Sectoral Risk in Italian Banks' Credit Exposures to Non-Financial Firms

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Abstract

Past episodes of bank distress have shown that excessive credit growth and concentration of credit risk may pose a threat to the stability of a single institution and the entire banking system. This paper analyzes the exposure of Italian banks to credit risk arising from different sectors of the economy. Using a structural multi-risk factor approach, we estimate measures of expected and unexpected losses at the level of individual banks and for the banking system at large. This work uses a unique and detailed supervisory dataset, including banks' credit exposure to non-financial firms, firm-level probabilities of default, and loss given default, overcoming approximations employed in previous studies. We find that at the level of the banking system, credit exposure is concentrated in a few sectors, including those sectors which are more vulnerable to credit risk due to their high cyclicality. We show that measures of portfolio risk are positively correlated with the concentration structure of economic sectors, and this may represent a problem if banks are excessively exposed toward concentrated sectors. At the level of individual banks, we find a negative relationship between credit risk measures and the size of a bank, although this is not related to the degree of sectoral concentration in small banks' portfolios.

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1. Introduction

Credit risk stemming from some economic sectors, notably the most vulnerable (sensitive) to the business cycle, can have a major impact on the credit portfolio of banks. If a portfolio is significantly concentrated towards such sectors, it might suffer large losses during economic downturn, hampering the loan capacity of a bank and imposing adjustments on its capital provisions. From a macroeconomic perspective, defaults of non-financial firms display positive correlations within and across industries, i.e. defaults are not independent events, and sectoral (systematic) risk factors might drive their dependence structure (De Servigny and Renault, 2002; Das et al., 2007; Saldías M., 2013).

The Basel framework suggests the calculation of capital requirements for credit risk under the internal ratings-based (IRB) approach using the Asymptotic Single-Risk Factor (ASRF) model whose consistency requires two key assumptions: firstly, borrowers-idiosyncratic risk is diversified away in banks' portfolios; secondly, macro-economy apart, there are no additional sources of credit risk at sectoral or geographical level, so there is only a single systematic risk factor driving correlations across obligors (Gordy, 2003). Under the latter assumption, if banks' portfolios are perfectly diversified across sectors (absence of sector concentration) the only residual risk exposure is to the overall dynamic of the economy. As a result, IRB risk-weights are portfolio invariant, i.e. capital requirements of any single credit exposure do not depend on the portfolio in which it is held, and this might lead to potential discrepancies between estimates under IRB models and the effective economic capital at risk. In fact, accounting for sector concentration of a bank's portfolio would increase economic capital by 20-40% (see BIS, 2006). This aspect is immediately relevant both for small size and sectoral specialized financial institutions and, for the stability of the banking system at large if banks credit portfolios are excessively exposed to sectoral risk.

This paper analyzes the exposure of the Italian banking system to credit risk arising from different sectors of the economy. In particular, we investigate whether credit exposures towards some economic sectors are particularly vulnerable to credit risk, this is due to both individual borrowers financial health and their joint-likelihood to default in adverse scenarios. Our analysis provides an assessment of potential systemic risk implications of sectoral vulnerabilities. In addition, we explore the link between sectoral credit risk and banks' characteristics, estimating risk measures at the level of individual banks portfolio.

Unlike the Basel framework which relates to the ASRF, we use a multi-risk factors approach which allows for the modelling of default dependencies due to a firm sectoral affiliation. In particular, we adopt a portfolio approach to credit risk modelling and we estimate two commonly used measure of credit risk: expected losses (EL) and unexpected losses (UL), the latter measured as Value-at-Risk (VaR) and Expected Shortfall (ES). In addition, an indicator of systemic relevance of economic sectors is given by their marginal contribution (MC) to unexpected losses by the banking system as a whole.

We obtain credit risk measures at different levels of granularity: (i) for each individual bank, (ii) for each economic sector, and also (iii) the banking system as a whole. Different levels of analysis allow us to perform an assessment of sectoral risks both from a micro and a macro-prudential perspective. As a result, this work might help micro and macro-prudential authorities to identify the build-up of sectoral risks in individual banks portfolios or within the banking system at large, setting the stage for a dynamic supervision of the evolution of credit risk capital requirement.

The analysis takes advantage of a unique supervisory dataset which combines firm-bank level data including: probabilities of default (PD) and loss given default (LGD) for non-financial firms retrieved from the Bank of Italy In-house Credit Assessment System (BI-ICAS) and the Archive of the historically registered losses on defaulted positions' (BI-AoL) respectively, while credit exposures are available from the National Credit Register (NCR).

This work has an immediate impact on our understanding of sectoral risk, exploring relevant indicators which can help detect and assess vulnerabilities for the banking sector. In addition, our analysis might guide the use of the new set of policy instruments available to macro-prudential authorities to address financial stability risks. The European Systemic Risk Board - ESRB - identifies among others the risk of excessive credit growth and exposure concentration as intermediate macro-prudential objectives relevant to the banking sector (see ESRB, 2014)[1] . Furthermore, there is evidence that concentration of exposures in credit portfolios increase banks' vulnerability to common shocks either via balance sheet exposures or via asset fire sales and contagion (BIS, 2006). The list of key instruments designed to address such intermediate objectives includes: sectoral capital surcharges, aimed at curbing excessive sectoral credit growth, and large exposure restrictions by sector, aimed at building resilience of banks to sectoral shocks. Both type of instruments operate as restrictions on banks' balance sheets and, their role is

[1] ESRB Recommendation of April 2013 on intermediate objectives and instruments of macro-prudential policy includes the prevention of: excessive credit growth and leverage, excessive maturity mismatch and market illiquidity, direct and indirect exposure concentrations, misaligned incentives and moral hazard, strengthening the resilience of financial infrastructures. These intermediate objectives help operationalize the main objective of achieving financial stability.

complementary to one another in dampening both upswings and the downswing of the financial cycle. However, currently few European countries have taken macro-prudential measures targeting only the real estate sector via increased risk weights on credit exposures (see ESRB, 2015).

Our work relates to a number of studies which focus on sectoral risk and sectoral concentration in banks' portfolios. Using a macroeconomic approach Virolainen (2004), proposed a credit risk model that links explicitly sectoral default rate series with common macroeconomic factors, such as GDP, interest rate, and corporate debt. The model is employed to stress test the impact of adverse shocks in macroeconomic factors on the aggregate Finnish corporate credit portfolio. Results of the stress scenario show that expected and unexpected losses are modest, accounting for 2.89-3.09% of the credit exposure in the case of unexpected losses, suggesting that credit risk stemming from the corporate sector in Finland does not represent a threat for the financial stability of the national banking system. Duellmann and Masschelein (2006), estimate the potential impact of sector concentration on the economic capital on the basis of German data. Credit risk is measured via a Credit Metrics-type model using Monte Carlo simulations under the simplifying assumption of homogeneous PD and constant LGD at sectoral level. Results show that, when accounting for sectoral concentration, unexpected losses are about 10% of the portfolio credit exposure, leading to a 20% to 37% increase in economic capital relative to a perfectly diversified portfolio. More closely related to our work is the analysis by Tola (2010), which provides estimations of the extent to which the Italian banking system is exposed to geo-sectoral centration risks. A multi-risk factors model, as in Pykhtin (2004) is used, allowing for a number of risk factors equal to the number of geo-sectoral cluster obtained from data on corporate defaults. Under the assumption of homogeneous PD and constant LGD within each cluster it is shown that, on average, geo-sectoral concentration implies a 26.87% increase economic capital with respect to the calculation based on ASRF assumption. Moreover, economic capital increase is negatively related to size, i.e. small and local banks (often cooperative banks) are more significantly exposed to geo-sectoral concentration risk.

We find that banks' credit exposures are heavily concentrated in some sectors of the economy, namely the industrial sector, trade, construction and real estate. Amongst these sectors, construction and trade are the most risky ones, presenting expected and unexpected losses above the average sectoral credit risk. At the other end of the spectrum, the oil and gas and telecommunications are the less risky ones due to their low cyclicality and low default risk. We show that measures of portfolio risk are positively correlated with the concentration structure of economic sectors, and this might represent a problem if banks are excessively exposed toward concentrated sectors. At the level of individual banks, we find a negative relation between credit risk measures and the size of a bank, and this is not related to the degree of sectoral concentration in small banks' portfolios.

