes a distinction between correlation and contagion, so cases where banks are sensitive to the crisis determinants (macro variables), and cases where the effect is due to the linkages (interbank exposures).

With respect to other existing methodologies, the LOO approach presents several advantages.

With respect to the market-based measures, this method allows quantifying the risk contribution of all banks, and not only the listed ones. Moreover, it can be applied also to banks that were not in distress, so when no market data are available on its behavior during crises. Even when not considering the limits in the quality of market-based measures, the

[9] Since the purpose of this paper is to test the LOO method and not to assess the actual riskiness of the considered banking system, we used the standard references for the interbank matrix (maximum entropy), not considering other sources of information.

possibility to include all banks in the estimation is fundamental for supervision and regulation purposes.

Another important advantage of this method is that it allows the subtle distinction between correlation and contagion, so cases where banks are sensitive to the crisis (or its determinants) and cases where the effect is due to the exposures.

For explaining this point we can consider the case of a small bank with high correlation with the crisis determinants. In case of an exogenous common shock, both the bank and the system will experience a high impact on its market value. So market based measures will capture this co-movement even if the impact of the considered bank to the system is small.

Instead, if the co-movement only comes from correlation the system results will be the same when the bank is linked to the system or not. Thus, LOO allows distinguishing cases where the bank suffers from the crisis without causing it (correlation, which is part of the stand-alone risk), from cases where the bank linkages induce relevant effects on the crisis dimension (contagion).

Referring to the banking system in a crisis setting, the LOO measure can account for the difference between the entire system losses and the system losses when a given bank is isolated, i.e. not linked to the rest of the system. Thus, it requires a simulation tool to generate: the loss distributions for each considered (sub)system, i.e. the system including all banks; the all-banks-but-one system (both accounting for contagion induced losses); the bank alone which can experience only primary losses. This exercise is repeated with reference to each bank in the system.

Considering the relevance of large crises recently experienced and that the small ones can be managed with the standard resolution tools, we focus on the tail of the loss distribution, corresponding to large crises, where the financial system stability is actually threatened.

For computing the Leave One Out risk contribution of each considered bank, we compute, via Monte Carlo simulation based SYMBOL model, the Expected Shortfall of the system including or not the considered bank. While the LOO method in principle can be applied by means of different measures of risk, in this test we quantify it via the Expected Shortfall (ES), because it is more suited for evaluating the tail risk related to systemic crises.

As in Puzanova Dullman (2013), we define the system risk as the Expected Shortfall of the banking system liabilities computed at a probability level q, (where the probability of a systemic event is $(1 - q)$). The ES represent the expected loss for a given portfolio in the worst $(1- q)$ share of cases and is therefore a more appropriate measure of externalities than the VaR, which only represent the minimum loss in the worst $(1 - q)$ share of cases.

The difference between the Expected Shortfall for the entire banking system (L) and the losses obtained in the same simulations when leaving the considered bank h out of the system ($L^{(h)}$) can be represented as the sum of two components, namely the autonomous risk contribution of the bank, i.e. the loss of the h bank as single, not connected to the system (L_h, stand-alone contribution) plus the "contagion risk contribution" of the h bank to the system (Sys_h).

$$L - L^{(h)} = L_h + Sys_h$$

In fact, Sys_h is the value of the higher losses for the system when the bank h is linked to it, quantifying the crisis induction or transmission role of the bank to the system.

This contagion risk contribution is generally positive, there are, indeed, cases where Sys_h is negative, signaling a barrier effect the bank plays in the system.

Since the sum of the contagion risk ($\sum_h Sys_h$) and stand-alone ($\sum_h L_h$) contributions does not match the system total (L), for having an additive measure we followed the same approach in Huang et al. (2011), and rescaled the systemic component as follows:

$$Sys_h^* = Sys_h \times \frac{L - \sum_h L_h}{\sum_h Sys_h}$$

Finally, the LOO risk contributions are obtained summing the stand-alone component L_h to the rescaled contagion risk component Sys_h^*.

Results show (see Appendix 1 for details) that the linkages (contagion) component of the risk and the stand-alone component, are not strictly linked, and that the risk contributions are relevantly affected by the threshold setting.

This means that banks can have different roles on different crises severity, so one bank which report a low contribution to the less severe crises, can actually result to be one of the most relevant contributors in more severe crises, and vice-versa.

More, banks can have a negative contribution to contagion, and here also the threshold plays a crucial role: some large banks have a barrier effect in smaller crises, while evidencing a positive and relevant risk contribution in large crises. Other banks show a growing loss absorbing capacity as crises dimension goes up.

4. Data and results

Regression analysis

For performing a regression analysis on the base variables, we tested the LOO risk allocation measure on a sample of 116 European financial institutions included in the 2014 EU-wide stress test exercise performed by the European Banking Authority (EBA, 2014). Data as of end December 2013 on risk-weighted assets (RWA) and total regulatory capital (TRC) originate from EBA (2014), while total assets (TA) and interbank positions come from Bankscope.[10]

The selected sample accounts for more than EUR 28 billion of total assets, representing around 74% of the total assets in the EU 27 banking sector.[11] Moreover, 13 European G-SIBs are included; they cover around EUR 16,180 billion (57% of the sample total assets).

Table 1: Sample description, aggregate values as of December 2013

Sample								Population (EU27)	
Year	**Number of banks**	**TA (bn €)**	**RWA (bn €)**	**TRC (bn €)**	**TRC (as % of RWA)**	**Interbank Assets (as % of TA)**	**Interbank Deposits (as % of TA)**	**Total Assets (bn €)**	**Sample coverage ratio**
2013	116	28,326	10,738	1,562	14,5%	7,2%	9,9%	38,197	74%

The complete results are reported in Appendix 4.

Based on a regression analysis, we analyzed the role of the input variables on the stand-alone, contagion, and total LOO contribution, and this for four different thresholds. Table 2~~Table 2~~, Table 3~~Table 3~~ and Table 4~~Table 4~~, report the results obtained, with reference to Total Regulatory Capital (TRC), Risk Weighted Assets (RWA), Total Assets (TA), InterBank Assets (IB_A) and InterBank Debts (IB_D).

Table 2: Stand-alone component of risk contribution regression coefficients and significance[12]

	L_h **99.900%**		L_h **99.950%**		L_h **99.990%**		L_h **99.999%**	
const	*-81.233*	***	*-121.988*	***	*-144.724*	***	*-229.249*	
TRC	-0.0919	***	-0.1305	***	-0.1584	***	-0.2368	***
RWA	0.0139	***	0.0198	***	0.0253	***	0.0432	***
TA	0.0022	***	0.0036	***	0.0049	***	0.0109	***
IB_A	0.0002		-0.0005		0.0032		-0.0069	
IB_D	-0.0031	**	-0.0071	***	-0.0073	***	-0.0195	**

[10] The original EU-wide stress test conducted by the EBA in 2014 included 123 banks. However, 7 institutions have been excluded from the present exercise since data on total assets or interbank positions are not provided by Bankscope.

[11] Data on the aggregate total assets of the EU27 banking sector come from Schoenmaker and Peek (2014).

12 *** signals parameter significance at 1%, ** significance at 5% and * significance at 10%.

R^2	0.964	0.954	0.967	0.949

The regression on the stand-alone component resulted in a determination coefficient of determination R^2 higher than 95%, and reports the fundamental role of capital as a barrier for limiting default risk, which is instead enhanced by high levels of RWA and of total assets. Interbank exposures are not relevant to the stand-alone risk, while interbank debts seem to limit the risk when the bank is not linked to the system.

Remarkably, all the coefficients are growing with the crisis severity, so all these effects are more effective in limiting or enhancing the risk of severe crises.

Table 3: Contagion component of risk contribution regression coefficients and significance

	Sys_h^* **99.900%**		Sys_h^* **99.950%**		Sys_h^* **99.990%**		Sys_h^* **99.999%**	
const	*-30*		*-8.836*		*-47.427*		*-2.091.240*	***
TRC	-0.1372	***	-0.2421	***	-0.6252	***	-1.1983	***
RWA	0.0084	**	0.0146	**	0.0357	**	0.0787	***
TA	0.0004		0.0007		0.0015		0.0112	**
IB_A	0.0657	***	0.1181	***	0.3450	***	0.9697	***
IB_D	0.0057		0.0116		0.0536	**	-0.0489	*
R^2	**0.701**		**0.709**		**0.774**		**0.950**	

For the contagion risk component which spreads out via the interbank exposures, the R^2 is lower than previously obtained but always higher than 70%, and shows that it can be mainly limited by the capital coverage. Results are more specific on the subjacent variables, so that only capital (with negative sign) and interbank assets (positive) are always at the maximum significance, while RWA have a lower role, possibly related to the effect of contagion superposing, thus being enhanced by the stand-alone risk, and dimension and interbank debts seems to be nearly irrelevant to this risk component. Here also, the more severe the crisis, the higher the coefficients.

