



IFC-ECCBSO-CBRT Conference on "*Uses of Central Balance Sheet Data Offices' information*"

Co-organised by the IFC, the European Committee of Central Balance Sheet Data Offices (ECCBSO) and the Central Bank of the Republic of Turkey (CBRT)

Özdere-İzmir, Turkey, 26 September 2016

Sectoral risk in the Italian Banking System¹

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¹ This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Sectoral Risk in the Italian Banking System¹

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Abstract

We apply a structural multi-factor credit risk model to assess the importance of sectoral risk for the Italian banking system. Using a unique and detailed supervisory dataset, we estimate the credit risk stemming from exposure of Italian banks to different sectors of the economy. We provide estimates of standard credit risk measures, such as expected and unexpected losses, and we investigate the contribution of each sector to credit risk as a whole. We identify the sectors which could pose a threat to the stability of the banking system, highlighting the macro-prudential actions that could be envisaged.

Keywords: Sectoral risk, Systemic risk, Structural Multi-Factor Model.

JEL classification: G21, G32.

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¹ This article is based on the results of a working paper of the same authors circulated as "Credit Risk in the Banking System: an Application to Sectoral Risk in Italian Banks".

Introduction²

In a large and diversified economy, business conditions tend to be different in different sectors. Profitability, investment opportunities and risks might follow different paths across sectors, leading to a diversified level of default risk for borrowers belonging to different sectors. Accordingly, the dynamic of defaults for the entire economy is better described when accounting for multiple sectoral risk factors (De Servigny and Renault, 2002; Das et al., 2007; Saldías, 2013).

In credit risk modelling, the contribution of these latent sectoral risk factors, influencing the correlation of defaults among firms, is defined "sectoral risk". As such, sectoral risk represents an additional risk component in credit portfolios, arising when there is a concentration of borrowers in a sector; however currently no specific capital requirement is prescribed.³ Sectoral risk might represent a threat for the stability of the banking system when capital requirements for exposures to a particular sector are significantly misaligned with respect to those that take into account sectoral risk.

In this paper we outline a methodological framework for the analysis of sectoral risk for macroprudential purposes. We analyse the corporate exposure of the Italian banking system and we estimate for each sector a set of credit risk measures, including: expected and unexpected losses. Moreover, we estimate the marginal contribution to total losses of each sector and we suggest this measure as an indicator that approximates the systemic relevance of economic sectors.

Assessing the impact of sectoral risk in macroprudential analysis is a relevant and relatively new perspective in financial stability monitoring. The European Systemic Risk Board identified, among others, the risk of excessive credit growth and sectoral risk as intermediate macro-prudential objectives relevant to the banking sector (see ESRB, 2014). The current regulatory framework for banking supervision in Europe provides to macroprudential authorities a differentiated set of tools to monitor and contain systemic risk arising from different sources.⁴ Among these tools sectoral risk weights are aimed at offsetting the risk that credit institutions may be excessively exposed to risk sources linked to a specific sector or to sectors highly correlated. A few European countries have taken macro-prudential measures in this regard, and existing measures have targeted only the real estate sector via increased risk weights (see ESRB, 2015).

Sectoral risk analysis can benefit from the availability of micro data on credit portfolios. In particular, the capacity of supervisors to use promptly macroprudential

² We thank all the participants to the ECCBSO/IFC/CBRT conference "Uses of Central Balance Sheet Data Offices' Information" held in CBRT Premises, Özdere-İzmir, September 26 th 2016 for useful comments and suggestions. We also thank Giorgio Gobbi and the members of the Financial Stability Directorate. All errors are our own. The views expressed in this paper are solely of the authors and do not necessarily reflect those of the Bank of Italy or of the Eurosystem.

³ The current Basel framework for credit risk is based on an Asymptotic Single-Factor (ASRF) model (see BCBS 2005).

⁴ The main regulatory references are the following: Directive 2013/36/EU on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms; (CRD IV); Regulation (EU) No 575/2013 on prudential requirements for credit institutions and investment firms (CRR); Regulation (EU) No 1024/2013 conferring specific tasks to the European Central Bank concerning policies relating to the prudential supervision of credit institutions.

tools depends also on the quality, granularity and timeliness of the information, and on the availability of models to use this information wisely.

