DOI: 10.1111/eufm.12138

ORIGINAL ARTICLE

WILEY EUROPEAN FINANCIAL MANAGEMENT

Credit risk in banks' exposures to non-financial firms

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Abstract

This paper outlines a framework based on microdata and a structural model to gauge credit risk in banks' exposures to non-financial firms. Sectoral risk factors are accounted for using a multi-factor model. We use expected and unexpected losses as indicators of credit risk stemming from the corporate sector as a whole, and we put forward a measure of systemic risk relevance of economic sectors. We apply the model to the Italian economy, showing the sensitivity of credit risk indicators to different characteristics of default risk, cyclicality and concentration of economic sectors.

KEYWORDS

credit risk, sectoral risk, systemic risk, structural multi-factor model

JEL CLASSIFICATION

*G*21, *G*32

The authors are thankful to Giorgio Gobbi, Valerio Vacca, Antonio Di Cesare and Francesco Columba for their time and effort in reviewing the paper, and to Carmelo Salleo and Alessio De Vincenzo, who co-ordinated the ESRB Expert Group on Sectoral Risk where a prototype of the work was prepared. Special thanks to Marco Orlandi for providing the authors with constructive comments and references, and to participants at the 2015 Banking Research Network workshop at the Bank of Italy in Rome and participants at the 2016 EFMA Annual Meeting in Basel. Furthermore, the authors are grateful to two anonymous referees and to the Editor John Doukas for helpful suggestions and comments. The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the Bank of Italy or of the Eurosystem. All errors are our own.

1 | INTRODUCTION

Past episodes of banking crises have highlighted the role that credit risk plays in undermining the stability of the banking system (BCBS, 2004). In downturn scenarios, increased correlation of defaults across different borrowers may cause severe losses in credit portfolios, hampering the lending capacity of banks and possibly imposing capital adjustments. Consequently, modelling credit risk has become an increasingly important topic, prompting new research into forward looking indicators that provide estimates of losses in adverse scenarios.

Dependence between defaults of different firms can be caused by fundamental factors, including: direct links between firms such as trade credit, and indirect links such as the exposure to the same markets. Moreover, sectoral or geographical factors may influence the default risk of otherwise unrelated firms (Lucas, 1995). In a diversified economy, it is therefore desirable to model default risk as being driven by multiple risk factors, as opposed to assuming a single risk factor driving correlations across borrowers (Gordy, 2003).

This paper outlines a framework to measure credit risk stemming from banks' exposures to the corporate sector as a whole. We account for the role played by sectoral risk factors using a multi-factor model with microdata. In our framework, we group banks' exposures into portfolios by economic sector and estimate the distribution of the potential losses for each sectoral portfolio. We characterize the loss distributions using two indicators: the expected loss and the unexpected loss, which capture losses in the average and adverse scenarios, respectively. In addition, the share of unexpected loss attributable to a sector is suggested as an indicator to assess the contribution to systemic risk of that sector.

The structural modelling approach used in this paper has found wide consensus in risk management, given its flexibility in the modelling of default dependence, i.e., the probability of joint defaults, which is key in financial stability analysis due to its role in determining the severity of losses in adverse scenarios. However, to date the lack of data has posed a challenge for the use of structural modelling in financial stability surveillance.

In the empirical section, we apply the model to the case of the Italian corporate sector as a whole and to a set of sectoral sub-portfolios. We show that expected losses in sectoral portfolios are not homogeneous, and that differences across sectors arise mostly from probabilities of default, which display a greater variability than recovery rates. Exposures in the property sectors display a remarkably higher default risk compared to other sectors. Unexpected losses also display great variability across sectors, and they are positively associated with the cyclicality of a sector.

Large sectoral portfolios (in term of exposure), contribute more than others to the credit losses of the aggregate corporate portfolio. However, consideration of other metrics, such as cyclicality and concentration, is also important to assess the systemic risk relevance of a sector. For instance some sectors, such as Construction, show a contribution to the unexpected loss of the aggregate Italian corporate portfolio which is markedly higher than its share of debt. To sum up, the analysis shows that the size of a sectoral portfolio is an insufficient metric to assess the systemic risk relevance of a sector, as the impact of a sector on losses in adverse scenarios depends crucially on its correlation with the rest of the economy.

Our work relates to a number of studies on credit risk. Using a macroeconomic approach Virolainen (2004) proposes a credit risk model that links 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. Duellmann & Masschelein (2006) estimate the potential impact of sector concentration on the economic capital using German data. As in our work, credit risk is measured via a structural multi-factor model using Monte Carlo simulations. Closely related to our work is Tola (2010), where a multi-risk factor model, as in Pykhtin (2004), is used, allowing for a number of risk factors equal to the number of geo-sectoral clusters obtained from data on corporate defaults.

We contribute to the literature adding new evidence on credit risk indicators based on portfolio theory. In particular, we estimate forward looking indicators that provide measures of losses in normal and adverse scenarios. We show that accounting for sectoral risk factors leads to credit risk indicators that differ from estimates based on single-factor model, and relatively larger differences arise for cyclical sectors. In the empirical section, we test the robustness of the multi-factor model and we show that it captures actual default correlation with great accuracy. Taken together, these findings advocate for the use of the multi-factor model to spot credit risk concentration in particular sectors, an issue which is gaining attention in macroprudential analysis. Another contribution of this work is given by our measure of the systemic risk relevance of a (variously defined) sub-portfolio. This measure can help to identify the economic sectors which might play a relevant role for the stability of the banking system in downturn scenarios, contributing more than others to potential losses. As an example, recently a few European countries have taken macroprudential measures to address vulnerabilities stemming from excessive credit growth and risk taking, and these materialized in the form of increased risk weights on credit exposures to the real estate sector (see ESRB, 2015).