It is worth noticing that the coefficients estimated for capital on the contagion component report higher effects than on the stand-alone one. This means that a higher capitalization not only has the well known effect of reducing the single bank riskiness, but it also induces a much higher reduction in contagion risk. In fact, the coefficients are of -0.0919 for the stand-alone component while the contagion one is of -0.1372 for the 99.9% threshold, and, respectively, -0.2368 and -1.1983 for the 99.999% threshold.

Table 4: Total LOO risk contribution regression coefficients and significance

	LOO **99.900%**		*LOO* **99.950%**		*LOO* **99.990%**		*LOO* **99.999%**	
const	*-81.263*		*-130.824*		*-192.151*		*-2.320.490*	***
TRC	-0.2291	***	-0.3726	***	-0.7836	***	-1.4352	***
RWA	0.0223	***	0.0344	***	0.0610	***	0.1219	***
TA	0.0026	***	0.0042	***	0.0065	*	0.0221	***
IB_A	0.0658	***	0.1176	***	0.3482	***	0.9628	***
IB_D	0.0026		0.0045		0.0464	*	-0.0684	**
$\mathbf{R^2}$	**0.804**		**0.783**		**0.813**		**0.957**	

With reference to the total risk, which is obtained by summing for each bank the two components, the positive effect of capital and negative of RWA and of total assets are obviously confirmed, the interbank assets keep the relevant role of risk enhancing, and interbank debts are irrelevant for small crises while have some relevance in limiting large crises.

For a more detailed analysis, we then considered worth verifying if the same variables, when considered per unit of total assets, maintain its relevance.

In the following tables we reported the results of regressing each configuration of the risk contributions per unit of total assets (L_h/TA, Sys_h^*/TA and *LOO/TA*) on: Total Regulatory Capital/Total Assets (TRC_TA), RWA/Total Assets, Interbank Assets/Total Assets, Interbank Deposits/Total Assets, logarithm of Total Assets, and squared logarithm of Total Assets.

Table 5: Unitary stand-alone component of risk contribution regression coefficients and significance

	L_h/TA **99.900%**		L_h/TA **99.950%**		L_h/TA **99.990%**		L_h/TA **99.999%**	
const	*0.0208*	***	*0.0335*	***	*0.0182*		*0.0293*	
Ln (TA)	-0.0025	***	-0.0039	***	-0.0021		-0.0032	
Ln (TA)sqr	0.0001	***	0.0001	***	0.0001		0.0001	
TRC/TA	-0.0195	***	-0.0277	***	-0.0638	***	-0.1256	***
RWA/TA	0.0040	***	0.0056	***	0.0125	***	0.0254	***
IB_A/TA	-0.0006		-0.0010		-0.0017		-0.0038	
IB_D/TA	0.0013	**	0.0017	**	0.0030	*	0.0020	

R^2	0.602	0.598	0.575	0.537

This regression reveals a clearer evidence of the for the stand-alone component determinants. Even in unitary terms the R^2 keeps an important value, between 53% and 60%, and the single variables coefficients show it is mainly determined by assets riskiness (RWA/TA, positive) and capital (TRC/TA, negative), while dimension is only affecting the smaller crises, losing all relevance as soon as crises become more severe.

Here also, all estimations result in rising coefficients for the significant variables as the crisis severity goes up.

Table 6: Unitary contagion component of risk contribution regression coefficients and significance

	Sys_h^*/TA 99.900%		Sys_h^*/TA 99.950%		Sys_h^*/TA 99.990%		Sys_h^*/TA 99.999%	
const	*-0.0302*		*-0.0553*		*-0.3797*		*-1.4213*	*
Ln (TA)	0.0032		0.0058		0.0404		0.1444	*
Ln (TA)sqr	-0.0001		-0.0002		-0.0011		-0.0036	*
TRC/TA	-0.1074	***	-0.1854	***	-0.4309	***	-0.8289	***
RWA/TA	0.0028		0.0043		0.0128		0.0782	*
IB_A/TA	0.0625	***	0.1113	***	0.3078	***	0.7512	***
IB_D/TA	0.0159	**	0.0285	**	0.0756	**	-0.1720	***
R^2	**0.515**		**0.525**		**0.588**		**0.705**	

The regression on unitary values for the contagion component reveals important differences from the total values regression for the same component. While in the total values regression contagion resulted to be affected by assets riskiness, here this variable significance disappears, and the contagion risk result to be mainly determined by capitalization and interbank assets, with rising coefficients as the crisis severity rises. Differently from the previous case, also the interbank debts reveal some significance, with positive correlation and limited significance for the small crises and a positive correlation and high significance for the largest crises.

Here also, higher capitalization results in an importantly higher reduction in the contagion component, the coefficients being of -0.0195 for the stand-alone component and -0.1074 for the contagion one at the 99.9% threshold, and, respectively, -0.1256 and -0.8289 for the 99.999% threshold.

These results confirm the importance of exposures, but mainly of capitalization for determining each bank risk contribution.

Table 7: Unitary Total LOO risk contribution regression coefficients and significance

	LOO/TA 99.900%		*LOO/TA* 99.950%		*LOO/TA* 99.990%		*LOO/TA* 99.999%	
const	*-0.0094*		*-0.0219*		*-0.3614*		*-1.3920*	*
Ln (TA)	0.0007		0.0019		0.0383		0.1412	*
Ln (TA)sqr	0.0000		0.0000		-0.0010		-0.0035	
TRC/TA	-0.1270	***	-0.2131	***	-0.4947	***	-0.9545	***
RWA/TA	0.0067		0.0099		0.0253		0.1036	**
IB_A/TA	0.0619	***	0.1103	***	0.3061	***	0.7474	***
IB_D/TA	0.0171	**	0.0302	**	0.0786	**	-0.1699	***
R^2	**0.513**		**0.524**		**0.588**		**0.707**	

The unitary LOO total contribution regression shows that the contagion determinants keep the higher impact, with no effects of dimension and of assets riskiness, that keeps some significance only for the largest crises.

Aggregate LOO contributions across the crisis

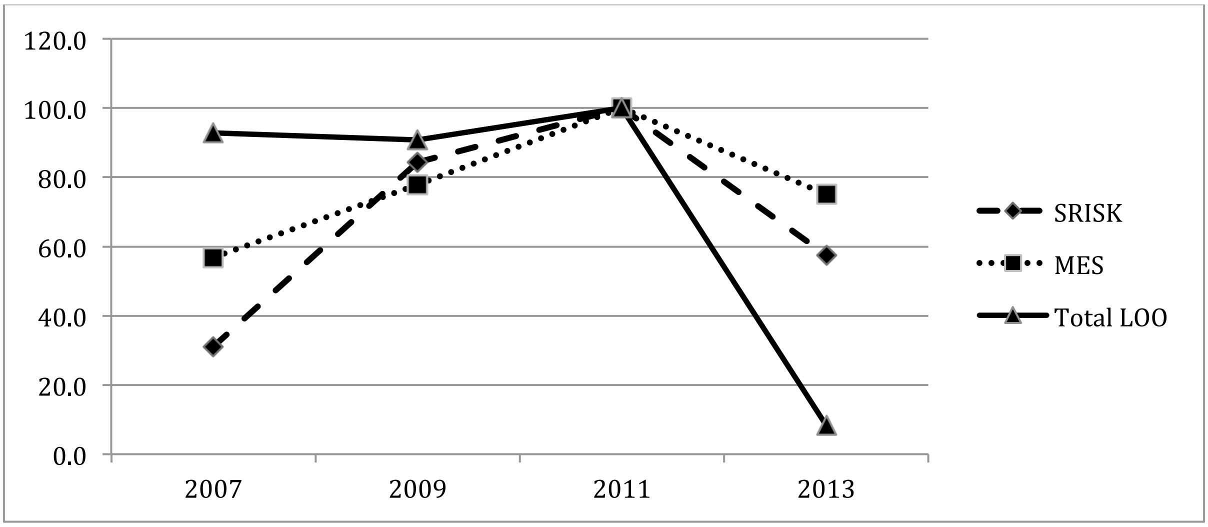
Computing the Leave-One-Out contributions on the same sample of banks presented in section 4.1 for the years 2007, 2009 and 2011, gives an interesting insight on the evolution of the European banking system in the period across the last financial crisis.