In this paper we identify those sectors that account for most of the credit risk exposure for the Italian banking system, including those relatively more risky due to their cyclical and default risk vulnerability. In terms of systemic relevance, *Industrial Goods and Services, Construction, Trade and Real Estate* are the most relevant sectors for the Italian banking system. This ranking is mainly determined by the size of the credit exposure of each sector. In some cases though, such as *Construction*, the contribution to risk is greater than that to total exposure because of relatively high default risk profile and positive correlation with other sectors.

Our contribution to the literature is twofold. First, our work overcomes the typical microdata limitations found in previous studies, i.e. lack of *PD* and *LGD* for individual firms. To the best of our knowledge, previous works assumed homogeneous *PD* within each sector and fixed *LGD* for every exposure. We use a unique supervisory dataset and we show that significant differences exist within and between sectors. Second, this work contributes to identify the build-up of sectoral risks by means of credit risk indicators, such as a sector's marginal contribution to the expected shortfall of the banking system, providing a useful warning signal of potential threats to the stability of the banking system.

The rest of the paper is organized as follows: Section 2 outlines the model, risk indicators and the dataset; Section 3 discusses results; and Section 4 concludes.

Methodology and data

The model

We use a structural multi-factor model as in Duellman and Masschelein (2006), and in Duellman and Puzanova (2013), prompted by the seminal work in Merton (1974). Composite latent risk factors \mathbf{Y} , affecting the standardized asset return X of a firm i belonging to a sector s drive default dependencies:

$$\begin{aligned} X_{i,s} &= \sqrt{r_i} Y_s + \sqrt{1 - r_i} \varepsilon_{i,s}, \quad \varepsilon_{i,s} \sim^{iid} N(0,1) \\ Y_s &= \sum_{k=1}^K \alpha_{s,k} Z_k, \quad \text{with } \sum_{k=1}^K \alpha_{s,k}^2 = 1, \quad Z_k \sim^{iid} N(0,1) \end{aligned} \tag{1}$$

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 \mathbf{Y} , one for each sector, are expressed as linear combinations of K iid standard normal factors 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 $\rho_{i,j} = \sqrt{r_i r_j} \cdot \sum_{k=1}^K \alpha_{i,k} \alpha_{j,k}$, and depends on the strength with which a sector is correlated with the others.

Defaults are triggered when a firm standardized asset return is below the threshold implied by the *PD* for that firm:

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

The distribution of the loss L 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.

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

where: i 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 risk factors and the factor loadings on the sectoral risk factors $\sqrt{r_i}$. Moreover, we assume an homogeneous factor loading equal to 0.5 for all sectors, as in Duellman and Masschelein (2006).

Risk measures

For a portfolio of loans the estimation of credit risk measures 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 1 with probability PD_i . At the portfolio level, total losses $L = \sum_i L_i$, are analysed using the expected and the unexpected losses, i.e. a level of losses 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), and the expected loss:

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

$$UL \equiv ES - EL$$

Estimating expected losses is a straightforward task, once PD and LGD are available. On the contrary, the calculation other risk measures from the loss distribution involves the consideration of dependences 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 prior assumptions on the homogeneity of PD and LGD (see Duellman and Masschelein, 2006 and Tola 2010).

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

$$ES_q(L_s) = E[L_s | L_s \geq VaR_q(L_s)]$$

ES for the total loss can be decomposed into marginal contributions (MC) of each sector (Duellman and Puzanova, 2011). Marginal contribution measures have a desirable full allocation property, i.e. they sum up to the overall ES so that for each sector they can be interpreted as the share of ES attributable to a sector, approximating the systemic relevance of a sector. Indicating with w_s the relative weight of the exposures in sector s , the marginal contribution is as follows:

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

Credit exposures, PD, LGD and correlations

Our dataset consists of a panel of firm-bank level data on credit exposures, PD and LGD for the years 2010-2015. Credit exposures of Italian banks towards non-financial firms based in Italy were gathered from different sources: i) the Italian National Credit Register (NCR), provided detailed information on individual exposures; ii) supervisory reports provided us with corporate debt securities holdings by banks. Banks' exposure towards economic sectors and concentration indices are reported in Table 1.⁵ At the banking system level, the distribution of banks' credit to non-financial firms is not even, with a few economic sectors accounting for a large part of the exposure. For the year 2015, *Industrial Goods and Services* (20%), *Trade* (14%), *Construction* (12%) and *Real Estate* (11%) account for about half of banks credit exposure toward the corporate sector. 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.

We use firm-level PD 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.⁶ We use LGD estimated from the Archive of historically registered losses on defaulted positions' available at the Bank of Italy (BI-AoL).⁷

In structural credit risk modelling it is common practice to approximate risk factors correlations by using equity correlations. According to the literature, we use equity indices correlations based on GARCH-DCC model as prompted in Engle (2002) and recommended in Puzanova and Duellmann, (2013) when dealing with portfolio credit risk models.

⁵ 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, firms were assigned to Others Sectors. We assume that all borrowers, including diversified firms, can be uniquely assigned to individual business sectors.

⁶ 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.

⁷ The statistical model underlying LGD estimates is presented in a previous working paper by the same authors circulated as "Credit Risk in the Banking System: an Application to Sectoral Risk in Italian banks".

Results

Figure 1 reports EL rate for each sector, this is the product between firm-level PD and exposure-level LGD and represents a measure of loss per unit of capital which ought to be priced in interest rates. For the year 2016, at the level of the banking system, EL accounts for about 2.1% of total exposure, however there is substantial difference across sectors. *Construction and Real Estate*, which represent a large part of banks' credit exposure, exhibit EL above the average; in contrast, *Industrial Goods and Services* and *Trade* present EL below the average. The least risky sectors are *Oil and Gas* and *Telecommunications* where low levels of PD are associated with high LGD. Turning to elementary components of EL rate, it is interesting to notice that the EL is strongly correlated with the average PD, but much less with the LGD, which actually appears to be high in sectors with very low expected losses. A possible explanation is that lenders try to minimize potential losses by asking for more and better quality collateral for borrowers with high default risk. Our LGD estimate averages around 54%, a value that is close to the parameter used in previous studies (Duellmann and Masschelein, 2006; Tola, 2010). However, our estimate show that there is significant variance in average LGD values across sectors, enriching the insight that can be gained by using microdata.

In Figure 2 the ES for the banking system, expressed as a percentage of the total exposure, is decomposed into its elementary components. The ES is calculated under the multi-factor approach (ES_{95_multi}) using Monte-Carlo simulations. Besides this estimate, a single-factor estimate is provided with at the same confidence interval (ES_{95_single}). Total losses identified by ES_{95_multi} can therefore been split into (i) EL (expected losses), (ii) the risk identified by the ES_{95_single} and (iii) the additional risk arising from the consideration of the sectoral risk, namely a sectoral component. Figure 2 suggests that sectoral risk represents a limited portion of total credit risk faced by the Italian banking system. Most of risk derives from the ES_{95_single} component, i.e. derives from the aggregate level of PD and LGD. Moreover, after several years of increase, sectoral risk has decreased in 2016.

Figure 3 decomposes the UL rate into its elementary components. The UL for the banking system is traced back to the contributing sectors and to the contributing risk component. The single-factor component is chiefly responsible for the increase in overall risk from 2011 to 2013 in the four most important sectors defined above, while the contribution of the sectoral component is stable over time. The sectoral component has a negative influence on total risk for several sectors in particular, among the most important sectors, *Trade* and *Real Estate*. This means that the economic capital for these sectors decreases when taking into account sectoral risk. This might be due both to a portfolio effect, a correlation effect or an interplay between the two effects.