The paper is organized as follows: Section 2 outlines the model and credit risk indicators; section 3 presents the empirical application and section 4 concludes.

2 | METHODOLOGY

2.1 | The model set-up

In a diversified economy, business conditions are not fully synchronized across industries so that multiple not fully correlated risk factors drive the dynamic of default risk for the entire economy. The identification of the risk factors which determine the default dependence is, however, a challenging task. Data limitations and the complexity of the specification of joint default probabilities have led to credit risk models that assume a specified exogenous dependence structure (Schönbucher, 2000).

There is evidence that defaults of non-financial firms display positive dependence within and across industries (Das et al., 2007; De Servigny & Renault, 2002; Saldías, 2013). In addition, similarities in the characteristics of firms belonging to the same sector and commonality of risk factors affecting their performance seem a reasonable and intuitive explanation for why (latent) sectoral risk factors can be employed to model the dependence structure of defaults. Unlike the asymptotic single risk factor (ASRF) model in the Basel framework, which might simplify the effective default dependence amongst borrowers (see McNeil et al., 2015), we model credit risk allowing for a richer dependence structure by considering multiple risk factors that affect borrowers depending on their industry affiliation.

We use a structural multi-factor model as in Duellman & Masschelein (2006) and Duellman & Puzanova (2013), as prompted by the seminal work of Merton (1974). Default dependencies are driven by composite latent risk factors $\boldsymbol{Y}$, affecting the standardized asset return $X_{i,s}$ of a firm i belonging to a sector s:

$$X_{i,s} = r_i Y_s + \sqrt{1 - r_i^2}\varepsilon_{i,s}, \ \ \varepsilon_{i,s} \overset{iid}{\sim} N(0,1) \tag{1}$$

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

where $r_i \in (0,1)$ is the factor loading which relates a firm's asset returns to the dynamic of a latent sectoral factor, ε_i *iid* is an idiosyncratic risk component. The composite risk factors $\boldsymbol{Y}$, one for each sector, are expressed as linear combinations of K *iid* standard normal factors $\boldsymbol{Z}$, which represent as many elementary risk factors as the number of sectors ($K = S$). The coefficients $\alpha_{s,k}$ are obtained by the Cholesky decomposition of the correlation matrix of the sectoral risk factors; the correlation between asset returns of two firms i and j is then $\rho_{i,j} = r_i r_j \sum_{k=1}^{K} \alpha_{i,k}\alpha_{j,k}$, and depends on the strength with which a sector is correlated with the others.

A default is triggered when a firm's standardized asset return is below the threshold implied by the probability of default (PD) for that firm:

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

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

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

where I_s is the number of borrowers in sector s, EXP is the credit exposure and LGD the loss given default. The implementation of the model requires a large set of data, including: PD at borrower level, exposures and LGD at loan level, the correlation matrix $\alpha_{s,k}$ of sectoral risk factors and the factor loadings r_i. However, given the uncertainties of estimating factor loadings at firm level for non-listed firms, due to the low frequency and accounting nature of the data available, we assume a homogeneous factor loading equal to 0.5 for all sectors, as in Duellman & 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 a given time is a random variable that can be decomposed as the product of three elements:

$$L_i = D_i \cdot EXP_i \cdot LGD_i$$

where $D_i \sim Ber(PD_i)$ is a binomial variable that assumes value one 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. 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:

$$EL \equiv E[L] = \Sigma_i E[L_i] = \Sigma_i \, PD_i \cdot EXP_i \cdot LGD_i$$

$$UL \equiv ES - EL.$$

The estimation of expected losses is straightforward, conditional on the availability of individual PD and LGD. In contrast, the calculation of other moments of the loss distribution may involve considering the dependence between individual losses. In our set-up, the default event is the only uncertain component, while credit exposures and *LGD* are considered as non-stochastic. By doing so, we relax previous assumptions on the homogeneity of *PD* and *LGD* (see Duellman & Masschelein, 2006; and Tola, 2010).

The *ES* of the potential loss *L* for the confidence level *q* of a portfolio is defined as:

$$ES_q(L) = E\left[L \middle| L \geq VaR_q(L)\right].$$

We assess systemic risk relevance of economic sectors by estimating their contribution to losses in adverse scenarios for the aggregate Italian corporate portfolio. We do so by decomposing the system-wide ES into Marginal Contributions (*MC*), an indicator that measures t share of ES attributable to sub-portfolios (Duellman & Puzanova, 2011; Tasche, 2008). With w_s indicating the relative weight of a sub-portfolio that aggregates the exposures in sector *s*, *MC* is as follows:

$$MC_s = \mathrm{w_s} \frac{\partial}{\partial \mathrm{w_s}} ES_q(L_{\mathrm{tot}}) = E\left[L_s | L_{tot} \geq VaR_q(L_{tot})\right]. \tag{3}$$

Therefore, the share of *UL* arising from a sector is:

$$UL_s \ = \ MC_s - EL_s. \tag{4}$$

We use the ratio between UL_s and the unexpected loss of the aggregate corporate portfolio as a measure of systemic relevance of economic sectors.

3 | EMPIRICAL APPLICATION

3.1 | Data

We apply the model to the case of the Italian corporate sector. Given the importance of banking credit for corporate financing in Italy, we focus on bank indebtedness of non-financial firms. We mapped Italian firms into sectors using the Industrial Classification Benchmark (ICB), which is commonly used by stock market indices. When a direct association was not possible, firms were aigned to *Other Sectors*. We assume that all borrowers, including diversified firms, can be uniquely assigned to individual business sectors.