In fact, for having a complete picture of this evolution it would be optimal to have a wider coverage of the years preceding the spreading of the financial crisis. Unfortunately, it is not possible to evaluate the riskiness of the banking system before 2007 by means of the considered model, as the previous reporting standard did not include the risk weighting and minimum capital requirements based on it, which is a crucial input for our estimations.

Comparing the LOO values with some of the most considered market based measures, SRISK[13] and MES, for a subsample of 41 banks for which these measures are reported in the NYU V-lab [14] (see Figure 4), we can see that the crisis evolution is perceived in deeply different ways.

[13] SRISK computation also includes some non-market values.
[14] The list of the banks considered is included in Appendix three.

Figure 1: Evolution of some measures of risk contribution, 2011=100



Posing for reference as 100 the 2011 the values registered by each of the three measures in 2011 (the maximum risk level for the considered subsample), both SRISK and MES reported for 2007 a risk level lower than 2013. According to these measures, the system registered an important risk growth from 2007 to 2009. Differently, the LOO measure reports high risk levels already in 2007, and a system much safer in 2013 than it was before the 2008 crisis.

The LOO results seem in this sense able to detect the general undercapitalization the European banking system suffered in 2007, before the spreading of the crisis, and positively accounting for the effects of the recapitalization that characterized the European banking sector after 2011.

Suggestions for macro prudential regulation

The methodology and results of this approach can give some important references for a more effective macroprudential regulation. The capability of this method to assess the macro (systemic) effects of micro (single bank) variations, allow for a more accurate targeting of specific supervisory interventions and regulation.

In this aim, our findings report that banking systems have a different behavior in different crises severity, so that is fundamental to identify the actual threats and a specific targeting of the supervision to the possibly forthcoming crises.

More specifically, with reference to the stand-alone risk component, the results of this study substantially confirm the validity of the Basel II framework approach, founded on a risk-weighted assets based capital coverage. Instead, with reference to the contagion component, our research suggests a highly relevant role of capitalization as barrier for limiting contagion, but also a high relevance of interbank exposures, that can substantially reduce the effects of capital. So, the introduction of capital surcharges for balancing the risk of highly exposed banks is one of the suggestions coming from our results. Conversely, with reference to supervision, the main suggestion for limiting the effects of contagion risks, coming from a near-to-distress bank, can be aimed to the ring-fencing, or at least to the reduction of the interbank exposures, so to limit its effects to each counterpart bank. Anyway the possibility to borrow money from any low capitalized banks should be forbidden for the other low capitalized banks.

5. Conclusions

The recent banking crisis highlighted the importance of a better understanding of the role of interconnectedness on banking systems stability.

The methodology and results of this study can actually contribute to this knowledge with some unprecedented results.

One important evidence coming from our findings is that the stand-alone and contagion components are not strictly linked each other, so one bank that is relatively safe as a single can turn out to be an important contagion vehicle as part of a network, or vice versa. Unexpectedly, it is not unusual that some banks have a barrier effect, so their presence in the system plays a stabilizing role, reducing the overall system riskiness.

We also showed that the magnitude of the crisis is a key variable when analyzing risk contributions. Moreover, the "barrier" or "contagion vehicle" roles sometimes change depending on the severity of the crisis.

Another important issue coming from this method is that even if size do matter, when neutralizing the size effect, unitary contributions maintain the clear linkage to the unitary base variables. Regression analyses on the base variables explain that the assets riskiness and capital coverage are the most relevant variables determining the stand-alone contribution, while interbank exposures and capital coverage mainly determine the contagion risk component in all crises dimensions. Interestingly, we find that capital affects more the contagion component than the stand-alone one.

An additional technical result is that, due to the high correlation between LOO and Shapley values (even when considering it per assets unit), and to the low computational complexity of the Leave-One-Out, this method can be an actually effective way to approximate the Shapley values even for large samples, for which the Shapley values are not possible to be computed.

In more general terms, the estimations and analyses developed in this paper can give some important contribution to a clearer picture of the banking systems stability determinants, and of their role in systemic crises, and to give important suggestions to regulation and supervision.

The different behavior of the systems in different crises severity, coming from our analyses, suggest a specific targeting of the supervision to the possible crises actually threatening the banking systems stability.

More, the possibility to measure the risk contribution of each single bank to the whole system stability, and the specific quantification of the role of each bank determinant (dimension, assets riskiness, capital coverage and interbank linkages) to it, so the capability of this method to assess the macro effects of micro variations, allow for a more accurate targeting of specific supervisory interventions, and possibly for the reduction in the risk of new financial crises.

References

Acharya, V., Engle R., Richardson M. (2012), *Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks*, American Economic Review Papers and Proceedings, 102, 59–64.

Acharya, V., Pedersen, L.H., Philippon, T., Richardson, M. (2010), *Measuring systemic risk*. Technical Report, Department of Finance, NYU.

Adrian, T., Brunnermeier, M.K. (2011), *CoVaR*. Federal Reserve Bank of New York Staff Reports No 348.

Basel Committee on Banking Supervision (2005), "An Explanatory Note on the Basel II IRB Risk Weight Functions".

Basel Committee on Banking Supervision (2006), "International Convergence of Capital Measurement and Capital Standards".

Basel Committee on Banking Supervision (2010, rev 2011), "A Global Regulatory Framework for More Resilient Banks and Banking Systems".

Basel Committee on Banking Supervision, (2011), *Global systemically important banks: assessment methodology and the additional loss absorbency requirement.* Bank for International Settlements, Basel (November)

Basel Committee on Banking Supervision (2013), "Revised Basel III Leverage Ratio Framework and Disclosure Requirements."

Brownlees, C. T., Engle R. (2012) *Volatility, Correlation and Tails for Systemic Risk Measurement*, New York University Working Paper.

Brunnermeier, M. K., A. Crocket, C. Goodhart, A. Perssaud, and H. Shin (2009): *The Fundamental Principals of Financial Regulation: 11th Geneva Report on the World Economy.*

Castro, C., Ferrari, S., (2014). *Measuring and testing for the systemically important financial institutions.* Journal of Empirical Finance, 25, 1-14.

De Lisa, R., S. Zedda, F. Vallascas, F. Campolongo M. Marchesi, (2011), *Modelling Deposit Insurance Schemes' losses in a Basel 2 framework*, by, Journal of Financial Services Research, 40(3), p. 123-141.

Drehmann M., Tarashev, N. (2013), *Measuring the systemic importance of interconnected banks*, J. Finan. Intermediation 22 586–607.

Elsinger H., Lehar A., Summer M. (2006), *Using market information for banking system risk assessment*, International Journal of Central Banking, 2 pp. 137–165.

European Banking Authority (2014), "*Results of 2014 EU-wide stress test*", released on 26 October 2014. http://www.eba.europa.eu/documents/10180/851779/2014%20EU-wide%20ST-aggregate%20results.pdf

European Commission (2011a), Directorate General for Economic and Financial Affairs, *Public finances in EMU 2011*. European Economy 3, 2011.

http://ec.europa.eu/economy_finance/publications/european_economy\\/2011/ee3_en.htm

European Commission (2011b), Directorate-General for Internal Market and Services: Commission Staff Working Document - *Impact Assessment accompanying the proposal for a Directive of the European Parliament and of the Council establishing a framework for the recovery and resolution*, SWD(2012) 166 final, http://ec.europa.eu/internal_market/bank/docs/crisis-management/2012_eu_framework/impact_assessment_final_en.pdf

European Commission (2014), Directorate-General for Internal Market and Services, "*Commission Staff Working Document - Economic Review of the Financial Regulation*

Agenda" http://ec.europa.eu/internal_market/finances/docs/general/20140515-erfra-working-document_en.pdf

Financial Stability Board (2010). *Reducing the moral hazard posed by Systemically Important Financial Institutions*. FSB Recommendations and Time Lines. http://www.financialstabilityboard.org/wp-content/uploads/r_101111a.pdf?page_moved=1

Furfine, C.H., (2003), *Interbank exposures: quantifying the risk of contagion*, Journal of Money, Credit and Banking 35 (1), 111–128.

Galliani C., Zedda S. (2015), *Will the bail-in break the vicious circle between banks and their sovereign?*, Computational Economics, vol. 45, pp. 597–614.

Gauthier, C., A. Lehar and M. Souissi (2012), *Macroprudential capital requirements and systemic risk*, Journal of Financial Intermediation, 21, pp. 594–618.

Huang, X., Zhou, H., Zhu, H. (2011), *Systemic risk contributions*. Journal of Financial Services Research, pp. 1-29.

Marchesi M., Petracco Giudici M., Cariboni J., Zedda S., Campolongo F. (2012), *Macroeconomic cost-benefit analysis of Basel III minimum capital requirements and of introducing Deposit Guarantee Schemes and Resolution Funds*, EUR Scientific and Technical Research series 24603 EN, European Commission, pp. 1- 25 (2012).