Figure 4 compares MC risk measures obtained from the two approaches, the single and the multi-factor model. The multi-factor model estimates show greater risk contribution with respect to the single-factor counterpart for those sectors that are highly correlated with the rest of the economy. To the extent to which the dependence structure between defaults is described more accurately by the multi-factor model, our comparison shows that economic capital could be misallocated when using a single factor model of credit risk, leading to over(under) estimation of capital requirements for some exposures with respect to their contribution to the overall risk.

Over time the four main sectors maintained a relevant role. Though, while *Industrial Goods and Services* is the sector having the largest share of credit, up to 2015 the largest part of risk has been concentrated in *Construction*. Moreover, while for all periods in *Industrial Goods and Services* and *Construction* MC based on the multi factor approach has been greater than the corresponding MC based on the single risk factor, the opposite has been true for the other two main sectors, *Trade* and *Real Estate*.

Conclusion

This paper outlines a framework for the estimation of potential losses on banks' corporate portfolios.

We apply a multi-factor credit risk model to a detailed dataset, consisting of exposures by Italian banks to Italian non-financial firms. We present credit risk measures at the sectoral level and assess the contribution of different sectors to the overall level of risk. Aggregated risk measures are analysed in their elementary components and their temporal dynamics.

Our analysis shows that the use of available data sources and credit risk models allows for the identification of those sectors which might become relevant for the stability of the banking system.

The analysis is also motivated by the macroprudential policy tools included in the Basel framework, which offer the possibility for supervisors to address vulnerabilities arising from specific classes of exposures.

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Table 1: Banks' exposure (a) to non-financial firms by sector

| | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|---------------------------------|-------|-------|-------|-------|-------|-------|
| Other sectors | 2.7 | 2.7 | 2.9 | 2.9 | 3.1 | 3.5 |
| Oil and gas | 2.0 | 1.9 | 1.5 | 1.4 | 1.4 | 1.5 |
| Chemicals and basic resources | 6.8 | 6.7 | 6.6 | 6.8 | 6.7 | 6.7 |
| Construction | 17.2 | 16.4 | 15.6 | 14.7 | 12.9 | 11.8 |
| Industrial goods and services | 18.8 | 19.2 | 19.4 | 19.1 | 19.7 | 20.2 |
| Automobiles and parts | 2.6 | 2.6 | 2.6 | 2.5 | 2.7 | 3.1 |
| Agriculture, food and beverages | 6.9 | 7.3 | 7.7 | 8.2 | 8.5 | 8.7 |
| Personal and household goods | 4.3 | 4.3 | 4.2 | 4.3 | 4.4 | 4.5 |
| Health care | 1.5 | 1.5 | 1.6 | 1.7 | 1.7 | 1.8 |
| Trade | 12.7 | 12.8 | 13.1 | 13.8 | 14.3 | 14.4 |
| Media | 0.6 | 0.6 | 0.5 | 0.5 | 0.4 | 0.4 |
| Travel and leisure | 4.1 | 3.9 | 3.9 | 4.0 | 3.9 | 4.0 |
| Telecommunications | 1.0 | 1.0 | 0.8 | 0.8 | 0.8 | 0.9 |
| Utilities | 4.8 | 5.4 | 5.9 | 5.6 | 6.0 | 5.7 |
| Real estate | 12.8 | 12.5 | 12.5 | 12.2 | 11.7 | 11.2 |
| Technology | 1.4 | 1.4 | 1.4 | 1.4 | 1.5 | 1.6 |
| Total | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| Total ^(b) | 870.1 | 870.0 | 800.2 | 706.2 | 681.7 | 664.4 |

(a) Percentage values; (b) Billions of euros.

Table 1 reports banks' exposure to non-financial firms by sector, as sourced from the NCR. Stock market indices and the NCR 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.