Our dataset consists of a cross section of firm-bank level data on credit exposures, *PD* and *LGD* for the year 2015. Credit exposure of Italian banks towards non-financial firms based in Italy was gathered from different sources: the Italian National Credit Register (CR) provided us with individual exposures, as well as on- and off-balance sheet items, and financial derivatives which are exposures typically overlooked in similar analysis. In addition, supervisory reports provided us with corporate debt securities holdings by banks; limiting our sample to domestic exposures has a negligible impact on the conclusion of the analysis, given that transactions of domestic Italian banks with non-residents amount to less than 2% of total exposure.

The distribution of banks' credit exposure across economic sectors is not even, with a few sectors accounting for about half of corporate indebtedness (Table 1). As of December 2015 the most relevant sectors are Industrial Goods and Services (20%), Trade (14%), Construction (12%) and Real Estate (11%). The shares of remaining sectors range from 1% to 9% with Media (0.4%), Telecommunications (0.9%), and Oil and Gas (1.5%) representing the smallest exposures. The distribution of banks' credit exposure across sectors is a scarcely investigated topic, and the

TABLE 1 Corporate indebtedness by sector

Table 1 reports corporate indebtedness by sector, as sourced from the National CR at December 2015. Stock market indices and the National CR 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, firms were assigned to Other Sectors. We assume that all borrowers, including diversified firms, can be uniquely assigned to individual business sectors.

Sector	EXP %	No. of firms	No. of banks	HHI borrowers	HHI banks
Industrial Goods and Services	20.2%	211,967	510	0.3%	9.0%
Trade	14.4%	244,314	508	0.1%	7.2%
Construction	11.8%	146,182	507	0.2%	6.8%
Real Estate	11.2%	82,656	492	0.2%	6.2%
Agriculture, Food and Beverages	8.7%	114,987	502	0.0%	6.0%
Chemicals and Basic Resources	6.7%	30,988	480	0.1%	8.7%
Utilities	5.7%	9,771	467	0.3%	10.6%
Personal and Household Goods	4.5%	43,137	484	0.1%	8.4%
Travel and Leisure	4.0%	83,377	499	0.1%	4.8%
Other Sectors	3.5%	72,876	503	0.4%	7.1%
Automobiles and Parts	3.1%	36,790	491	1.2%	5.4%
Health Care	1.8%	24,969	465	0.4%	10.0%
Technology	1.6%	20,550	466	0.8%	10.2%
Oil and Gas	1.5%	234	143	22.2%	10.1%
Telecommunications	0.9%	879	188	48.2%	14.2%
Media	0.4%	3,746	321	2.2%	11.0%
Total	100%	1,127,423	511	0.0%	7.4%

international evidence provides limited examples as a term of comparison. Our finding is similar to the case in Holub Nyklicek, & Sedlar (2015), where some sectors, namely Real Estate, have a prominent role in banks' credit exposure although they account for a small fction of the economic production. In other cases, however, there is also evidence of an overlap between corporate debt and GDP distribution, this is the case for the oil producer countries wre concentration risk is present (IMF, 2014). While results for Italy do not indicate excess concentration, they point to a variety of demand and supply factors which might explain the observed distribution of banks' credit amongst economic sectors, including: firm size and financial soundness, firms' direct access to capital markets (e.g., Media, Telecommunications, and Oil and Gas firms show low dependence from banks' credit because of their size and direct access to capital markets), firms' capital structure choices, the availability of collateralizable assets and henceforth the willingness of banks to support industries with more collateral (e.g., Real Estate and Construction). In addition, banks' lending decisions may follow a precise strategy, for example sectoral exposure might correlate to a scenario where the likelihood of being bailed-out is maximized; i.e., when other systemically important banks are distressed (in the spirit of the model proposed in Farhi & Tirole, 2012).

Firm-level probabilities of default were retrieved from the Bank of Italy In-house Credit Assessment System (BI-ICAS). These are 1-Year point-in-time probabilities of default of Italian non-financial firms available on a monthly basis.[1] Loss Given Default figures were estimated at the level of individual exposure using the Archive of Losses on defaulted positions available at the Bank of Italy (BI-AoL).[2]

Finally, risk factor correlations used by the multi-factor model in equation (1) are estimated from equity indices as in Servigny & Renault (2002) and Duellmann et al. (2010).[3] We estimated equity indices correlations based on $GARCH - DCC$ model as prompted in Engle (2002) and recommended in Duellman & Puzanova (2013) when dealing with portfolio credit risk models. We employ log return series of FTSE Italy Supersectors indices at daily frequency. Table 2 reports $GARCH - DCC$ sectoral correlations estimates at December 2015. Estimated correlations among sectoral equity indices are positive, and range from 0.75 for Industrial Goods and Services and Utilities (or Constructions) to 0.32 for Trade and Telecommunications. Certain sectors show low sensitivity to the overall performance of the market, as they report low correlations against the market index and the other sectors; this is the case for Chemicals, Agriculture, Health Care and Trade. In contrast, Industrial Goods and Services, Oil and Gas, Construction and Utilities show high cyclicality. It is worth noting that no sector is strictly countercyclical, i.e., correlations never turn to negative values.

3.2 | Sectoral risk indicators

We estimate the set of credit risk measures for Italian banks' corporate portfolio as a whole. Corporate exposures were grouped in 16 portfolios using ICB sectoral classification, and for each portfolio the loss distribution is summarized using the *EL* and *UL* measures described above. FIGURE 1 reports *EL* rate, which is the product between firm-level *PD* and exposure-level *LGD*. and represents a measure of the expected loss per unit of capital. At the level of the aggregate corporate portfolio, at the end of 2015 *EL* accounts for about 2.1% of total exposure, although there are substantial differences aoss sectors. Among the largest sectoral portfolios, Construction and Real Estate exhibit *EL* above the average, while Industrial Goods and Services and *Trade* present *EL* below the average.