We contribute to the literature in a number of ways. First, our work overcomes the typical micro-data limitations found in previous studies, i.e. lack of PD and LGD for individual firms. To the best of our knowledge, previous works did not overcome the assumption of homogeneous PD and constant LGD when estimating economic capital, as in Duellmann and Masschelein (2006) and Tola (2010). Second, this work contributes to identify and monitor at a high degree of granularity the build-up of sectoral risks, providing a useful warning signal for macro-prudential authorities when assessing the stability of the banking system. Third, we are able to link credit risk measures to actual individual banks' portfolios allowing an assessment of sectoral concentration risk.

The rest of the paper is organized as follows: Section (2) outlines the multi-risk factors credit model employed to estimate unexpected losses; Section (0) presents our rich dataset including banks credit exposures, PD, LGD and estimates of equity correlations; Section (4) discuss results and Section (5) concludes.

2. Methodology

2.1 The model set-up

In a large economy business conditions might not be fully synchronized across industries hence multiple risk factors might drive the dynamic of default risk for the entire economy. Unlike the ASRF model in Basel framework, which might overlook the effective default dependence amongst borrowers (see McNeil et al., 2005), we allow for a richer dependence structure considering multiple risk factors that affect borrowers depending on their industry affiliation.[2]

[2] Modelling the effective dependence structure of default events across borrowers is a challenging problem due to: (i) data limitations, i.e. joint defaults of small firms are mostly unique, non-repeatable events; (ii) the complexity of the specification of full joint default probabilities (see Hannenstein 2003, Schönbucher 2000). Hence, a theoretical model for default dependences is often preferable.

We use a structural multi-risk factors model as outlined in Düllman and Masschelein (2006), and in Düllman, Puzanova (2011) and prompted by Merton (1974) seminal work. Default dependencies are driven by a composite latent risk factors Y, affecting the standardized asset return X of a firm i belonging to a sector s:

$$X_{s,i} = \sqrt{r_i}\; Y_s + \sqrt{1-r_i}\; \varepsilon_{s,i}\;, \quad \varepsilon_{s,i} \sim^{iid} N(0,1) \tag{1}$$

$$Y_s = \sum_{k=1}^{S} \alpha_{s,k} Z_k\,, \quad \text{with } \sum_{k=1}^{S} \alpha_{s,k}^2 = 1 \quad , \quad Z_k \sim^{iid} N(0,1)$$

where: $r_i \in (0,1)$ is the factor loading which relates a firm assets return to the dynamic of a latent sectoral factor, $\varepsilon_i \sim iid$ is an idiosyncratic risk component. The composite risk factors $\boldsymbol{Y}$, one for each sector, are expressed as linear combinations of iid standard normal factors $\boldsymbol{Z}$ and $\alpha_{s,k}$ are obtained by the Cholesky decomposition of the correlation matrix of the sectoral risk factors $\{\rho_{s,k}\}$. The correlation between asset returns of two firms i and j is then obtained as $\rho_{i,j} = \sqrt{r_i r_j} \cdot \sum_{k=1}^{K} \alpha_{s,k}\alpha_{s,k}$, that depends on the strength with which a sector is correlated with the others. Within this model set-up, a default is triggered when a firm standardized asset return is below the threshold implied by the PD for that firm:

$$X_i \leq F^{-1}(PD_i)$$

The loss distribution is estimated via Monte Carlo simulations of systematic and idiosyncratic factors, and comparing the simulated standardized return with the threshold $F^{-1}(PD_i)$ to identify the individual defaults in each scenario.

$$L = \sum_{s=1}^{S} \sum_{i=1}^{I_s} D_{\{X_{s,i} \leq \Phi^{-1}(PD_i)\}} \cdot EXP_{s,i} \;\cdot LGD_{s,i} \tag{2}$$

where: s is the number of borrowers in sector s and EXP is the credit exposure. The implementation of the model requires a large set of data, including: PD at borrower level, exposures and LGD at loan level, the correlations matrix of sectoral factors and the factor loadings on the sectoral risk factors $r_{s,i}$. However, it is difficult to estimate factor loadings at individual level for non-listed firms, given the low frequency and accounting nature of the data available. [3] We assume an homogeneous factor loading for all sectors, as in Düllman and Masschelein (2006).

2.2 Credit risk measures

The estimation of credit risk measures for a portfolio of loans is based on the distribution of potential losses L for that portfolio. The loss resulting from the default of a single borrower i at given time is a random variable that can be decomposed as the product of three elements:

$$\mathrm{L_i = D_i \cdot EXP_i \cdot LGD_i}$$

where: $D_i \sim Ber(PD_i)$ is a binomial variable that assumes value 1 with probability PD_i. The total loss of the portfolio, $L = \sum_i L_i$, is characterized using two moments of its distribution, the expected and the unexpected loss, i.e. a variously defined level of loss that can exceed the expected value. The latter is generally calculated as the difference between a measure of tail risk, typically the expected shortfall (ES) or the Value-at-Risk (VaR), and the expected loss:

$$\mathrm{EL} \equiv \mathbb{E}[\mathrm{L}] = \Sigma_{\mathrm{i}}\mathbb{E}[\mathrm{L_i}] = \Sigma_{\mathrm{i}}\ \mathrm{PD_i \cdot EXP_i \cdot LGD_i},$$

$$\mathrm{UL \equiv ES - EL}$$

The estimation of expected losses is straightforward, conditional on the availability of individual PD and LGD. In contrast, the calculation of higher moments of the loss distribution involves considering the dependences between the individual losses. In our set-up, the default event is the only uncertain component, while credit exposures and LGD are considered as non-stochastic. This represent an improvement compared to existing empirical evidence, where homogeneous PD and constant LGD are used (see Düllman and Masschelein, 2006 and Tola 2010).

The ES for confidence level q and the potential loss L_s of the sub-portfolio s is defined as:

$$\mathrm{ES_q(L_s)} = \mathbb{E}[\mathrm{L_s} |\ \mathrm{L_s} \geq \mathrm{VaR_q(L_s)}]$$

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[3] In the context of equity cost estimation, the estimation in a CAPM fashion of accounting betas or fundamental betas (obtained by regression of a firm earnings on market earnings) presents similar issues. In both cases the results provide very low overall explanatory power and are biased by accounting adjustments.

The ES for the total loss can be decomposed in marginal contributions of each industrial sector (Tasche, 2008; Dullman and Puzanova, 2011).

$$\mathrm{MC_s} = \mathrm{w_s} \frac{\partial}{\partial \mathrm{w_s}} \mathrm{ES_q}(\mathrm{L_{tot}}) = \mathbb{E}[\mathrm{L_s} | \ \mathrm{L_{tot}} \geq \mathrm{VaR_q}(\mathrm{L_{tot}})]$$

Marginal contribution measures have a desirable full allocation property, i.e. they sum up to the overall ES so that for each sector it can be interpreted as the share of ES attributable to a sector, approximating the systemic relevance of a sector.

3. Data

We compiled a comprehensive cross-sectional dataset which includes banks' credit exposures to non-financial firms, firm-level PD and model-based estimations of LGD, as of December 2014. Credit exposures of Italian banks towards non-financial firms were gathered from different sources: the Italian credit register provided detailed information on individual loans, as well as on- and off-balance sheet items and financial derivatives which are typically overlooked form of exposures; the Bank of Italy supervisory reports provided us with corporate debt securities holdings by banks. Our estimation of exposures at default implements, where possible, the provisions from Capital Requirements Regulation.[4] In Appendix, each component of credit exposures is described.

Table 1. Banks' credit exposure to non-financial firms by instrument

Instrument Type	**Exposure[(a)]**	**N. Borrowers**	**N. Banks[(b)]**	**HHI by Borrowers**	**HHI by Banks**
Undrawn Credit Facilities	1.39	15,904	399	1.7%	9.3%
Bonds	2.69	108	112	5.5%	14.5%
Financial Derivatives	5.84	17,128	84	1.1%	21.6%
Guarantees	55.57	169,742	516	0.7%	9.7%
Loans	597.26	1,166,883	536	0.0%	7.3%
Total	**662.75**	**1,180,387**	**537**	**0.0%**	**7.5%**

(a) In billions; (b) Number of banking groups and individual banks not belonging to banking groups.

[4] Regulation (EU) No 575/2013 of The European Parliament and of The Council (CRR).

Table 1 reports banks' credit exposure to non-financial firms by instrument type, including: loans, guarantee, financial derivatives, bonds and credit lines. For each financing instrument, we calculated concentration indices (HHI) of credit exposures both in terms of lenders and borrowers market shares. As regards to the lenders, in what follows we consider only banking groups, i.e. exposures of individual banks and financial intermediaries belonging to banking groups are consolidated with the parent company.