Puzanova N. Dullmann K. (2013), *Systemic risk contributions: A credit portfolio approach*, Journal of Banking & Finance 37 (2013) 1243–1257.

Shapley, L.S. (1953) *A Value for n-person Games*. In Contributions to the Theory of Games, volume II, by H.W. Kuhn and A.W. Tucker, editors. Annals of Mathematical Studies v. 28, pp. 307–317. Princeton University Press.

Upper, C. (2011), *Simulation methods to assess the danger of contagion in interbank markets*. Journal of Financial Stability 7 (3), pp. 111–125.

Zedda S., Cariboni J., Marchesi M., Petracco Giudici M., Salto M. (2012), *The EU sovereign debt crisis: potential effects on EU banking systems and policy options*, EUR Scientific and Technical Research series 25556 EN, European Commission, pp. 1- 26.

Zedda S. (2017), *Banking systems simulation: theory, practice, and application of modeling shocks, losses, and contagion*, John Wiley & Sons, forthcoming.

Zhang Q., Vallascas F., Keasey K., Cai C.X. (2015), *Are market-based measures of global systemic importance of financial institutions useful to regulators and supervisors?* Journal of

Appendix 1: Leave-One-Out risk contribution computation details

For describing in practice the Leave-One-Out model we considered a sample of nine French banks included in the last EBA stress test. Data, referring to end December 2013, are summarized in Table 8~~Table 10~~.

Table 8: Sample description

Banks	Assets PD	Total Customer Deposits (th €)	Total Regulatory Capital (th €)	Total Assets (th €)	Interbank Deposits (th €)	Interbank Assets (th €)
French Bank 1	0.53%	1,334,000	2,678,585	25,117,000	6,268,000	1,439,000
French Bank 2	2.17%	2,568,500	13,921,974	34,733,900	11,179,600	460,000
French Bank 3	0.08%	166,885,651	7,297,800	201,376,765	14,757,450	82,893,845
French Bank 4	0.51%	5,136,000	2,638,000	29,505,000	3,227,000	1,160,000
French Bank 5	0.01%	-	1,483,491	83,528,000	10,472,000	2,948,000
French Bank 6	0.12%	553,497,000	77,071,677	1,810,522,000	85,256,000	57,545,000
French Bank 7	0.10%	640,725,000	80,733,234	1,688,264,000	103,019,000	95,356,000
French Bank 8	0.13%	458,013,000	51,454,327	1,124,857,000	88,783,000	108,201,000
French Bank 9	0.08%	334,172,000	48,256,020	1,214,193,000	90,355,000	75,420,000

For the purpose of the present exercise, each Monte Carlo simulation is performed for obtaining 10 million cases, this ensuring a sufficient degree of stability in the extreme tail of the loss distributions. From the simulation resulting sets, we selected the simulated crises above some different thresholds, and estimated the risk contributions values for each of these crises categories.

Table 9~~Table 11~~ reports the results for the sample at 99.99% threshold for giving some more details on its computation and values. For each bank we reported the single bank losses for the selected simulations, the losses after contagion, the system losses when dropping the considered bank, the leave-one-out direct effect $L - L^{(h)}$, the contagion risk contribution Sys_h, and the rescaled contagion risk contribution Sys_h^*.

Table 9: Leave-one-out risk contributions, 99.99% threshold

Banks	Overall contagion losses when dropping bank i (th€) $L^{(h)}$	LOO direct effect (th€) $L - L^{(h)}$	Average single bank losses in systemic runs (th€) L_h	Contagion risk contribution Sys_h	Rescaled contagion risk contribution Sys_h^*	LOO contributions (th€) $Sys_h^* + L_h$
French Bank 1	100,497,848	233,917	29,058	204,859	151,072	180,130
French Bank 2	101,789,718	(1,057,954)	-	(1,057,954)	(780,183)	(780,183)
French Bank 3	91,693,226	9,038,539	476,975	8,561,564	6,313,685	6,790,660
French Bank 4	100,368,488	363,277	84,956	278,320	205,246	290,202
French Bank 5	99,646,685	1,085,080	43,914	1,041,166	767,803	811,717
French Bank 6	65,956,930	34,774,835	33,116,891	1,657,944	1,222,643	34,339,534
French Bank 7	75,687,871	25,043,894	20,759,872	4,284,022	3,159,232	23,919,104

French Bank 8	75,405,627	25,326,138	14,644,868	10,681,270	7,876,852	22,521,720
French Bank 9	86,773,019	13,958,746	9,007,908	4,950,837	3,650,972	12,658,880
Total		**108,766,472**	**78,164,443**	**30,602,029**	**22,567,322**	**100,731,765**
Total system losses L	**100,731,765**					

The table above shows some important evidences.

Comparing the Sys_h values, the linkages (contagion) component of the risk, with the L_h ones, the single bank losses when not linked to the system (stand-alone component), we can see that the two effects are not strictly linked. The higher stand-alone risk contribution comes from bank 6, while the higher contagion risk contribution is for bank 8, with a value one order higher than bank 6.

For a more detailed analysis and test of the method, we conditioned the measure to the crises above four different probability thresholds, the values obtained are reported in Table 10~~Table 12~~.

Table 10: LOO value unitary contributions by crisis probability level

LOO unitary contribution	All	99.900%	99.950%	99.990%	99.999%
French Bank 1	3.21	3.38	3.29	7.17	21.41
French Bank 2	(5.15)	(6.61)	(9.41)	(22.46)	(52.22)
French Bank 3	10.14	13.05	15.75	33.72	90.89
French Bank 4	4.71	4.44	4.08	9.84	20.74
French Bank 5	5.37	6.64	7.25	9.72	15.06
French Bank 6	2.60	3.58	7.20	18.97	41.91
French Bank 7	1.64	2.27	4.69	14.17	37.20
French Bank 8	4.28	5.75	9.84	20.02	35.65
French Bank 9	2.12	2.89	5.30	10.43	20.94
Weighted average	**2.80**	**3.78**	**6.78**	**16.22**	**35.91**

Table 10~~Table 12~~ shows that the risk contributions are relevantly affected by the threshold setting. This not only is due to the fact that the higher the threshold, the larger the crisis and the average contribution, but also on different roles for different banks. As an example, bank 6 has a relevantly lower unitary contribution (3.58) with respect to bank 5 (6.64) at the 99.9% threshold, while it is the opposite at the 99.999%, where bank 6 unitary contribution (41.91) is higher than bank 5 (15.06).

For higher evidence of the different contributions in Table 11~~Table 13~~ we reported the percentages of contribution to the sample total.

Table 11: LOO contribution shares by crisis probability level

Leave One Out	All	99.900%	99.950%	99.990%	99.999%
French Bank 1	0.5%	0.4%	0.2%	0.2%	0.2%
French Bank 2	-1.0%	-1.0%	-0.8%	-0.8%	-0.8%
French Bank 3	11.7%	11.2%	7.5%	6.7%	8.2%
French Bank 4	0.8%	0.6%	0.3%	0.3%	0.3%
French Bank 5	2.6%	2.4%	1.4%	0.8%	0.6%
French Bank 6	27.1%	27.6%	30.9%	34.1%	34.0%
French Bank 7	15.9%	16.4%	18.8%	23.7%	28.1%

French Bank 8	27.7%	27.6%	26.3%	22.4%	18.0%
French Bank 9	14.8%	14.9%	15.3%	12.6%	11.4%
TOTAL	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

The table above shows that the different thresholds give different contributions for the same banks, so that bank 7 and bank 8, going from the first column to the last one, have opposite trends: while bank 7 raises from 15.9% to 28.1%, bank 8 lowers its role from 27.7% to 18.0%.

With reference to the risk contribution splitting, results in Table 12~~Table 14~~ show that the higher relevance is for the stand-alone component, which weights for 85.5%, when considering all crises, but, when focusing on larger crisis, the contagion component gains a more relevant role, with an incidence of 35.7% for the largest ones (99.999% threshold).