Differences in *EL* rate across sectors arise mostly from probabilities of default, which show greater variability than recovery rates. Exposures in the property sectors, *Construction* and *Real Estate*, display a remarkably higher default risk when compared to other sectors; probabilities of default average around 8.5% and 5.6% for these sectors while the rest of the economy averages around 4%. This finding is consistent with the outlook of default rate series for the Italian economy; notwithstanding the conjunctural improvement recorded since 2014, the construction sector is sll hhly vulnerable to default risk compared to the rest of the economy (ABI-Cerved, 2016).

[1]A Basel III compliant definition of default is used to calibrate the model which uses information sourced from financial statements, the National CR and geo-sectoral information. The statistical model underlying BI-ICAS is a reduced form logit model which combines two credit scores obtained from a set of financial and credit variables at the level of individual firms.

[2]A regression model for LGD estimates was calibrated using data from the BI-AoL (see Appendix 1). This dataset spans from 1997 to 2015 and covers recovered amount on defaulted exposures, characteristics of the single exposure (such as the type and amount of collateral) and of the borrower (sector and geographic area).

[3]In structural credit risk models, asset correlations are estimated following two different approaches: using correlations between equity indices, or extracting asset correlations from observed default series. Empirical studies acknowledge that default implied asset correlations tend to be small and below those estimated using equity correlations (Tola, 2010; Zhang, Zhu, & Lee, 2008); as a consequence, they lead to less conservative estimates of extreme losses. Given the small sample size of our default dataset, spanning from 2005 to 2015, the bias in default correlation estimates is potentially high; as a result, we relied on equity indices correlations as proxies for asset correlations.

TABLE 2 Equity correlations by sector

Table 2 reports GARCH-DCC correlations estimates at December 2015 based on FTSE-Italy Supersectors Indices. Daily log return data for the period spanning 2010-01-31 to 2015-12-31 were used. The row Market, shows correlations between the FTSE All Share and FTSE Supersectors Indices.

	Chem	Auto.	Agri	Tech	Health C	House	Indust.	Media	Oil and G	Travel	Real Estate	Trade	Construc	Telecom	Utilities	Market
Chem	1															
Auto.	0.46	1														
Agri.	0.4	0.46	1													
Tech.	0.45	0.48	0.41	1												
Health C.	0.35	0.47	0.43	0.48	1											
House.	0.49	0.55	0.56	0.56	0.54	1										
Indust.	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 G.	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				
Construc.	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			
Telecom.	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	
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

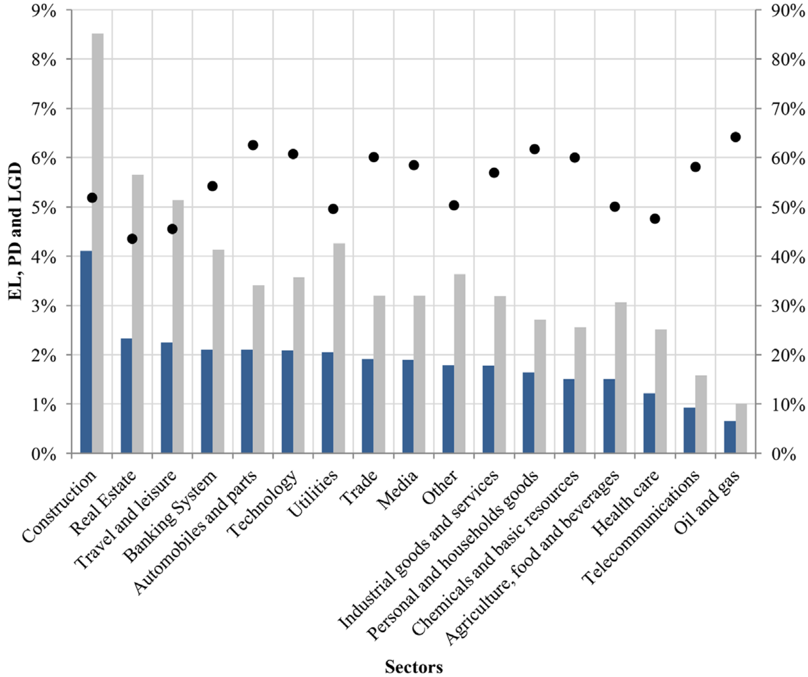

FIGURE 1 Sectoral risk indicators: EL and its components. This figure reports average *EL* rate (dark grey bars, left axis), *PD* (light grey bars, left axis) and *LGD* (black dots, right axis) by sector. Sectors are sorted by decreasing level of *EL* rate. *EL* rate was computed as the product between firm-level *PD* and exposure-level *LGD* at December 2015; *PD* were sourced from the In-House Credit Assessment System of the Bank of Italy, while *LGD* estimates were based on the Archive of Losses on defaulted positions of the Bank of Italy.

Our estimate for *LGD* averages around 54% for the banking system, and is close to the pameter used in previous studies (Carpinelli *et al.*, 2016; Duellmann & Masschelein, 2006; Tola, 2010); however, there is significant variance across sectors which is possibly due to the dferent degree of liquidity of firms' assets. This might explain low recovery rates in sectors ccterized by fm-specific assets such as Oil and Gas (64%), Automobile and Parts (62%) a Telecommunications (58%).