Indeed corporate loans are the most spread type of financing instrument, accounting for the largest proportion of total credit exposure (89%). The market for corporate loans also displays the lowest concentration level both from the banks and from the borrowers perspective. In contrast, corporate bond and financial derivatives represent concentrated markets, with a few banks holding large proportions of securities. The low proportion of exposures derived by undrawn credit facilities depends on the particular regulatory-weighting system used for this kind of contracts (see Appendix).

3.1 Probabilities of Default

We use firm-level probabilities of default retrieved from the BI-ICAS. These are 1-Year point-in-time probabilities of default of Italian non-financial firms available on a monthly basis. A Basel III compliant definition of default is utilized to calibrate the statistical model which combines information sourced from financial statements, the credit register and geo-sectoral information. The use of firm-level PD represent a significant advantage, in terms of accuracy, of this work when compared to other studies (Duellmann and Masschelein, 2006; Tola, 2010; Saldías, 2013) which use historical default rate or median Expected Default Frequency at the industry level, as proxies of individual PD.

3.2 Loss Given Default

We estimate loss given default of individual exposures using data available from the archive of historically registered losses on defaulted positions of the Bank of Italy. The use of model-based estimations for LGD is a significant improvement of this work, in fact, allowing the consideration of collateralization degrees and value of collateral on single exposures makes credit losses different for borrowers with the same probability of default. Our dataset contains a rich set of information on positions defaulted between 2002 and 2014, including: the recovery value on defaulted exposures, the discounted values of the amounts recovered following a default, information regarding the characteristics of the exposures such as degree of coverage and type of guarantees, and geo-sectoral information about a borrower. Only LGD greater than zero (although slightly negative values are possible because of administrative sanctions) and smaller than two were included in our dataset. Figure 1 shows the distribution of the LGD in our sample:

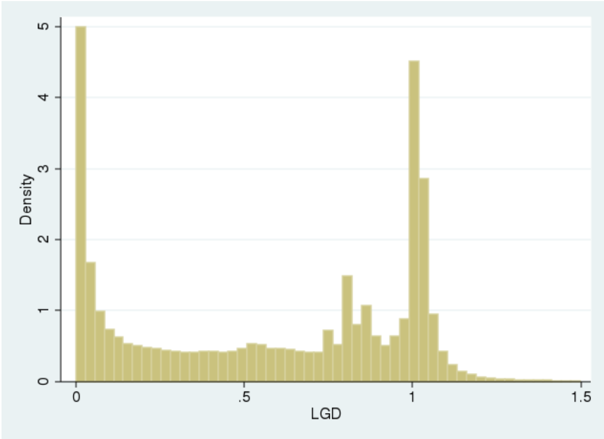

Figure 1. LGD distribution

We estimate LGD on each credit exposure as of December 2014 through a linear regression model. In particular, for IRB banks[5] the model is as follows:

$$\mathrm{LGD_i} = \beta_0 + \beta_1 \mathrm{Log(EXP)} + \beta_2 \mathrm{Coverage\ ratio} + \beta_3 \mathrm{Sector} + \beta_4 \mathrm{Region} + \beta_5 \mathrm{Guarantee\ type} + \varepsilon_i \tag{3}$$

Results from Equation (3) are reported in Table 3 in Appendix. Guarantees have the strongest impact on LGD (-24%), reducing losses when their amount increases. Similarly, an increase in the coverage ratio is expected to lead to a reduction of the loss rate (-3%). The size of the exposure at default has a significant negative effect, although it is of modest size equal to -2% on average. However the total exposures attributable to a debtor tend to be positively correlated with the coverage ratio, so that large exposures tend to be associated with higher recovery rates. Firms belonging to Oil and Gas, Telecommunications and Technology, record ceteris paribus higher loss rates. Finally, southern regions, and to a less extent central regions, present significantly higher loss rates (up to 13% more than the base case represented by Piemonte region).

[5] For the current exposures of non-IRB banks, we used the same model but without the bank dummies. The results without controls for bank level effects are similar, although explanatory power is lower.

Overall, the explanatory power of the model is modest (R^2 0.16). This is partly due to the fact that the LGD distribution is bimodal, with a significant share of the observations grouped around 0 and 1 values. Average values predicted by the model tend to fall between the two extremes. Classes of models that allow a more precise estimation for bimodal distributions are available in literature, and additional information on banks and borrower characteristics can be gathered to improve fitting. However, this was not deemed likely to improve dramatically the robustness of the current analysis.[6]

3.3 Risk factor correlations

In structural credit risk modelling it is a common practice to approximate risk factors correlations by using equity correlations. For instance Servigny and Renault, (2002) provide evidence on the empirical link between equity correlation and default correlation, and Duellmann et al., (2006) compare the impact of the use of individual asset correlations and sector-specific correlations on credit portfolio risk.

We estimate correlations of equity indices based on GARCH-DCC as prompted in Engle (2002) and recommended in Puzanova and Düllmann, (2013) when dealing with portfolio credit risk models. This approach accounts for two figures of financial time series: (i) volatility clustering, that is volatility in *t* tend to be high if it was high at time *t-1*, and (ii) correlation clustering, that is correlations are time-varying and, as for volatilities, tend to be high in a certain period if it was high in the previous one. The estimation proceeds in two stages. In the first stage N univariate GARCH (1,1) models are estimated for each of the return series. This results in an estimate of conditional standard deviations for each *t* which are utilized to standardize return series. In the second stage, the temporal dynamics of conditional covariance matrix is characterized as a GARCH (1,1) model. We employ log return series of FTSE - Italy Supersectors indices at daily

[6] In particular, much of the literature that analyzes the goodness of fit of alternative models for LGD focuses on beta distribution, fractional regression, and other models that assume that LGD values are contained in the [0,1] interval. This is a suitable hypothesis for market traded instruments, but not for loans that are held on the balance sheet, which often present values that are negative, especially because of administrative costs, or greater than one, because of administrative sanctions imposed on the defaulted borrower. With the purpose of verifying whether other classes of models and additional data could be used to improve fitting we plan to undertake further analytical research on this subject in the near future.

frequency sourced by DATASTREAM; Figure 8 in Appendix report cumulative returns of sectorial indices.

Table 4 reports GARCH-DCC sectoral correlations estimates at December 2014. We observe that sectoral correlations range from 0.75 between Industrial Goods and Services and Utilities to 0.32 between Trade and Telecommunication while the median correlation is 0.52. Certain sector show low sensitivity to the overall performance of the Italian stock exchange, as they report low correlations against the other sectoral indices, this is the case for: Chemicals, Agriculture, Health Care, Trade. In contrast, Industrial Goods and Services, Oil and Gas, Construction and Utilities show high cyclicality. Overall, we anticipate that the existence of significant dispersion amongst correlations (standard deviation equals 0.09) imply a greater departure of estimates of economic capital obtained via the ASRF set-up and the multi-risk factors environment.

3.4 Sectoral exposures and concentration

Stock market indices and Italian firms follow different industry classification systems, the ICB and NACE respectively. We mapped NACE taxonomy into ICB codes in order to consistently assign a firm to its sector. When a direct association was not possible a firms were assigned to Others Sectors. We assume that all borrowers can be uniquely assigned to individual business sectors. Banks' exposure towards ICB industries and degree of concentration of credit exposures, measured by Herfindahl–Hirschman Index, is reported in Table 2 as of December 2014.

Table 2. Exposures and concentration by sector

	EXP%	N. Firms	Av. EXP	N. Banks	HHI by Borrowers	HHI by Banks
Industrial Goods and Services	20.0%	223,424	0.59	536	0.090	0.004
Trade	14.2%	260,530	0.36	529	0.076	0.001
Construction	13.0%	161,431	0.53	530	0.069	0.001
Real Estate	11.2%	85,758	0.87	513	0.063	0.002
Agriculture, Food and Beverages	8.4%	117,912	0.47	519	0.062	0.001
Chemicals and Basic Resources	6.8%	34,011	1.32	498	0.093	0.003
Utilities	6.2%	10,146	4.07	493	0.100	0.004
Personal and Household Goods	4.4%	46,728	0.54	513	0.085	0.001
Travel and Leisure	3.8%	85,887	0.24	522	0.045	0.001
Other Sectors	3.1%	62,730	0.32	526	0.074	0.005
Automobiles and Parts	2.8%	38,941	0.47	511	0.062	0.005
Health Care	1.8%	25,093	0.46	483	0.101	0.004
Technology	1.6%	22,411	0.47	490	0.107	0.012
Oil and Gas	1.5%	252	38.81	164	0.091	0.229
Telecommunications	0.8%	927	5.98	201	0.125	0.454
Media	0.5%	4,206	0.72	341	0.111	0.040
Total	**100%**	**1,180,387**	**0.56**	**537**	**0.004**	**0.090**

Table 2 shows that more than half of banks' credit exposure is concentrated within four sectors: Industrial Goods and Services (20%), Construction (14%), Real Estate (13%), and Trade (12%). In contrast, the shares of remaining sectors range from 1% to 9% with Media (0.45%), Telecommunication (0.1%), and Oil and Gas (1.46%) representing the lowest exposed sectors; In turn, this might be related to their direct access to capital markets via equity and bond issuances.