Table 12: Stand-alone and contagion risk component by crisis probability level

Stand-alone component	**All**	**99.900%**	**99.950%**	**99.990%**	**99.999%**
French Bank 1	35,330	26,875	14,277	29,058	86,218
French Bank 2	-	-	-	-	-
French Bank 3	521,149	671,711	346,659	476,975	1,221,386
French Bank 4	87,494	64,972	33,876	84,956	296,663
French Bank 5	37,823	34,168	19,462	43,914	149,033
French Bank 6	5,330,619	7,234,941	13,553,458	33,116,891	64,677,090
French Bank 7	3,117,811	4,231,231	7,913,447	20,759,872	46,811,215
French Bank 8	3,369,533	4,573,239	8,073,730	14,644,868	17,576,397
French Bank 9	2,368,129	3,211,132	5,561,175	9,007,908	12,644,398
TOTAL	**14,867,890**	**20,048,270**	**35,516,084**	**78,164,443**	**143,462,399**

Contagion risk component	**All**	**99.900%**	**99.950%**	**99.990%**	**99.999%**
French Bank 1	45,299	57,938	68,374	151,072	451,586
French Bank 2	(178,886)	(229,759)	(326,989)	(780,183)	(1,813,728)
French Bank 3	1,521,137	1,956,763	2,824,096	6,313,685	17,081,993
French Bank 4	51,330	66,003	86,446	205,246	315,406
French Bank 5	410,535	520,609	586,322	767,803	1,109,302
French Bank 6	(622,490)	(753,142)	(526,704)	1,222,643	11,200,632
French Bank 7	(353,336)	(391,407)	11,988	3,159,232	15,990,555
French Bank 8	1,447,515	1,894,910	2,993,872	7,876,852	22,520,371
French Bank 9	200,497	296,502	878,574	3,650,972	12,784,960
TOTAL	**2,521,600**	**3,418,415**	**6,595,980**	**22,567,322**	**79,641,078**

With reference to the contagion risk component of single banks, it is interesting to note that for some large banks (bank 6 and 7) there is a barrier effect in smaller crises, while large crises evidence a positive and relevant risk contribution. Other banks (bank 2) instead show a growing loss absorbing capacity as crises dimension goes up.

Appendix 2: Comparing LOO and Shapley values

The LOO approach, comparing the results of the whole system when including or not one bank, is in someway related to the Shapley value, which accounts for the difference of including or not a bank into all possible subgroups.

From this point of view the LOO can be considered as a first order approximation of the Shapley value. In fact, from a theoretical point of view, both LOO and the Shapley Values are based on two main factors: the stand-alone riskiness and the nonlinearities in the system contagion. Both methods include the stand-alone riskiness.

The main difference is that Shapley Values derives the nonlinear effects on all possible groups, while LOO derives it only from the marginal contribution to the whole system.

However, the idea behind the LOO approach seems more realistic with reference to banking systems. In fact, banks usually do not act as part of subgroups, which is rather the case e.g. in voting games, where each actor can join different parties: calculating the value added in each of all possible parties represents the standard framework the Shapley value is designed for. Instead, it is possible for the authorities to ring-fence a (risky) bank from the interbank market (e.g. for preserving the system safeness), which is exactly the case considered in the LOO approach.

Moreover, the computational complexity of the Shapley value also makes the number of subgroups to be considered really high, so that its application is limited to small samples of banks (around 20 at most). In fact, in a set of N players, the number of all possible subgroups is equal 2^N: for example, a game with 20 players requires computing results for more than 1 million of subgroups.

Even just focusing on the shortlist of banks included in the last stress test performed by the EBA (see EBA, 2014) that includes around 120 banking groups, the application of the Shapley value is infeasible, as it implies the computation of 2^{120} different subgroups, (greater than 10^{36}), each one requesting a set of Monte Carlo simulations. Note that the whole Euro area system approximately includes 6,000 banks. The LOO computation time is instead proportional to the number of banks in the system, which makes the calculation of risk contributions not limited by the system dimension.

With reference to the resulting values, Table 13~~Table 15~~ show that the total LOO contributions and Shapley values are really similar in value, with a really high correlation of about 99.96%. Even when neutralizing the dimension effect, so comparing unitary LOO contributions (risk contributions on total assets) to unitary Shapley values, the values are remarkably similar, and the correlation remains really high, near 98.9%. This means that the first order decomposition of the system, leaving one out, is the most important, accounting for the main part of the systemic contribution captured by the Shapley values.

Table 13: Leave-one-out risk contributions and Shapley values, 99.99% threshold

Banks	LOO contributions (th€) $Sys_h^* + L_h$	Shapley values (th €)	LOO unitary contributions	Unitary Shapley values
French Bank 1	180,130	104,838	7.17	4.17
French Bank 2	(780,183)	(805,117)	(22.46)	(23.18)
French Bank 3	6,790,660	7,191,800	33.72	35.71
French Bank 4	290,202	100,132	9.84	3.39
French Bank 5	811,717	869,701	9.72	10.41
French Bank 6	34,339,534	34,894,867	18.97	19.27
French Bank 7	23,919,104	24,177,345	14.17	14.32
French Bank 8	22,521,720	21,992,857	20.02	19.55
French Bank 9	12,658,880	12,205,341	10.43	10.05
Total	**100,731,765**	**100,731,765**		
Correlation	**0.9996370**		**0.988930**	

For a further substantiation of this result, we tested the same method on two more samples from small banking systems, namely Lithuania (6 banks) and Slovakia (10 banks), and for the same sample of France, for 2007, 2009, 2011 and 2013, and on different thresholds (99.9%, 99.95%, 99.99% and 99.999%). The results (see Table 14~~Table 16~~ and Table 15~~Table 17~~) confirm the high correlation between the two measures, always higher than 99.5% already for the first quartile of the 48 estimations for base values, and higher than 96.7% for the correlation between unitary values.

Table 14: Correlation between LOO and Shapley values – Base values

	1th quartile	median	3rd quartile
SK	99.877%	99.942%	99.974%
FR	99.522%	99.907%	99.972%
LT	99.988%	99.995%	99.996%

Table 15: Correlation between LOO and Shapley values – unitary values

	1th quartile	median	3rd quartile
SK	99.292%	99.627%	99.817%
FR	96.798%	97.761%	99.015%
LT	99.875%	99.938%	99.963%

Appendix 3: Analysis of the European top banks system evolution from 2007 to 1013

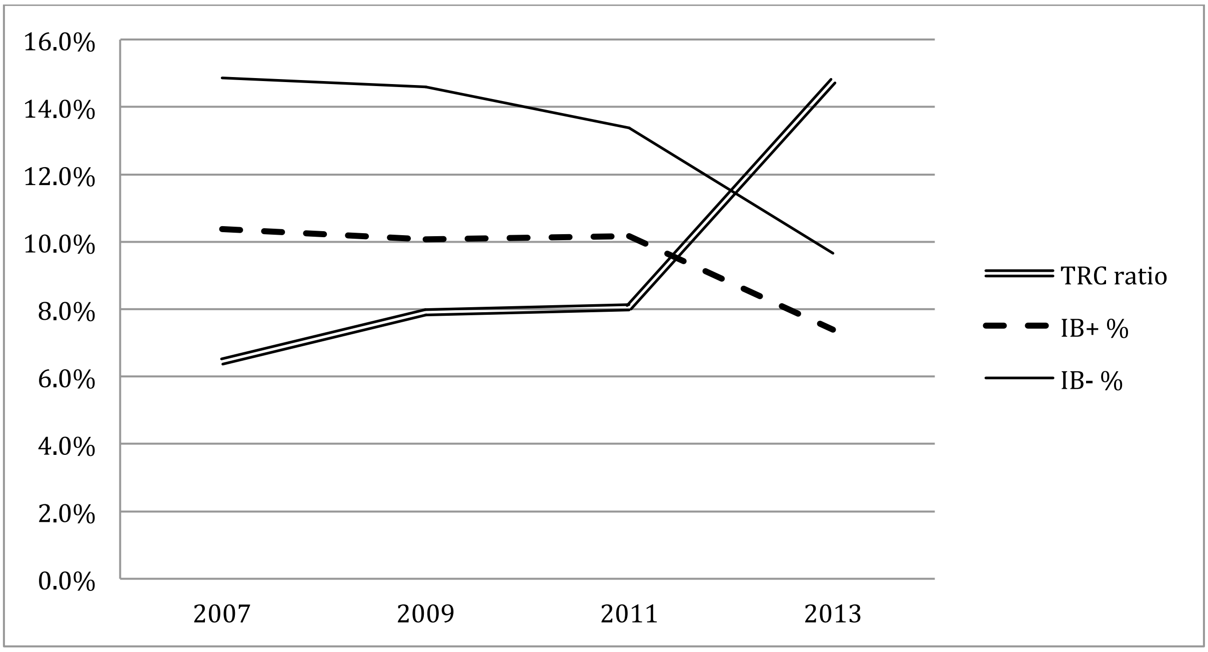
The European banking system registered important changes in its balance sheet equilibriums, as shown by Table 16~~Table 16~~ with reference to the EBA panel**Errore. L'origine riferimento non è stata trovata.**.[15]

Table 16: Sample description, aggregate values as of end December 2007, 2009 and 2011

Year	Sample							Population (EU27) Total Assets (bn €)	Sample coverage ratio
	Number of banks	TA (bn €)	RWA (bn €)	TRC (bn €)	TRC (as % of RWA)	Interbank Assets (as % of TA)	Interbank Deposits (as % of TA)		
2007	103	26,925	13,659	883	6.5%	10.3%	14.8%	35,552	76%
2009	109	28,979	14,017	1,096	7.8%	10.1%	14.5%	37,483	77%
2011	110	31,004	12,981	1,037	8.0%	10.9%	13.9%	40,710	76%

The system experienced an important increase in its capitalization already from 2007 to 2011, but mainly from 2011 to 2013, that was also accompanied by a reduction in interbank exposures, that dropped in the same time span as reported by Figure 2~~Figure 2~~.