Figure 2 shows *UL* rate on sectoral portfolios estimated using Monte Carlo simulations in model (2). At the level of the aggregate corporate portfolio, *UL* accounts for about 7% of total exposure, and ranges from about 3% for Oil and Gas, Telecommunications and Health Care to 8–11% for Construction, Other Sectors, Automobiles and Parts and Industrial Goods and Services. Among the most relevant sectors in terms of exposure, Construction stands out as the riskiest both in terms of expected and unexpected loss; in addition Industrial Goods and Services display above average *UL*. Differences in *UL* rate across sectors arise from the joint effects of probabilities of default, firms' asset correlations and the concentration in sectoral portfolios. For example, sectoral portfolios cracterized by borrowers of low credit quality tend to face more defaults in negative scenarios. In addition, when firms' assets are highly correlated with the rest of the economy, defaults for that portfolios tend to follow cyclically the states of the economy: in terms of *UL*, Industrial Goods and Services is riskier than Real Estate and Trade despite a lower *EL*, providing an example for a cyclical portfolio characterized by the presence of large a risky exposures. Finally, name concentration increases unexpected losses, as previous sulation studies have shown (Duellman & Masschelein, 2006). We find that Oil and Gas and Telecommunications, characterized by relatively

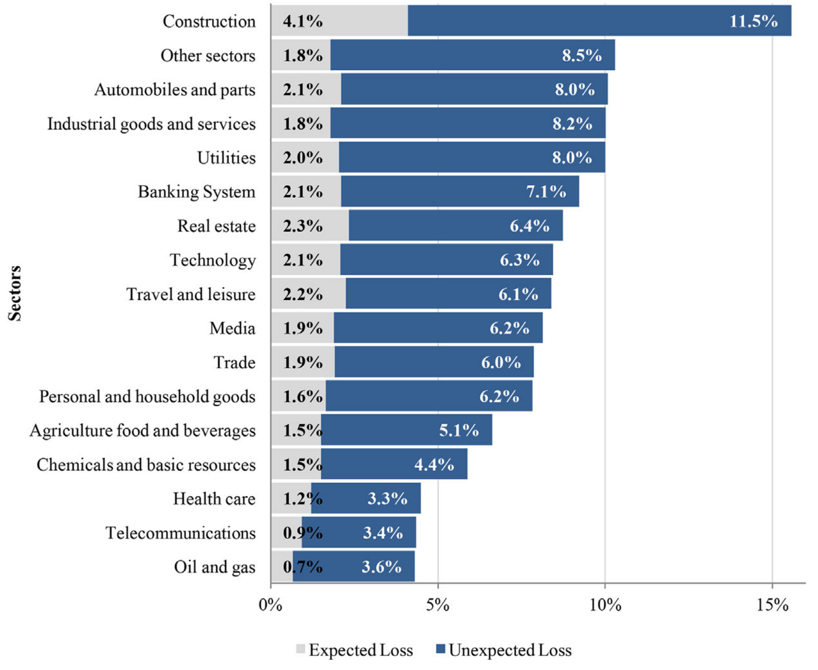

FIGURE 2 **Sectoral risk indicators: EL and UL rates by sector.** This figure reports *EL* and *UL* rates by sector. Sectors are sorted by *UL* rate. *EL* rates were computed as the product between firm-level *PD* and exposure-level *LGD* at December 2015. *UL* rate was computed as the ratio between the sectoral unexpected loss and the sectoral exposure. Expected Shortfall 95% was used as tail risk measure, and was estimated under multi-factor model in (1) and (2) using Monte Carlo simulations. *PD* were sourced from the In-House Credit Assessment System of the Bank of Italy, while *LGD* estimates were based on the Archive of Losses on defaulted positions of the Bank of Italy. Equity indices correlations were used to approximate correlations amongst sectoral risk factors.

higher name concentration, display a markedly high ratio between *UL* and *EL* (about 5.5 and 3.7) compared to the other sectors.

3.3 | Systemic risk relevance indicator

We assess systemic risk relevance of economic sectors by estimating their contribution to uxpected losses for the aggregate corporate portfolio. Firstly, we decomposed the system-wide *ES* into *MC* stemming from each sectoral sub-portfolio, and secondly we calculated unexpected loss for each sector as in (4). Figure 3 reports estimated UL_s as a share of overall *UL* for the year 2015. Compared to the results from the previous section, the UL_s indicator also accounts for the size of a sectoral portfolio in terms of share of total debt; therefore assessment of systemic revance considers both size and riskiness.

Industrial Goods and Services, Construction, Trade and Real Estate are the most relevant sectors, accounting for more than half of overall expected and unexpected losses. These sectors also display very high risk, as measured by *EL* and *UL* rates (see Figure 2) due to a combination of default risk, cyclicality and concentration. In contrast, Media, Telecommunications, Oil and Gas account for the smallest part of credit risk for the aggregate corporate portfolio. The systemic relevance of a sector is influenced by its size; for this reason, relatively less risky sectors such as Agriculture and Chemicals display non-negligible contributions (6–4%, respectively) due to their importance in terms of credit