Sectors are heterogeneous in terms of number and size of borrowers, as approximated by the average level of their exposures, with Oil and Gas, Telecommunications, Utilities and Media representing sectors with large-size borrowers. Consistently, these sectors show a remarkable level of concentration from the side of borrowers, as approximated by HHI. Turning to the degree of concentration from the lenders side, from Table 2 it is apparent that lowly exposed sectors are also the ones to be financed by a few banks; in this instance the HHI is higher than 7% for Oil and Gas, Technology, Media and Telecommunication. For these sectors, some banks might be excessively exposed to sectoral risks if their portfolios are not adequately large and diversified.

4. Results

4.1 Banking system sectoral exposure

Figure 2reports EL by sectors and its elementary components: median PD and LGD. Sectors are sorted by decreasing level of the ratio EL to EXP. At the level of the banking system at large EL account for about 2.4% of total exposures, however their incidence differs substantially across sectors. Construction and Trade, which represent a large part of banks' credit exposures exhibit EL above the average; in contrast, Industrial Goods and Services and Real Estate present EL below the average. Turning to elementary components of EL it is interesting to notice that model-based LGD estimates average around 50%, which is the value usually hypothesized in previous studies (Duellmann and Masschelein, 2006; Tola 2010), with outliers such as Real Estate and Oil and Gas. Real Estate firms are very risky with PD exceeding 6%, however the low value of LGD contributes to limit the amount of EL. This is probably due to the liquidation value of collateral which allows to increase the recovery rate in this sector. The least risky sectors are Oil and Gas and Telecommunications where low levels of PD are associated with high LGD.

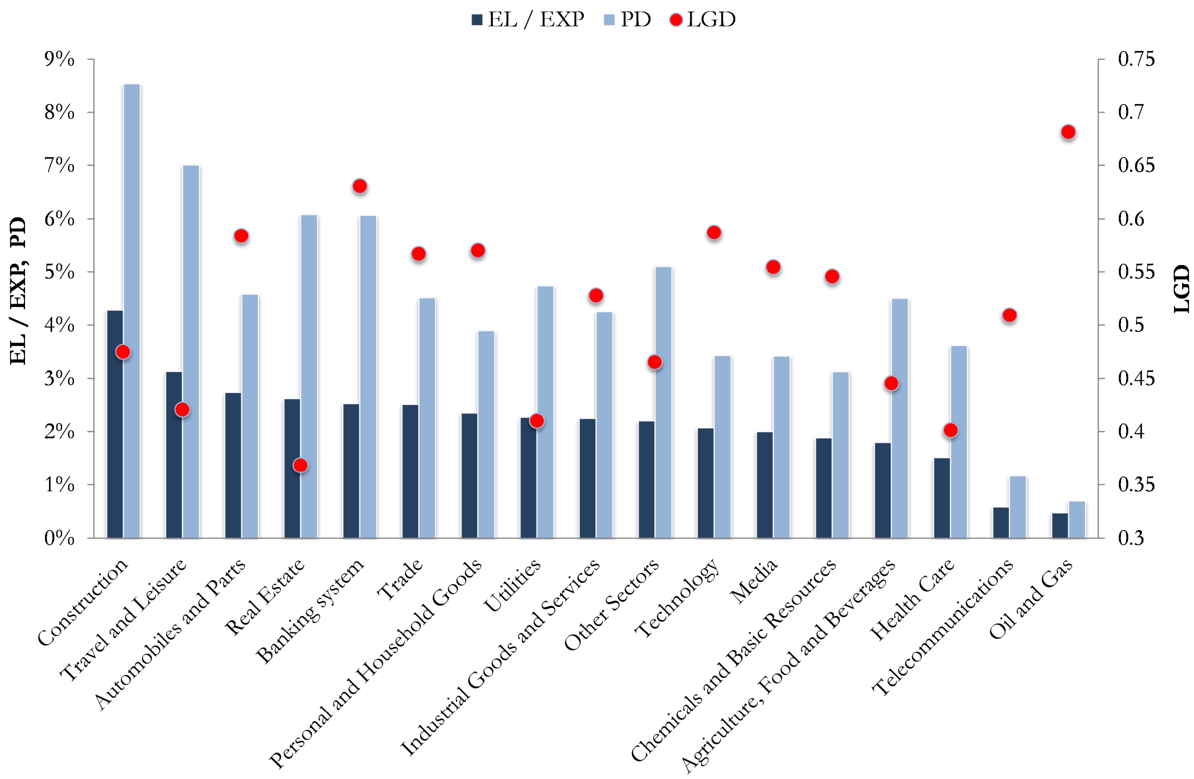

Figure 2. Expected Loss and its components

However, these results might be sensitive to the size of risky borrowers, i.e. defaults of a few large firms might drive EL in a given sector especially the most concentrated ones. In order to assess the extent of this aspect we report the contribution to EL by large firms within a sector, identified by the top 1% of exposures. In Technology and Telecommunications large exposures contribute to more than half of EL within those industries. In contrast in Agriculture, Travel and Leisure and Personal and Households Goods the contribution of large exposures to sectoral EL is the lowest, reflecting low degree of concentration prevailing in those sectors.