Figure 2: Evolution of TRC ratio and interbank exposures



[15] Some banking groups out of the 116 selected for 2013 have been excluded because of missing values in Bankscope. Anyway, these exclusions do not affect the validity of results since the sample coverage ranges between 76% and 77% of the population total assets.

The recapitalization effect itself can be split into three components, namely a reduction in total assets, a lowering of risk weights and an actual increase of capital.[16] To identify the main driver of the recapitalization effect in our sample, we computed the index numbers for the aggregate TRC, RWA and TA, by setting the starting values in 2007 at 100 (Figure 3~~Figure 3~~). The reference panel experienced a reduction in total assets from 2011 to 2013 that lowered its initial value of about 4%, a higher reduction in RWA that dropped to 71.8% of their initial value, and a huge recapitalization such that the aggregate TRC in 2013 was of 64.4% higher than its initial value.

Figure 3: Evolution of capital, total assets and risk weighted assets

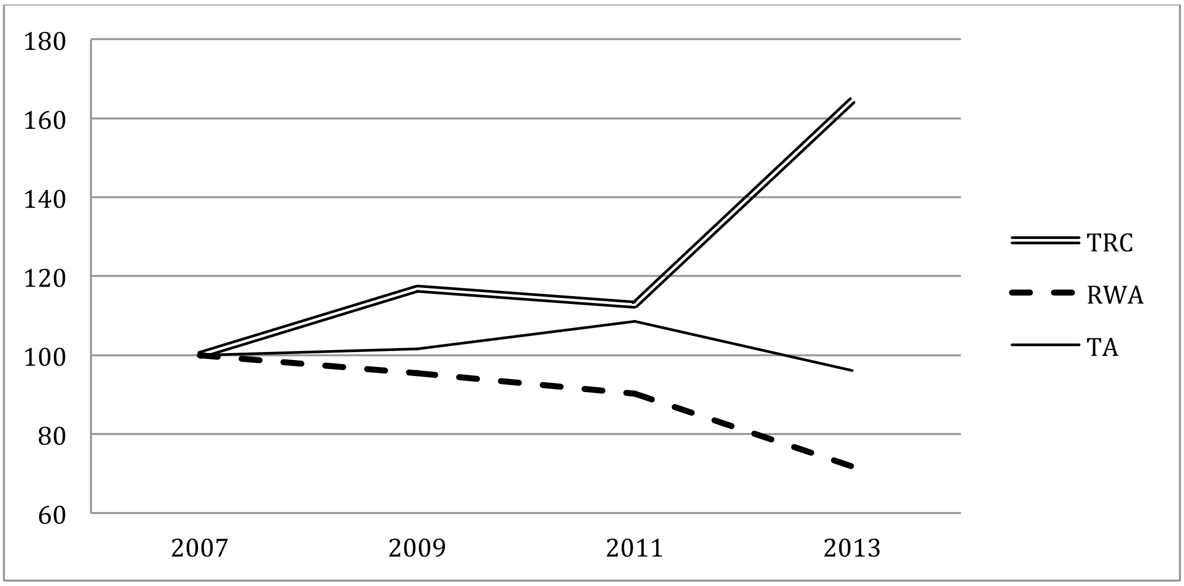
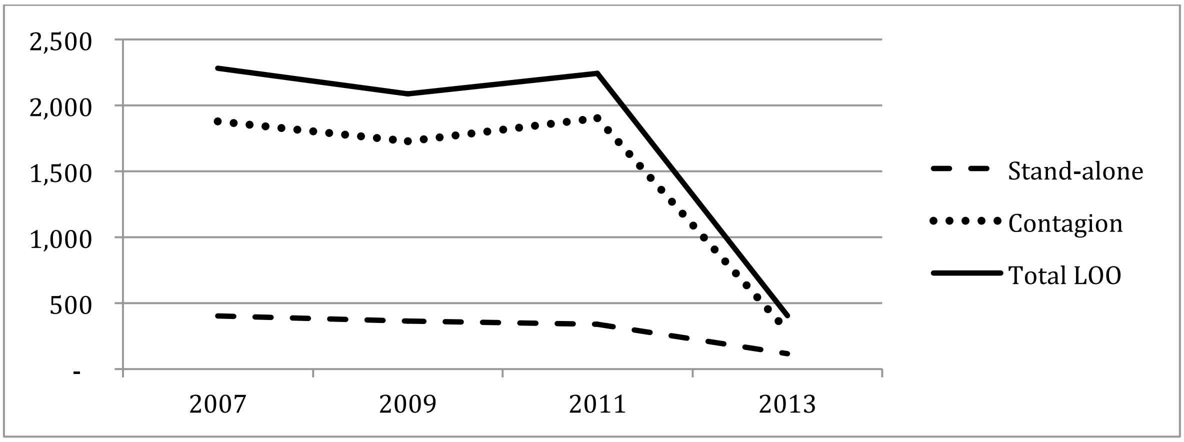


Figure 4: Evolution of aggregate LOO risk contributions, stand-alone and contagion components



[16] We remind that an observed increase of capital can be achieved through an issuance of new equity shares, an increase in retained earnings, or can be the outcome of public money support in the form of capital injected into troubled financial institutions (State aid). The present analysis does not distinguish between these three forms.

Figure 4~~Figure 4~~ reports the aggregate values of the LOO contributions (solid line), the stand-alone part (dashed line) and the contagion one (dotted line) for 2007, 2009, 2011 and 2013, showing that the main driver of the total risk contribution was in the contagion component.

Table 17: Leave-One-Out overall system risk (99.99% threshold)

	2007	2009	2011	2013
Stand-alone component	404	362	341	117
Contagion component	1.878	1.726	1.901	288
Total LOO contribution	2.282	2.089	2.243	405

The overall system risk (i.e. the expected shortfall of the whole system above percentile 99.99, see Table 17~~Table 17~~) dropped after 2011 from around EUR 2,243 billion to a much more comfortable value of about EUR 405 billion in 2013. This huge drop is mainly due to the fall of the contagion risk component, while the stand-alone risk shows a much smaller decline over the considered time span. In fact, as the regression analysis reported, the impact of capital is much higher on the contagion component than on the stand-alone one. Therefore, the undercapitalization observed since 2007 resulted in a high risk for the system, in particular in terms of possible contagion while the huge recapitalization observed since 2011 resulted in the contagion component reduction. In conclusion, the sharp reduction in the system riskiness is due to the combined effect of lower interbank exposures and, to a much larger extent, of increased capital. These effects actually improved the stability of the European banking system.

List of banks considered for the analysis of risk contributions evolution:

Aareal Bank AG
Allied Irish Banks PLC
Alpha Bank AE
AXA SA
Banca Carige SpA
Banca Monte dei Paschi di Siena SpA
Banca Popolare dell'Emilia Romagna SC
Banca Popolare di Milano Scarl
Banco Bilbao Vizcaya Argentaria SA
Banco BPI SA
Banco Comercial Portugues, S.A.
Bank BPH SA
Bank Handlowy w Warszawie SA
Bank of Cyprus Plc
Bank of Valletta PLC
Bankinter SA
Barclays PLC

Deutsche Bank AG
Dexia SA
Erste Group Bank AG
Hellenic Bank PLC
HSBC Holdings PLC
IKB Deutsche Industriebank AG
ING Groep NV
KBC Groep NV
Lloyds Banking Group PLC
Mediobanca SpA
Nordea Bank AB
Permanent TSB Group Holdings PLC
PKO Bank Polski SA
Royal Bank of Scotland Group PLC
Skandinaviska Enskilda Banken AB
Societe Generale SA
Svenska Handelsbanken AB

BNP Paribas SA
Commerzbank AG
Credito Emiliano SpA
Danske Bank A/S
Swedbank AB
UniCredit SpA
Unione di Banche Italiane SpA