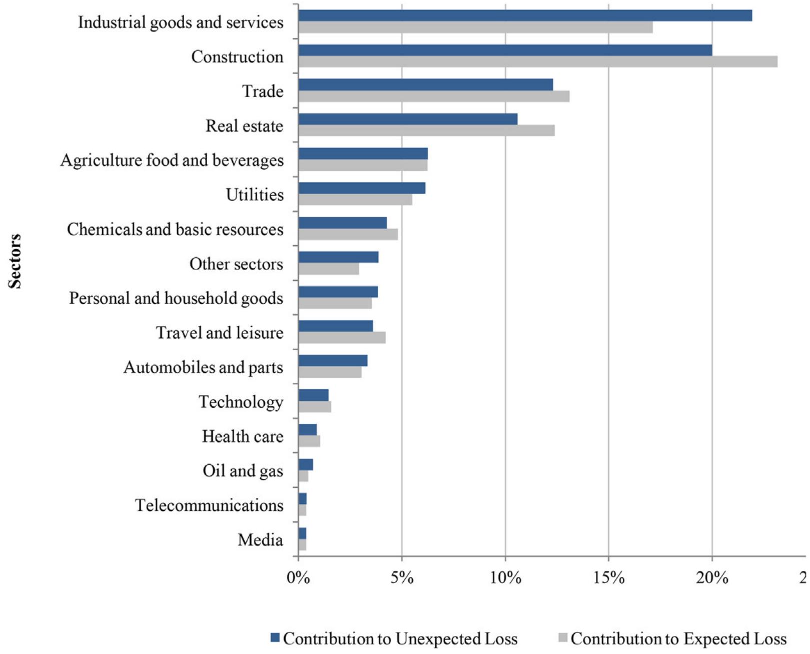

FIGURE 3 Sectoral contribution to EL and UL. This figure reports the incidence of *EL* and *UL* at the sectoral level on the overall *EL* and *UL* stemming from the aggregate corporate portfolio. Sectors are sorted by their contribution to the overall *UL*, calculated using the Expected Shortfall 95% as tail risk measure. *EL* was computed as the product between firm-level *PD*, exposure-level *LGD* and *EXP* at December 2015. *UL* was estimated under multi-factor model in (1) and (2) using Monte Carlo simulations. *PD* were sourced from the In-House Credit Assessment System of the Bank of Italy, while *LGD* estimates were based on the Archive of Losses on defaulted positions of the Bank of Italy. Equity indices correlations were used to approximate correlations amongst sectoral risk factors.

exposure (9–7%). However, size is not a sufficient metric to assess systemic relevance: consideration of other metrics such as default risk, cyclicality and concentration, is also important. For instance, Construction shows a contribution to the unexpected loss of the aggregate corporate portfolio (20%) which is markedly higher than its contribution to exposure (12%).

Using the longitudinal dimension of our dataset, we explored changes over time in system-we expected and unexpected loss and we investigated the sectors that contributed the most to their dynamic. Figure 4 and Figure 5 report *EL* and *UL* for the banking system and for the main sectors as a share of total exposure of the banking system.

Over the time span 2010–15, both expected and unexpected losses from the corporate sector have reduced; in particular, unexpected losses ranged between 7.1% and 9.4%, reaching the peak in conjunction with the Sovereign Crisis in the eurozone. Since 2012 *UL* has declined at a moderate pace (–2.3%) reaching the minimum level since 2010. The Construction sector has played a major role in this dynamic, due to a marked reduction in risk indicators for this industry (2.4% to 1.3%). Other relevant sectors have also experienced improvements, although less sharply. Finally, we note that Industrial Goods and Services, the most relevant sector for the Italian banking system as of December 2015 (Figure 4), has gained major relevance only after 2014, due to the relatively stable credit risk condition for this sector within a context of overall risk decline.

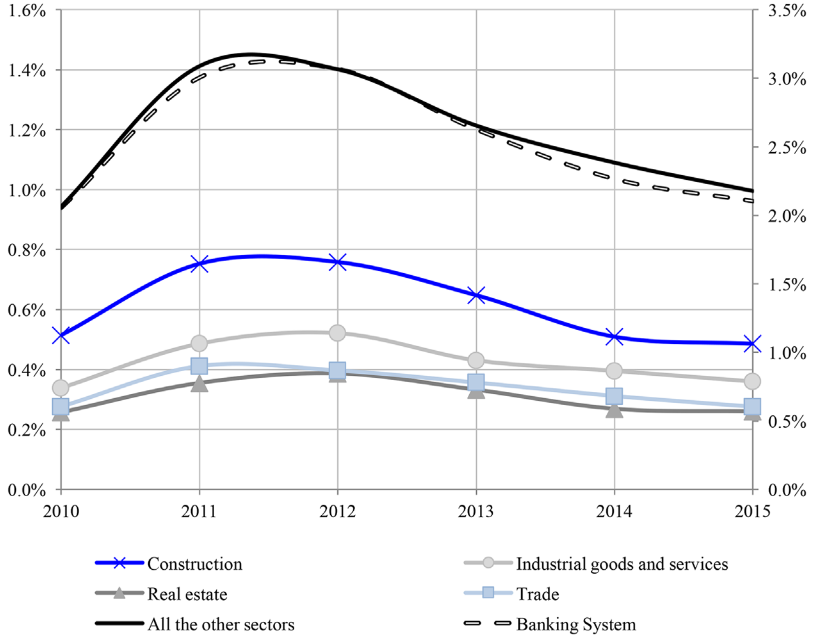

FIGURE 4 EL over time and the main contributing sectors. This figure reports for the time span 2010–15 the ratio between expected loss and the total exposure of the banking system (right axis), and the ratios between sectoral expected losses and the total exposure of the banking system (left axis). *PD* were sourced from the In-House Credit Assessment System of the Bank of Italy, while *LGD* estimates were based on model in (4).

3.4 | Comparison between the single-factor and multi-factor model

To show the sensitivity of unexpected losses to different modelling approaches, we compare estimates of sectoral *MC* under the multi-factor model with those obtained from a single-factor model with homogeneous asset correlation.