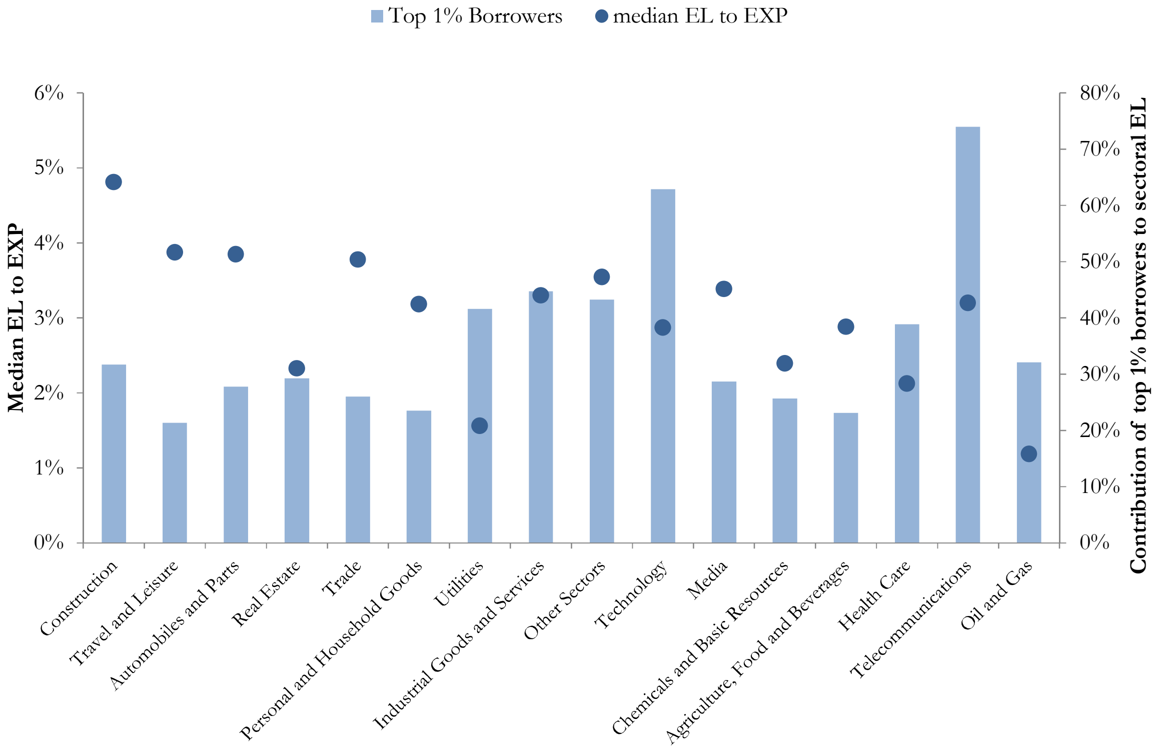

Figure 3. Large exposures EL by sector

Portfolio credit risk measures calculated by Monte-Carlo simulation display a pattern slightly different from that of expected losses. Figure 4 reports expected and unexpected losses to exposure ratios by sector, and this is an approximation of the capital requirements on a single unit of credit exposure. The share of expected shortfall on exposures has a weighted average value that equals 14% and ranges from 3.8% and 5.5% for Telecommunications and Oil and Gas, to 22% and 18% for Construction and Other sectors. Note that both Oil and Gas and Constructions are highly correlated to with the rest of the economy, therefore it is interesting to compare the increase in credit risk due to portfolio effects, i.e. correlated defaults. Construction show an increase in risk of about 5 times (from 4.29% to 21.98%) while Oil and Gas by 11 times. Consequently, while Oil and Gas is an industry that show the lowest absolute credit risk, it is important to notice that in a negative scenario credit losses increase significantly more than in other sectors and this is probably due to the concentration structure of these sectors, i.e. a few large borrowers appear in default when the economy is in negative scenarios. Amongst the most relevant sectors in terms of exposures, Construction and Industrial Goods display above average risk measures while Trade and Real Estate are below the average. Contrary to what observed for expected losses travel and leisure enterprises exhibit a ratio of unexpected losses on exposures well below the mean. Overall, the analysis suggest that credit risk exposures in some sectors of the economy are not portfolio neutral, the increase in credit losses is sensitive to the correlations amongst sectoral risk factors, the PD and the concentration structure of the sector.

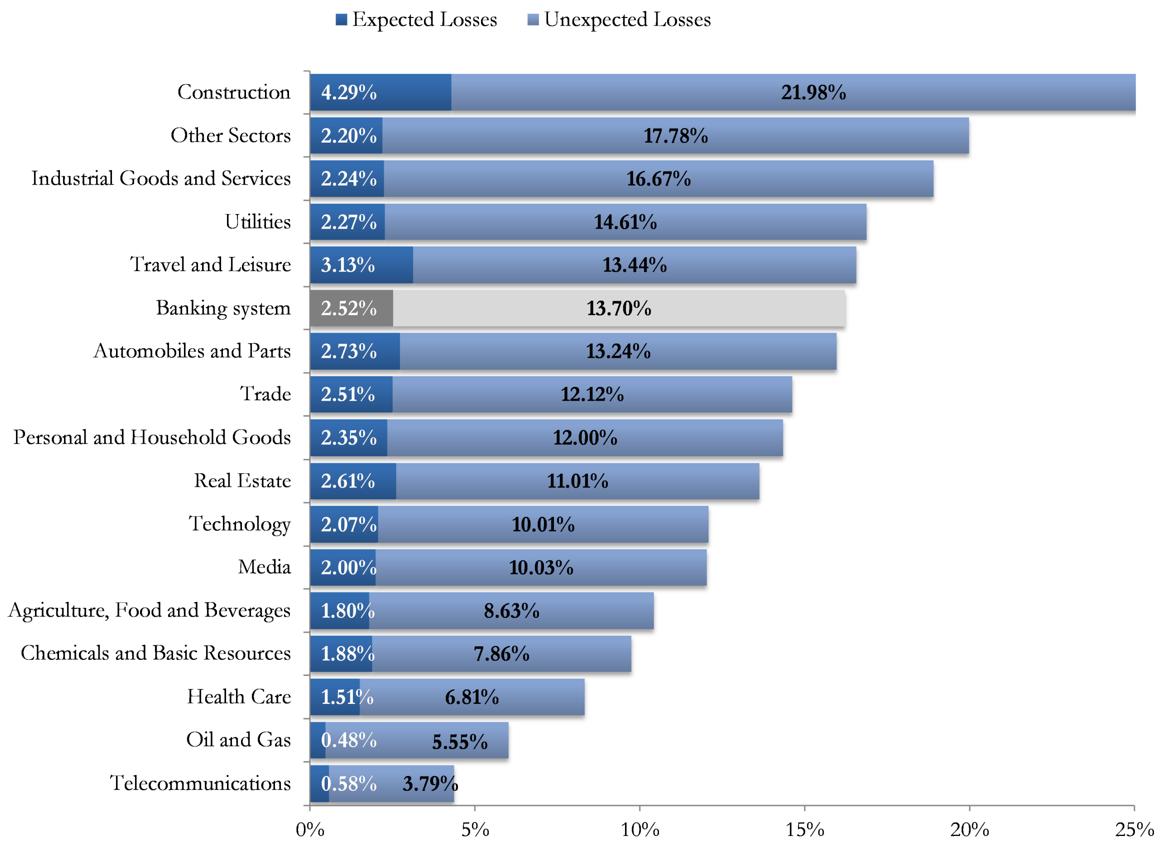

Figure 4. Expected and Unexpected Losses by sector

Figure 6 reports the contribution of each sector to the expected shortfall of the banking system, this is an indicator of systemic relevance of sectors. This figure combines the assessment of the riskiness of a sector and of its weight in terms of credit exposures. At the sectoral level, credit risk is significantly concentrated in two sectors, namely Industrials and Constructions, which account for almost half of the Expected shortfall of the banking system. These sectors are also the ones with the highest UL to EXP ratio because of their cyclical nature and level of default risk. A comparison between Figure 4 and Figure 5 shows that for some sectors, for example Technology and Media, capital requirements per unit of exposure are relatively high, however, given their low importance in terms of overall exposure, their contribution to credit risk is negligible.

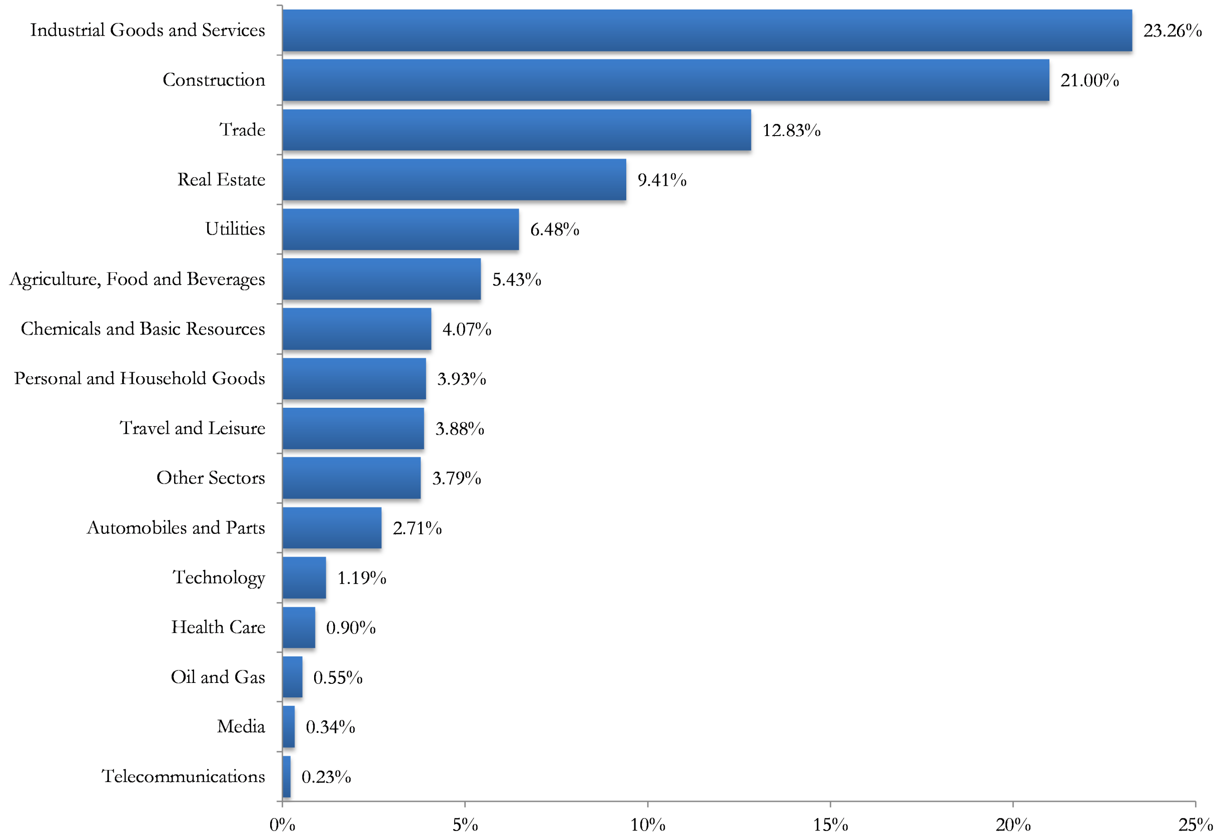

Figure 5. Sectoral Marginal Contribution to Banking System Expected Shortfall

4.2 Comparison between single-factor and multi-factor model

The multi-factor model in (1) - (2) allows for heterogeneous joint default probabilities which depend on the sector of economic activity and can vary over time. However, capital requirements under the Basel framework are computed using a single-factor model which implicitly assumes joint defaults as not being dependent on a firm sectoral affiliation. As a result, estimates of capital requirements may overlook actual economic capital, especially when defaults are highly correlated across industries. In order to gain insight regarding this potential discrepancy we compare the expected shortfall estimates under the multi-factor model with those obtained from a single-factor model with homogeneous asset correlation equal to 0.25 (see art.153 Regulation (EU) No 575/2013). Figure 6 presents the results from the two models and the differences are due to the different structure of statistical dependence between defaults.