Appendix 4: LOO risk contributions by crisis probability level

	99.9%			99.95%			99.99%		
	L_h (th€)	Sys_h^* (th€)	**LOO Contribution (th€)**	L_h (th€)	Sys_h^* (th€)	**LOO Contribution (th€)**	L_h (th€)	Sys_h^* (th€)	**LOO Contribution (th€)**
Bank 1	13,922	(45,216)	**(31,294)**	22,360	(60,224)	**(37,863)**	71,961	25,861	**97,821**
Bank 2	7,470	105,164	**112,634**	13,453	232,884	**246,336**	42,714	1,576,862	**1,619,575**
Bank 3	30,998	95,071	**126,069**	47,320	201,137	**248,458**	115,035	1,324,266	**1,439,301**
Bank 4	180,206	(353,187)	**(172,980)**	235,729	(613,138)	**(377,408)**	651,412	(1,233,161)	**(581,750)**
Bank 5	127,951	523,378	**651,329**	182,494	1,029,563	**1,212,057**	455,144	4,446,204	**4,901,347**
Bank 6	2,712	(10,146)	**(7,433)**	4,362	19,042	**23,403**	16,234	764,942	**781,176**
Bank 7	143,239	(503,510)	**(360,271)**	204,582	(782,921)	**(578,339)**	545,199	(1,079,829)	**(534,630)**
Bank 8	156,769	2,260,897	**2,417,666**	232,220	4,164,821	**4,397,041**	638,613	13,724,119	**14,362,732**
Bank 9	132,068	(238,228)	**(106,161)**	181,033	(398,237)	**(217,204)**	497,556	(467,316)	**30,240**
Bank 10	13,438	(42,477)	**(29,039)**	23,007	(78,579)	**(55,572)**	71,325	(43,252)	**28,074**
Bank 11	4,812	2,335	**7,147**	6,651	4,343	**10,994**	16,960	13,527	**30,487**
Bank 12	7,581	20,825	**28,406**	11,830	36,864	**48,694**	29,667	82,036	**111,702**
Bank 13	121,621	62,091	**183,712**	168,186	84,761	**252,947**	397,674	65,218	**462,891**
Bank 14	8,279	(87,175)	**(78,896)**	14,055	(135,077)	**(121,022)**	51,205	(176,233)	**(125,028)**
Bank 15	10,398	(295,997)	**(285,599)**	15,131	(506,672)	**(491,541)**	43,701	(854,421)	**(810,720)**
Bank 16	16,175	(34,785)	**(18,610)**	23,165	(29,343)	**(6,178)**	60,299	88,046	**148,346**
Bank 17	2,980	(511,982)	**(509,002)**	4,236	(872,797)	**(868,561)**	15,894	(1,676,717)	**(1,660,824)**
Bank 18	38,515	2,156,245	**2,194,759**	59,952	3,993,954	**4,053,907**	170,042	11,790,828	**11,960,870**
Bank 19	34,884	1,547,899	**1,582,783**	56,639	2,833,033	**2,889,672**	176,508	9,241,163	**9,417,671**
Bank 20	20,007	154,515	**174,522**	32,145	302,703	**334,847**	93,992	1,289,918	**1,383,910**
Bank 21	3,791	(1,509,270)	**(1,505,479)**	5,296	(2,607,993)	**(2,602,697)**	10,650	(5,463,057)	**(5,452,407)**
Bank 22	190,606	(214,934)	**(24,327)**	259,160	(398,751)	**(139,592)**	599,767	(1,060,080)	**(460,313)**
Bank 23	32,046	247,239	**279,285**	46,633	463,205	**509,837**	113,139	1,458,007	**1,571,146**
Bank 24	17,013	104,869	**121,882**	25,645	206,321	**231,966**	64,862	527,207	**592,069**
Bank 25	2,884,651	1,963,313	**4,847,965**	4,219,646	3,816,255	**8,035,900**	8,035,304	16,105,633	**24,140,937**
Bank 26	801,584	3,810,381	**4,611,965**	1,090,271	7,032,378	**8,122,650**	2,435,964	24,694,253	**27,130,217**
Bank 27	128,880	1,877,812	**2,006,691**	185,056	3,507,709	**3,692,765**	481,482	14,090,692	**14,572,174**
Bank 28	467,506	9,876,509	**10,344,015**	645,791	17,907,995	**18,553,787**	1,484,292	51,028,079	**52,512,371**
Bank 29	196,427	2,953,904	**3,150,331**	289,519	5,533,134	**5,822,653**	802,116	19,143,620	**19,945,736**
Bank 30	208,120	2,518,037	**2,726,157**	299,277	4,628,359	**4,927,636**	758,423	13,928,593	**14,687,016**
Bank 31	34,696	(118,012)	**(83,316)**	48,720	(187,836)	**(139,116)**	139,363	(63,367)	**75,995**
Bank 32	43,562	(507,612)	**(464,050)**	75,601	(870,905)	**(795,304)**	216,772	(1,762,966)	**(1,546,195)**

Bank 33	123,136	752,568	**875,704**	170,798	1,465,942	**1,636,740**	455,827	6,306,341	**6,762,167**
Bank 34	112,316	1,454,167	**1,566,483**	171,033	2,683,845	**2,854,878**	487,784	8,130,689	**8,618,473**
Bank 35	68,598	4,038,982	**4,107,581**	105,737	7,335,159	**7,440,897**	298,104	20,954,873	**21,252,977**
Bank 36	134,636	4,489,165	**4,623,801**	191,978	7,661,475	**7,853,453**	475,206	17,197,399	**17,672,604**
Bank 37	219,627	(1,296,462)	**(1,076,835)**	324,358	(2,240,559)	**(1,916,202)**	808,357	(4,102,065)	**(3,293,708)**
Bank 38	21,733	(115,708)	**(93,976)**	33,027	(184,869)	**(151,842)**	87,667	(114,686)	**(27,019)**
Bank 39	11,248	(64,317)	**(53,069)**	18,374	(90,247)	**(71,873)**	51,513	(106,506)	**(54,993)**
Bank 40	87,545	(199,059)	**(111,515)**	143,824	(336,755)	**(192,930)**	403,047	(693,687)	**(290,640)**
Bank 41	531,234	(1,265,996)	**(734,761)**	676,074	(2,240,955)	**(1,564,881)**	1,490,609	(5,277,903)	**(3,787,295)**
Bank 42	71,599	(184,015)	**(112,416)**	109,023	(338,546)	**(229,524)**	280,400	(633,400)	**(352,999)**
Bank 43	69,797	(256,214)	**(186,417)**	100,232	(442,479)	**(342,247)**	265,627	(717,599)	**(451,972)**
Bank 44	80,984	(64,171)	**16,814**	124,926	(94,362)	**30,565**	364,087	(103,430)	**260,657**
Bank 45	96,945	(157,159)	**(60,214)**	134,878	(297,145)	**(162,267)**	333,638	(553,591)	**(219,953)**
Bank 46	102,192	(158,394)	**(56,201)**	146,970	(274,396)	**(127,426)**	369,356	(442,297)	**(72,941)**
Bank 47	60,254	163,872	**224,126**	94,364	312,469	**406,833**	260,637	1,330,571	**1,591,208**
Bank 48	4,438,272	1,260,141	**5,698,413**	6,090,469	2,470,872	**8,561,340**	7,780,645	10,681,134	**18,461,779**
Bank 49	1,302,862	(1,958,493)	**(655,631)**	1,601,666	(3,398,284)	**(1,796,617)**	3,050,925	(6,339,224)	**(3,288,299)**
Bank 50	250,166	(1,798,926)	**(1,548,760)**	371,088	(3,166,224)	**(2,795,136)**	910,042	(7,692,217)	**(6,782,174)**
Bank 51	275,300	(248,738)	**26,562**	373,216	(457,807)	**(84,590)**	919,445	(818,762)	**100,684**
Bank 52	236,613	(551,464)	**(314,851)**	327,721	(969,030)	**(641,310)**	806,050	(2,268,064)	**(1,462,015)**
Bank 53	107,547	(158,668)	**(51,120)**	156,527	(282,566)	**(126,039)**	409,355	(429,349)	**(19,994)**
Bank 54	60,777	(114,832)	**(54,055)**	90,755	(207,524)	**(116,769)**	252,920	(52,404)	**200,515**
Bank 55	31,871	(80,246)	**(48,375)**	51,377	(122,886)	**(71,509)**	133,380	(192,562)	**(59,181)**
Bank 56	16,162	(125,938)	**(109,777)**	24,520	(203,265)	**(178,746)**	59,067	(266,272)	**(207,205)**
Bank 57	-	(588,096)	**(588,096)**	-	(1,031,550)	**(1,031,550)**	-	(2,418,896)	**(2,418,896)**
Bank 58	248,437	5,727,272	**5,975,709**	366,533	10,237,072	**10,603,605**	1,030,780	30,885,071	**31,915,851**
Bank 59	31,807	(100,225)	**(68,418)**	48,288	(161,514)	**(113,226)**	118,783	(163,342)	**(44,559)**
Bank 60	17,966	9,947	**27,913**	28,852	54,108	**82,960**	89,520	500,419	**589,939**
Bank 61	6,052,400	(1,440)	**6,050,960**	9,623,076	132,963	**9,756,039**	13,464,705	2,387,145	**15,851,850**
Bank 62	3,725,185	17,884	**3,743,069**	5,990,265	346,487	**6,336,752**	9,564,456	5,232,518	**14,796,974**
Bank 63	3,350,042	4,570,820	**7,920,862**	4,728,126	8,285,873	**13,014,000**	7,696,900	26,905,125	**34,602,025**
Bank 64	2,499,516	1,637,984	**4,137,500**	3,399,775	3,122,082	**6,521,857**	6,023,263	12,429,607	**18,452,870**
Bank 65	212,143	109,844	**321,988**	311,190	113,471	**424,661**	713,512	(132,037)	**581,475**
Bank 66	364,113	(89,983)	**274,131**	514,093	(219,094)	**294,999**	1,188,554	(576,329)	**612,225**
Bank 67	58,566	(522,981)	**(464,415)**	94,729	(885,652)	**(790,923)**	276,631	(1,831,716)	**(1,555,084)**
Bank 68	178,175	(720,749)	**(542,574)**	251,644	(1,264,142)	**(1,012,497)**	609,310	(2,947,410)	**(2,338,100)**
Bank 69	4,952	(143,028)	**(138,077)**	8,482	(235,621)	**(227,140)**	28,849	(361,563)	**(332,714)**