In the Basel framework, there are different values for asset correlation (ρ) depending on the size and riskiness of a borrower. For exposures to non-financial firms, ρ ranges between 12–24% and it is inversely related to a firm's *PD*. This parametrization is based on the assumption that for highly risky borrowers, default risk is mostly idiosyncratic and less related to the macroeconomy. As in Duellman & Masschelein (2006) and in Tola (2010) we assume a unique factor loading (r) for all exposures equal to 0.50. In the context of the single-factor model this implies a conservative value for asset correlation equal to 0.25. In contrast, in the multi-factor model, factor loadings were calibrated so that the average assets correlation would equal the single-factor one, with differences across sectors which replicate the cyclicality of different sectors.

Figure 6 compares *MC* measures obtained from the two models. Overall, *MC* estimates are not too sensitive to the chosen default dependence structure: gaps between the single and multi-factor estimates range between −1.8 and +3.7%. However, for some sectors the difference is not negligible. For those sectors that are highly correlated with the rest of the market, such as Industrial Goods and Services and Construction, the multi-factor model estimates for *MC* are greater than the single-factor counterparts. Vice versa less cyclical sectors such as Trade and Real Estate present higher *MC* under the single-factor model.

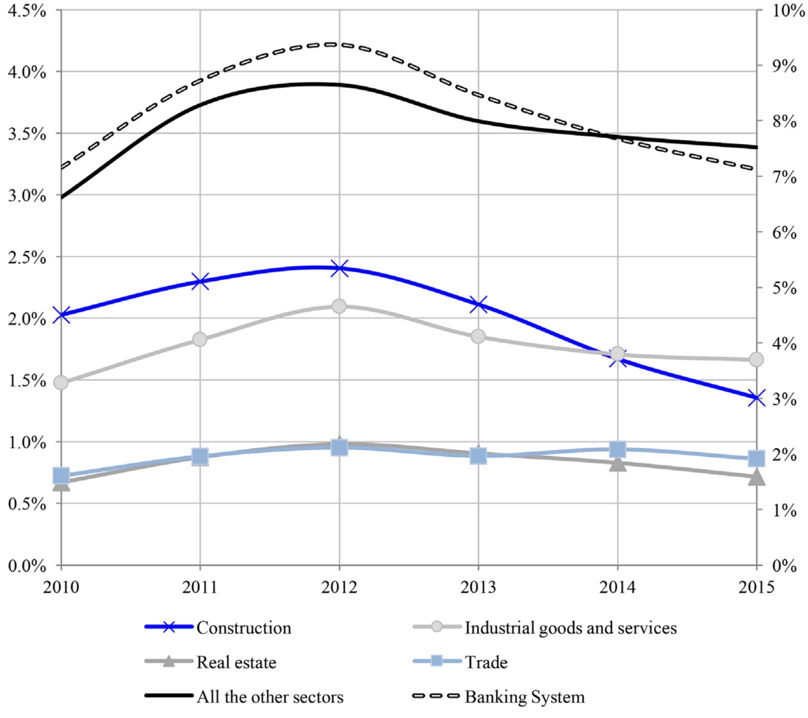

FIGURE 5 UL over time and the main contributing sectors. This figure reports for the time span 2010–15 the ratio between unexpected loss and the total exposure of the banking system (right axis), and the ratios between sectoral unexpected losses and the total exposure of the banking system (left axis). *UL* is estimated under the multi-factor model in (1) and (2) using Monte Carlo simulations. *PD* were sourced from the In-House Credit Assessment System of the Bank of Italy, while *LGD* estimates were based on the model in (4). Equity indices correlations were used to approximate correlations amongst sectoral risk factors.

We test whether the heterogeneous default dependence structure implied by the multi-factor model is closer to observed default data than the homogeneous dependence implied by the single-factor model. We consider a class of validation tests that compares probabilities of default ainst realized default rates under alternative hypotheses of default dependence. We use a test pposed in Resch (2011) based on the Squared Mahalanobis distance (SMD) as in the following equation:

$$SMD(m) = (m - \mu)' \sum (d)^{-1} (m - \mu),$$

where m denotes the realized default pattern, i.e., the number of defaults recorded in each sector; μ represents the expected number of defaults in each sector, i.e., obtained as the average PD times the number of firms in each sector; and $\sum (d)$ is the diagonal default covariance matrix, which represents the hypothesized dependence structure. We estimate default covariance between sector i and j as follows: $N\left(N^{-1}(PD_i); N^{-1}(PD_i), \rho_{ij}\right) - \left(PD_i \cdot PD_j\right)$, using asset correlation ρ_{ij} from section 0. The value of the Mahalanobis distance obtained from realized default is compared to the values of SMD statistic obtained using simulated defaults in each Monte Carlo scenario both under the single and the multi-factor model. The p-value of the test is computed as the probability of simulated SMD values exceeding the realized SMD value. If the p-value is lower than the desired significance level,