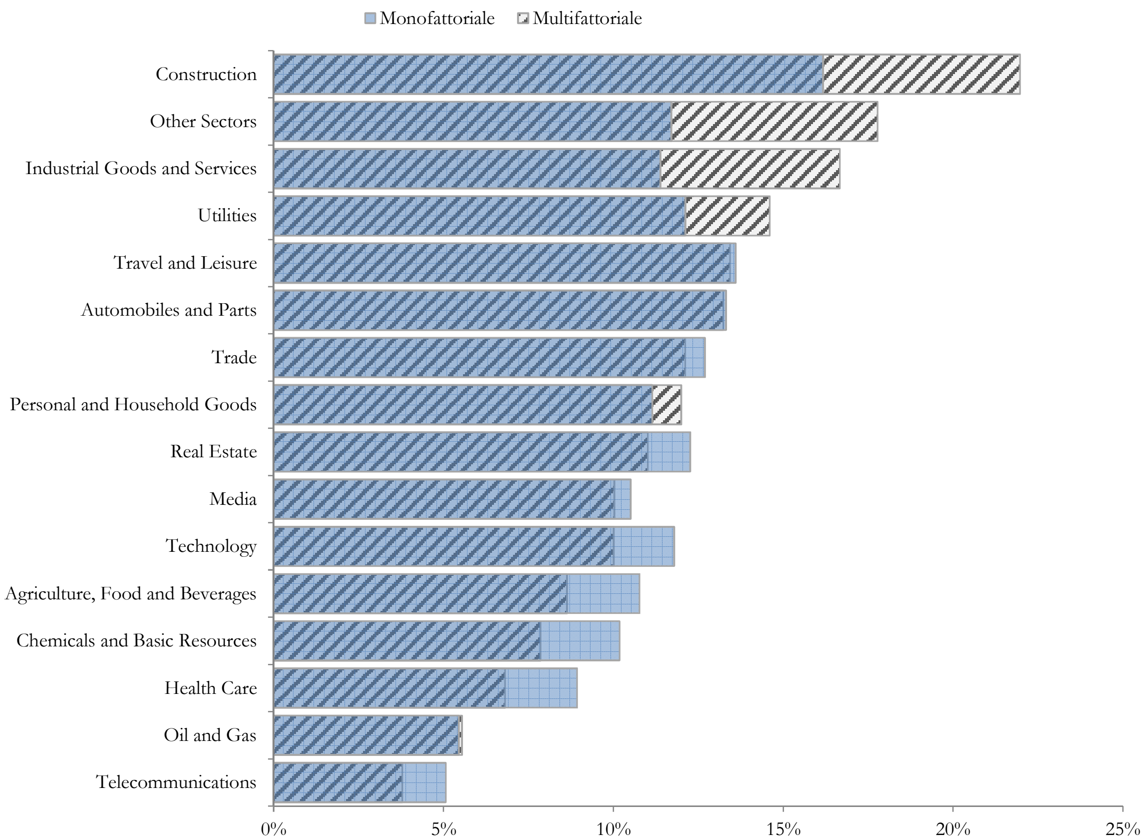

Figure 6. Single and Multi risk factor model

This comparison shows that the use of single factor model when posting economic capital may overlook a significant proportion of credit risk. The extent of the discrepancy between single and multi-risk factor estimation is proportionally larger for strongly correlated sectors, i.e. sectors that are highly (lowly) correlated with the economy tend to record higher (lower) expected shortfall under a multi-factor model. As a consequence, potential misallocation of economic capital due to the use of single-factor model may pose a problem especially for economic sectors that may have systemic relevance, i.e. Industrials and Construction.

4.3 Individual banks sectoral exposure

In order to assess the extent to which individual banks are exposed to sectoral risks, we estimated credit risk measures at the level of a single banking group. By doing so, we were able to account for the actual diversification level of banks' credit portfolios. Banks for which credit to non-financial firms represent a marginal part of their lending activity were removed from the analysis[7].

We grouped credit risk measures by size of banks, results are reported in Table 6. We observe a negative correlation between credit risk exposure and the size of a bank. In particular, the first five groups and the other large banks exhibit a lower incidence of expected losses than small and minor banks; large banks expected losses are about 1.5 times lower than small banks. Accounting for default dependences, portfolio measures of credit risk display a similar picture: large banks losses are about 1.3 times lower than small banks.

At a first sight, the difference between banking groups of different size could reflect the different diversification of credit exposure across sectors. For example, smaller banks might be more exposed to riskier sectors, e.g. construction, then other banks. To evaluate this aspect, we calculated expected losses for small banks using sectoral weights from large banks. Results showed a small reduction of the ratio EL to EXP for small banks, revealing that the higher vulnerability of their exposures may be due to idiosyncratic factors, e.g. PD of borrowers within the same industry. Table 6 in Appendix compares average PD credit exposure by bank size and shows that for small banks the average PD is always higher that large banks. This result is not new in the literature and adds further evidence to the work of Iosifidi and Kokas (2015) who found that banks with higher credit risk are associated with more risky firms; see also (Peek and Rosengren, 2005 and Jones et al., 2005).

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[7] Banks whose exposure to non-financial firms is below 10% of total lending portfolio (e.g. banks specialized in households financing) are excluded from the analysis. Similarly, banks which present a negligible number of borrowers (less than 30) are excluded. Overall banks removed are 99 accounting for 1.3 per cent of the total exposure.