Bank 70	59,869	(764,365)	**(704,497)**	80,639	(1,307,840)	**(1,227,201)**	238,691	(3,037,794)	**(2,799,103)**
Bank 71	123,227	(182,500)	**(59,273)**	185,160	(327,384)	**(142,223)**	441,254	(326,782)	**114,471**
Bank 72	30,396	(214,191)	**(183,795)**	42,190	(359,542)	**(317,352)**	104,967	(568,888)	**(463,921)**
Bank 73	166,766	4,174	**170,940**	235,868	(8,608)	**227,260**	543,902	78,348	**622,250**
Bank 74	40,648	(74,678)	**(34,030)**	61,721	(115,327)	**(53,607)**	184,677	(55,333)	**129,345**
Bank 75	96,278	(233,124)	**(136,846)**	139,865	(406,118)	**(266,253)**	367,133	(863,686)	**(496,553)**
Bank 76	86,182	(148,570)	**(62,387)**	122,077	(254,446)	**(132,369)**	255,005	(418,140)	**(163,135)**
Bank 77	61,271	(64,263)	**(2,992)**	85,732	(98,573)	**(12,841)**	228,951	(150,163)	**78,788**
Bank 78	111,314	61,264	**172,578**	151,958	111,311	**263,268**	398,276	656,527	**1,054,803**
Bank 79	26,369	(205,223)	**(178,854)**	39,634	(349,391)	**(309,757)**	122,437	(620,409)	**(497,972)**
Bank 80	57,082	3,947,237	**4,004,319**	77,202	6,862,263	**6,939,465**	181,394	16,166,777	**16,348,171**
Bank 81	223,168	220,462	**443,630**	327,075	387,277	**714,352**	861,426	1,432,524	**2,293,951**
Bank 82	127,556	75,878	**203,433**	186,606	135,477	**322,083**	433,111	437,555	**870,666**
Bank 83	885,954	(1,662,403)	**(776,449)**	1,139,341	(2,972,778)	**(1,833,437)**	2,109,952	(6,568,019)	**(4,458,068)**
Bank 84	1,833,812	(56,989)	**1,776,823**	2,388,089	141,053	**2,529,142**	4,080,526	5,430,971	**9,511,496**
Bank 85	332,737	142,687	**475,424**	449,357	282,620	**731,978**	1,204,526	1,643,897	**2,848,423**
Bank 86	215,963	(143,588)	**72,375**	326,847	(241,513)	**85,334**	803,686	(346,976)	**456,711**
Bank 87	60,533	(575,850)	**(515,316)**	93,754	(1,001,250)	**(907,496)**	246,194	(2,234,791)	**(1,988,598)**
Bank 88	16,425	100,990	**117,415**	23,697	204,079	**227,776**	81,616	895,213	**976,829**
Bank 89	15,856	36,831	**52,687**	22,943	90,255	**113,197**	62,020	502,816	**564,837**
Bank 90	1,833	9,600	**11,433**	2,809	17,250	**20,060**	8,264	18,857	**27,121**
Bank 91	6,092	29,420	**35,512**	9,930	52,406	**62,336**	26,465	79,108	**105,572**
Bank 92	31,889	122,648	**154,537**	48,167	240,464	**288,632**	142,698	1,119,659	**1,262,358**
Bank 93	1,503,961	413,724	**1,917,686**	1,779,462	758,820	**2,538,282**	2,981,640	3,292,313	**6,273,952**
Bank 94	393,883	2,460,198	**2,854,081**	552,436	4,507,374	**5,059,810**	1,471,043	15,237,518	**16,708,561**
Bank 95	261,291	73,780	**335,071**	325,765	144,466	**470,231**	659,004	921,018	**1,580,021**
Bank 96	43,094	202,728	**245,822**	63,649	384,544	**448,193**	172,973	1,610,879	**1,783,852**
Bank 97	3,902	(3,336)	**566**	6,523	(5,952)	**571**	20,420	(16,439)	**3,981**
Bank 98	3,145	(1,182)	**1,962**	5,306	(2,099)	**3,207**	17,094	(5,683)	**11,411**
Bank 99	4,605	(77,119)	**(72,514)**	7,196	(116,941)	**(109,745)**	23,059	(119,302)	**(96,244)**
Bank 100	4,167	(1,428)	**2,738**	6,346	(2,572)	**3,774**	18,889	(7,333)	**11,556**
Bank 101	18,624	(47,355)	**(28,731)**	27,618	(86,986)	**(59,368)**	67,963	(49,151)	**18,812**
Bank 102	25,292	(55,659)	**(30,367)**	41,065	(101,495)	**(60,431)**	116,348	(89,214)	**27,134**
Bank 103	145,158	(239,791)	**(94,634)**	209,859	(415,649)	**(205,790)**	597,506	(778,181)	**(180,675)**
Bank 104	133,109	(224,164)	**(91,055)**	201,066	(381,323)	**(180,256)**	513,394	(685,431)	**(172,036)**
Bank 105	28,700	(121,037)	**(92,337)**	48,735	(218,847)	**(170,112)**	143,819	(262,676)	**(118,857)**
Bank 106	558,160	(1,567,949)	**(1,009,789)**	691,911	(2,782,920)	**(2,091,009)**	1,317,813	(5,349,449)	**(4,031,636)**

Bank 107	157,797	(311,925)	**(154,128)**	208,355	(515,081)	**(306,726)**	613,102	(945,523)	**(332,422)**
Bank 108	90,297	(477,168)	**(386,871)**	138,397	(797,230)	**(658,833)**	438,191	(1,458,546)	**(1,020,355)**
Bank 109	77,464	(356,239)	**(278,775)**	129,423	(612,018)	**(482,595)**	375,885	(1,097,759)	**(721,873)**
Bank 110	755	16,522	**17,277**	1,312	29,314	**30,626**	3,944	90,314	**94,258**
Bank 111	8,285	890	**9,175**	12,792	1,518	**14,311**	39,703	4,300	**44,003**
Bank 112	2,590	1,990	**4,581**	4,201	3,658	**7,859**	12,793	13,152	**25,946**
Bank 113	3,241,061	(168,042)	**3,073,019**	4,640,618	(197,477)	**4,443,141**	7,209,447	2,007,084	**9,216,531**
Bank 114	3,779,506	(201,194)	**3,578,312**	6,367,039	(50,443)	**6,316,596**	12,283,002	4,387,331	**16,670,332**
Bank 115	3,242,614	(1,291,196)	**1,951,418**	5,096,463	(2,220,226)	**2,876,237**	7,146,658	(3,685,815)	**3,460,843**
Bank 116	895,337	87,853	**983,191**	1,302,729	183,711	**1,486,440**	2,132,860	1,419,009	**3,551,869**
Total	**50,571,637**	**37,613,647**	**88,185,284**	**73,836,078**	**72,120,168**	**145,956,246**	**132,365,938**	**302,937,940**	**435,303,878**