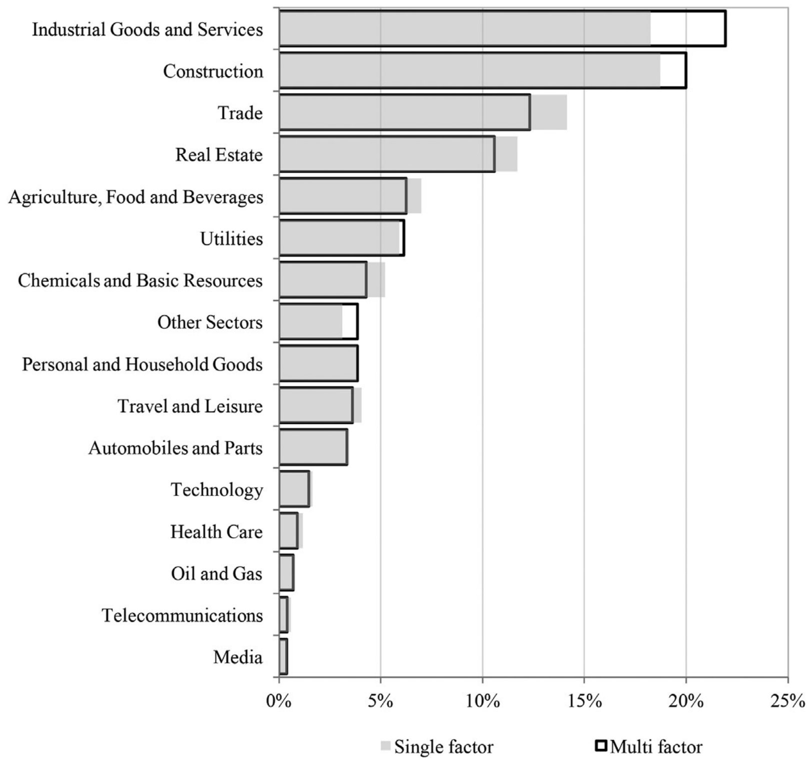

FIGURE 6 Sectoral contribution to *UL*: Single and multi-factor model. This figure reports the ratio of MC_s to the Expected Shortfall of the aggregate corporate portfolio at December 2015. Sectors are sorted based on their MC_s which were computed using Monte Carlo simulations as in (3). Expected Shortfall was estimated under both the single-factor model and the multi-factor model in (1) and (2) using Monte Carlo simulations. *PD* were sourced from the In-House Credit Assessment System of the Bank of Italy, while *LGD* estimates were based on the Archive of Losses on defaulted positions of the Bank of Italy. Credit data were sourced from the National CR while equity indices correlations were used to approximate correlations amongst sectoral risk factors.

we reject the null hypothesis that the model is able to accurately predict the number of defaulting firms in each sector using a specified dependence structure.

We performed the SMD test for the period 2010–14 plugging-in default covariance matrices obtained under the single and multi-factor models and, in both cases, we fail to reject the null hypothesis with p-values of about 0.99 and 0.83, respectively. The difference between the two approaches is small, however the higher p-value showed by the multi-factor model is a piece of evidence in favour of this model, given its greater accuracy in capturing actual default correlation.

4 | CONCLUSION

In a diversified economy, credit risk developments are not fully synchronized across sectors. In downturn scenarios, some economic sectors can play an adverse role in the stability of the banking system due to their size and riskiness, contributing more than others to losses in adverse scenarios.

This paper outlines a framework for measuring credit risk in banks' exposures to non-financial firms which accounts for the role played by sectoral risk factors. A structural multi-factor model as developed in Duellman & Masschelein (2006) is used, allowing for firms' joint default probabilities to depend on their sectoral affiliation. We use expected and unexpected losses as indicators of credit risk stemming from the corporate sector as a whole, and we put forward a measure of systemic risk relevance of sectoral sub-portfolios.

We apply the model to the case of the Italian economy, using a granular firm-bank level dataset covering credit exposure of Italian banks towards non-financial firms, probabilities of default and loss given default. This represents a significant improvement over previous studies which neglected the role of heterogeneity in risk parameters in determining losses in adverse scenarios.

We show that indicators of both average and adverse scenarios losses on banks' corporate portfolios differ across sectors, and their variability is largely accounted for by default risk. However, in the case of adverse scenarios losses, default correlation across borrowers also plays an important role. The systemic risk relevance of a sector is influenced by its size, large portfolios contribute more than others to overall credit losses, however consideration of cyclicality and concentration is also important.

Our contribution is multifold. First, this paper provides a set of forward looking indicators which may help macroprudential analysis of credit risk stemming from the corporate sector, both in normal and adverse scenarios. Second, while both the single and multi-factor models satisfy the usual validation tests, we offer evidence that the multi-factor model beats its single-factor counterpart in explaining actual default correlation in the data. This result points to greater capacity of a multi-factor model in describing the dependence structure across borrowers in large and diversified portfolios. Third, our measure of systemic risk relevance can help to identify the economic sectors which might play a relevant role for the stability of the banking system in downturn scenarios, contributing more than others to potential unexpected losses.

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How to cite this article: Accornero M, Cascarino G, Felici R, Parlapiano F, Sorrentino AM. Credit risk in banks' exposures to non-financial firms. *Eur Financ Manag*. 2017;1–17. https://doi.org/10.1111/eufm.12138

APPENDIX 1

TABLE A1 LGD estimation results

Table A1 reports OLS estimations with HAC standard errors of loss given default. The dataset was retrieved from the archive of losses on defaulted positions available at the Bank of Italy (BI-AoL).

Variable	Coeff.
Constant	0.24***
Log (Exposure)	–0.01***
Size (base group: Sole proprietorship)	
Small firms	–0.02***
Medium and big firms	0.01***
Guarantee coverage ratio	–0.04***
Type of guarantee (base group: No guarantees)	
Real	–0.17***
Personal	–0.07***
Pledges	–0.16***
Other	–0.03***
Multiple guarantees	–0.13***
Sector (base group: Other)	
500. Oil and Gas	–0.08**
1000. Chemicals and basic resources	0.03***
2300. Construction	0.04***
2700. Industrial goods and services	0.03***
3300. Automobiles and Parts	0.05***
3500. Agriculture, food and beverages	–0.05***
3700. Personal and household goods	0.08***
4500. Health Care	–0.10***
5300. Trade	0.04***
5500. Media	0.03***
5700. Travel and leisure	0.01***
6500. Telecommunications	–0.09***
7500. Utilities	–0.03***
8600. Real estate	–0.03***
9500. Technology	0.03***
Geographical fixed effects	yes
Bank fixed effects	yes
Observations	1,789,051
R-squared	0.19