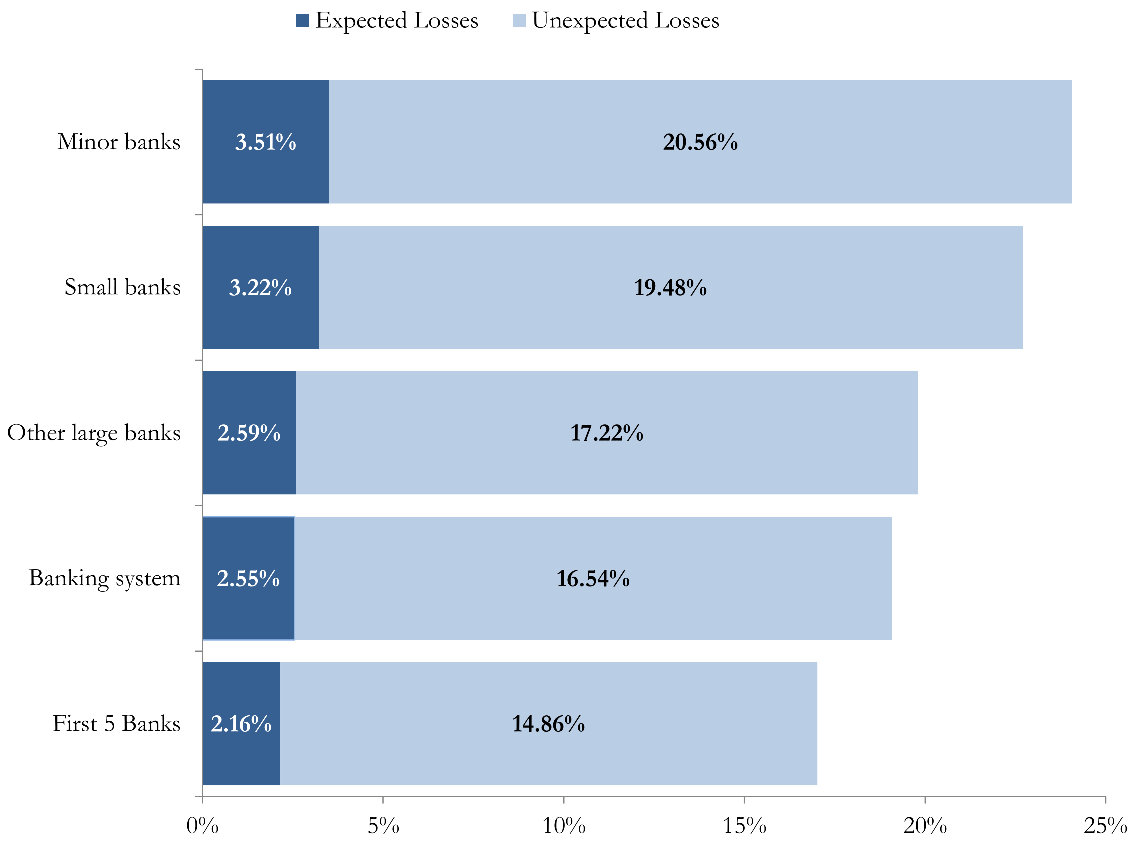

Figure 7. Expected and Unexpected Losses by Bank Size

5. Conclusions

Concentration of exposures in credit portfolio may represent a source of systemic risk. This paper provides an analysis of the extent to which different economic sectors are vulnerable to credit risk and whether credit losses are excessively concentrated in a few of them posing, hence, a treat to the stability of the banking system. Our analysis is also motivated by the introduction of macroprudential policy in Basel framework which provides instruments to address vulnerabilities at the sectoral level.

We use a large and unique set of firm-bank level data covering credit exposures towards non-financial companies; this is a significant improvement over previous studies. A multi-factor structural methodology is employed for the estimation of commonly used measures of credit risk and marginal contributions of individual sectors to these measures. Both expected and unexpected credit loss over a one-year horizon are estimated, providing a measure of risk at the portfolio level.

At the sectoral level, credit exposures are significantly concentrated in a few sectors: Industrials, Trade, and Construction account for approximately 20%, 14%, and 13% of the total exposure. In terms of systemic relevance, Industrials and Constructions account for almost half of the expected shortfall of the banking system. These sectors are also the most risky ones, displaying the highest ratio of unexpected losses to exposure, because of their strong correlation with the economy and level of default risk.

At the bank level, we find a negative link between the size of a bank and the risk of its credit portfolio. Small banks' portfolios tend to be more concentrated, however, conditionally on concentration levels, credit risk of their portfolios does not reduce significantly. The analysis reveals that, higher vulnerability of small banks' exposures may be driven by lower financial health of their borrowers; in fact the average probability of default in each sector is higher.

Finally, we compare expected shortfall estimates with the ones which can be obtained by using a single-factor model, an approximation of the Basel II (Pillar I) capital requirements model. The results show that these two measures are of comparable magnitude for less correlated sectors, while for the more correlated ones the multi-factor model leads to higher values. As the most correlated sectors are also the ones towards which banks are more exposed, single-factor estimates of capital requirements underestimate unexpected losses associated to these sectors.

Further analysis is needed on a time-series basis, allowing to explore the temporal dimension of the relationship between credit risk and the financial and business cycle. Ultimately, this approach may guide the use of the new set of policy instruments available to macro-prudential authorities to address financial stability risks coming from economic sectors characterized by high expected and unexpected losses and high systemic relevance.

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6. Appendix

Credit exposures

Credit exposures of Italian banks towards non-financial firms are included in our dataset when they meet the following criteria:

- exposures are held by Italian banks, foreign banks' branches and financial intermediary controlled by a bank, including SPV whose assets are not derecognized;
- exposures towards non-financial firms represent a relevant portion of the credit portfolio of the holder;[8]
- the counterparty is an Italian or foreign corporate, or an Italian or foreign sole proprietorships;
- the counterparty is not defaulted at the reference date.[9]

Exposures are computed taking into account the gross amount of the different type of instrument.[10] Specific regulatory-weights,[11] were applied to Guarantees and Undrawn Credit Facilities for the conversion of off-balance sheet positions to exposures. Given the limited information in this regards, this computation is an approximation of the correspondent value attributed by the single banks.

6.1.1 Loans

Loans account for the major part of credit exposures considered both in terms of amount and number of borrowers. Data on loans, are sourced from the Italian NCR which uses a threshold of

[8] Relevance is defined at the bank group level by the means of two variables: the ratio of loans towards non-financial firms to loans towards all non-financial sector and the total number of borrowers. The threshold for the two variables amount respectively to the 5^{th} and the 10^{th} percentile of the respective distributions (which means a ratio of at least 10% and a number of borrower greater than 30).

[9] A Basel III default compliant definition of default is used for the identification of defaulted borrowers.

[10] CRR requires the use of the net value (nominal value, deducted the value of the provisions) under the standard approach. The IRB approach entails the use of gross exposures where not differently indicated. See Regulation (EU) No. 575/2013 of the European Parliament and of the European Council, Art. 111 and 166.

[11] See Regulation (EU) No. 575/2013 of the European Parliament and of the Council, Art. 111 and Annex I.

30,000 Euros,[12] below which performing loans are not reported. The risk-mitigating effect associated with hedging instruments related to a loan (e.g., guarantee and collateral) is taken into account when estimating LGD. The amount of a loan included in the bank-borrower exposure is therefore always the 100% of the loan itself.

6.1.2 Guarantees

The Italian NCR includes a wide variety of off-balance sheet positions, including exposures that have both commercial and financial nature. The first category of items are letters of credit, surety arrangements and other arrangements by which a bank guarantees a third party (a non-bank) against the insolvency of its client. The second category of off-balance sheet items are credit substitutes, such as guarantees for the good payment of credit facilities granted by another intermediary. When computing exposures stemming from guarantees we applied the following regulatory-weights: 100% to guarantees having financial nature, and 50% to guarantees having commercial nature.

6.1.3 Financial derivatives

Within the CRR framework,[13] financial derivatives are taken into account for the computation of the counterparty risk, which represents a separate building block of the total capital requirements and is not included in the credit risk. The NCR allows an estimation of the net positive value of financial derivatives, which corresponds to the credit risk exposure of a bank portfolio stemming from financial derivatives.

Banks' exposure from financial derivatives is obtained using an approximation of the market approach.[14] Swaps contracts represent the largest proportion of derivatives used by non-financial

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[12] The threshold masks performing loans having an amount of total credit granted to a borrower lower than 30,000 Euros. This means that the Credit Register can report performing exposures lower than 30,000 Euros only in case there is an undrawn credit portion.

[13] See Regulation (EU) No 575/2013 of The European Parliament and of The Council, Art. 92, Title II, Chapter 6 (Art 271 and following) and Annex II.

[14] For financial derivatives, the computation of exposure at default under the market approach is as follows: EAD = CRC + PFCE, where: CRC is the Current Replacement Cost, and PFCE is the Potential Future Credit Exposure. From the NCR we were able to obtain the Current Replacement Cost of the contract, while the potential future credit exposure cannot be computed and it is omitted from the EAD.

firms (more than 90%). Interest rates (approximately 90%), foreign exchange rates and currencies (approximately 9%) represent the categories most often underlying these contracts. Medium to large-size firms, which are often highly levered, are the typical users of these contracts for hedging purposes (Graziano, 2012).

6.1.4 Bonds

Corporate bonds account for a residual proportion of the total exposures of banks towards non-financial firms. Though, bonds tend to be used by particular types of firms and sectors and their market is particularly concentrated both from the firm and from the bank side. Securities were selected when appearing both in the banking and in the trading book portfolios. This choice derives from the fact that the attribution of a security to a particular accounting portfolio does not change the nature of the risk itself. The computation of all corporate debt securities within the credit portfolio of banks represent a more conservative and therefore preferable approach for the evaluation of credit risk.

6.1.5 Undrawn credit facilities

Within the framework of the Capital Requirements Regulation, the undrawn portion of a credit line can contribute to the total amount of the exposure towards a counterparty. Credit register data on loans served as the basis for the production of figures concerning undrawn credit facilities, in particular:

- Undrawn portions of term-loans with original maturity of more than one year have been computed into the total exposure with a weight of 50%;
- Undrawn portions of term-loans with original maturity of less than one year have been computed into the total exposure with a weight of 20%;
- Undrawn portions of revolving loans and overdrafts have been weighted 0%.

Table 3.LGD estimation results

Variable	IRB - Bank	Non - IRB Bank
Constant	0.87***	0.96***
Log(Exposure)	-0.02***	-0.02***
Guarantee coverage *ratio*	-0.06***	-0.09***
Size		
(base group: Sole proprietorship)		
Small firms	0.01***	0.01***
Medium and big firms	0.04***	0.03***
Type of guarantee:		
(base group: No guarantees)		
Real	-0.19***	-0.18***
Personal	-0.00	0.02***
Pledges	-0.05***	-0.05***
Other	-0.08***	-0.01
Multiple guarantees	-0.10***	-0.07***
Sectoral dummies	Yes	Yes
Geographical dummies	Yes	Yes
Bank dummies	Yes	No
Observations	258199	258199
R-squared	0.21	0.10

Table 3 reports OLS estimates of model in (3) both for IRB and Non – IRB Banks.

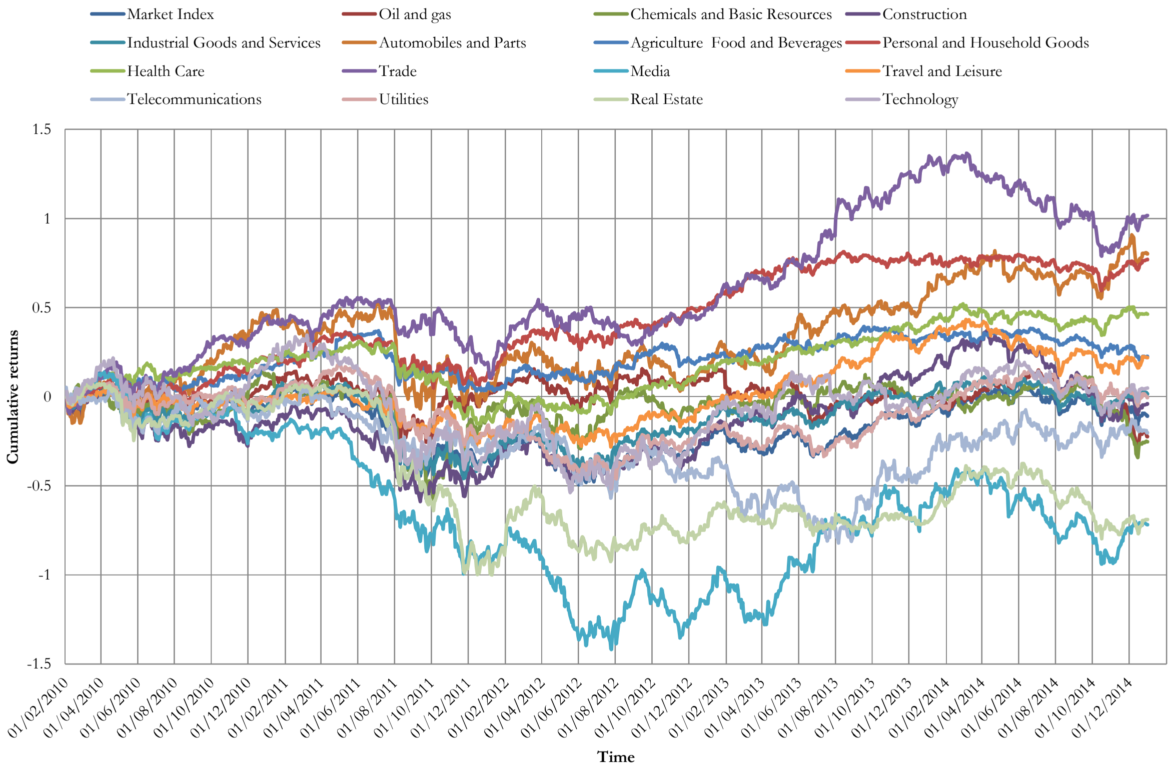

Figure 8. FTSE - Italy Supersectors indices

Figure 8 plots cumulative returns of FTSE Italy sectoral indices for the time period spanning from 2010-01-31 to 2014-12-31. As it is apparent from the graph the performance of different sectors was very heterogeneous. Worst performance were achieved by Real Estate (-0.68), Media (-0.71), Chemicals and Basic Resources (-0.25), in contrast best performance were recorded by Trade (+1.02), Automobiles and Parts (+0.80), Personal and Household Goods (+0.77).

Table 4. Equity correlations by sector

	Chemicals	Automobiles	Agriculture	Technology	Health Care	Household G.	Industrial G.	Media	Oil and G.	Travel	Real Estate	Trade	Construction	Telecom.	Utilities	Others (Market)
Chemicals	1															
Automobiles	0.46	1														
Agriculture and Food	0.4	0.46	1													
Technology	0.45	0.48	0.41	1												
Health Care	0.35	0.47	0.43	0.48	1											
Household Goods	0.49	0.55	0.56	0.56	0.54	1										
Industrial Goods	0.59	0.65	0.56	0.64	0.55	0.69	1									
Media	0.46	0.55	0.4	0.52	0.45	0.54	0.65	1								
Oil and Gas	0.66	0.56	0.51	0.55	0.46	0.6	0.73	0.57	1							
Travel	0.46	0.56	0.46	0.5	0.48	0.58	0.63	0.56	0.57	1						
Real Estate	0.37	0.48	0.38	0.46	0.44	0.45	0.55	0.51	0.49	0.49	1					
Trade	0.39	0.46	0.42	0.46	0.43	0.54	0.54	0.47	0.48	0.46	0.44	1				
Construction	0.52	0.63	0.5	0.61	0.53	0.61	0.75	0.65	0.65	0.64	0.57	0.52	1			
Telecommunications	0.39	0.41	0.36	0.4	0.42	0.44	0.55	0.49	0.49	0.48	0.4	0.32	0.49	1		
Utilities	0.53	0.55	0.57	0.55	0.53	0.6	0.75	0.58	0.7	0.62	0.53	0.46	0.66	0.58	1	
Others (Market)	0.64	0.69	0.6	0.66	0.58	0.69	0.86	0.72	0.84	0.7	0.62	0.56	0.8	0.65	0.88	1

Table 4 reports GARCH-DCC sectorial correlations estimates at December 2014 based on FTSE - Italy Supersectors indices. Daily log return data for the period spanning from 2010-01-31 to 2014-12-31 were utilized.

Table 5. PD and LGD by sector

	Average PD	Average LGD	Weighted Average PD	Weighted Average LGD
Oil and Gas	3.0%	78.4%	0.7%	68.2%
Chemicals and Basic Resources	5.9%	66.4%	3.1%	54.6%
Construction	10.0%	63.4%	8.5%	47.5%
Industrial Goods and Services	6.3%	64.8%	4.2%	52.8%
Automobiles and Parts	7.3%	68.5%	4.6%	58.4%
Agriculture, Food and Beverages	6.1%	56.5%	4.5%	44.5%
Personal and Household Goods	6.5%	67.0%	3.9%	57.0%
Health Care	5.1%	51.5%	3.6%	40.1%
Trade	6.9%	66.7%	4.5%	56.7%
Media	6.4%	68.8%	3.4%	55.4%
Travel and Leisure	9.0%	58.5%	7.0%	42.1%
Telecommunications	6.7%	68.4%	1.2%	50.9%
Utilities	4.8%	55.3%	4.7%	41.0%
Real Estate	7.1%	51.1%	6.1%	36.8%
Technology	5.2%	69.9%	3.4%	59.4%
Other Sectors	7.5%	57.8%	5.1%	46.5%

Table 6. Sectoral Exposure and PD by Bank Size

	EXP		Average PD	
	Large Banks	Minor and Small Banks	Large Banks	Minor and Small Banks
Industrial Goods and Services	0.207	0.149	0.059	0.067
Trade	0.146	0.154	0.065	0.072
Construction	0.126	0.160	0.095	0.099
Real Estate	0.109	0.127	0.066	0.068
Agriculture, Food and Beverages	0.080	0.115	0.060	0.062
Chemicals and Basic Resources	0.076	0.048	0.052	0.067
Utilities	0.063	0.039	0.045	0.049
Other Sectors	0.047	0.042	0.058	0.072
Personal and Household Goods	0.032	0.070	0.087	0.088
Travel and Leisure	0.031	0.032	0.073	0.076
Automobiles and Parts	0.024	0.029	0.068	0.075
Health Care	0.018	0.017	0.050	0.051
Technology	0.018	0.010	0.048	0.055
Oil and Gas	0.013	0.003	0.029	0.035
Telecommunications	0.007	0.001	0.067	0.069
Media	0.005	0.003	0.060	0.070