Figure 1: Sectoral risk measures: EL and its components

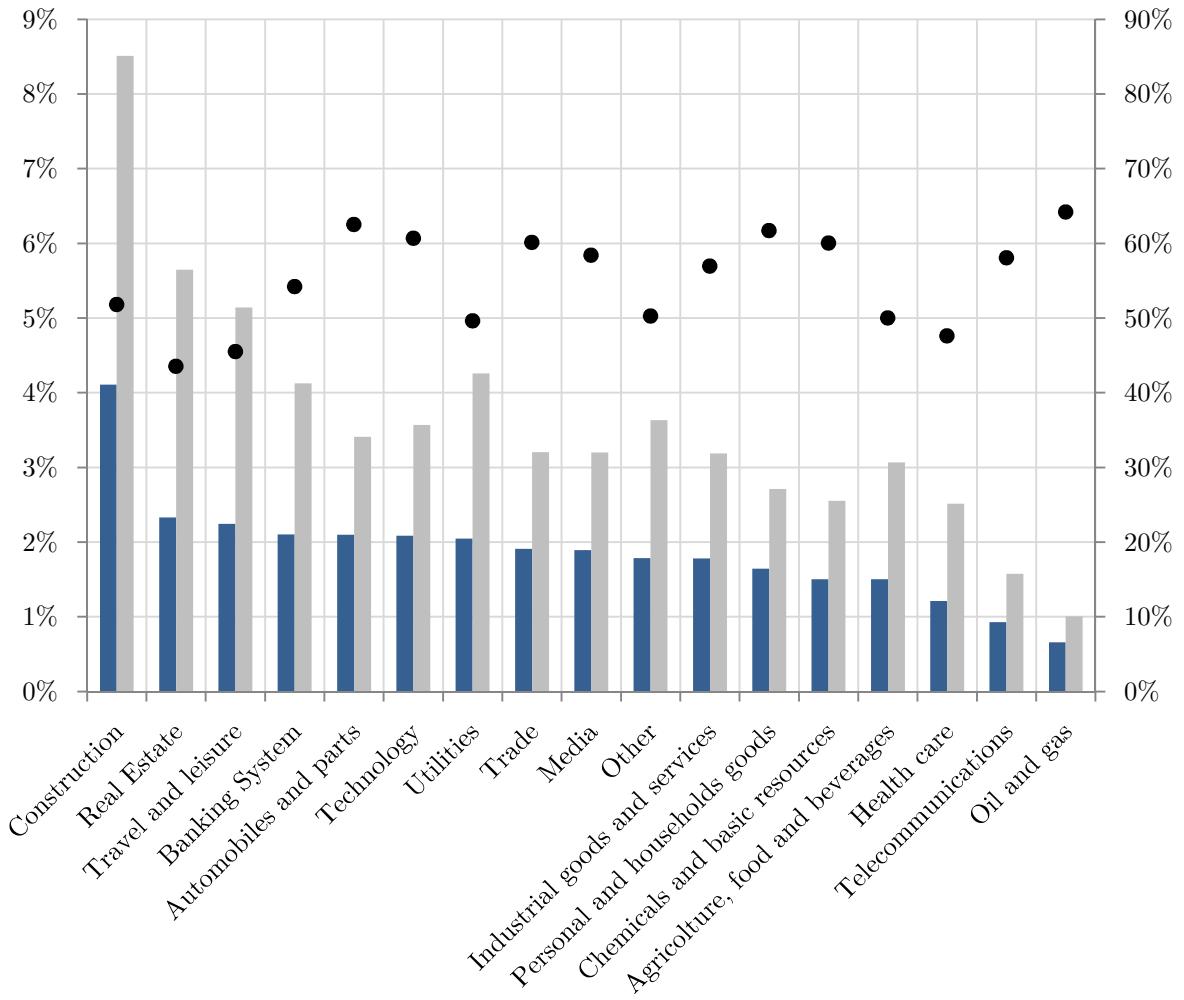


Figure 1 reports average EL rate (dark blue bars, left axis), *PD* (light grey bars, left axis) and *LGD* (black dots, right axis) by sector. Sectors are sorted by decreasing level of EL rate. EL rate were computed as the product between firm-level *PD* and exposure-level *LGD* at December 2015; *PD* were sourced from the In-House Credit Assessment System of the Bank of Italy, while *LGD* estimates were based on Archive of historically registered losses on defaulted positions' available at the Bank of Italy (BI-AoL).

Figure 2. ES and its components

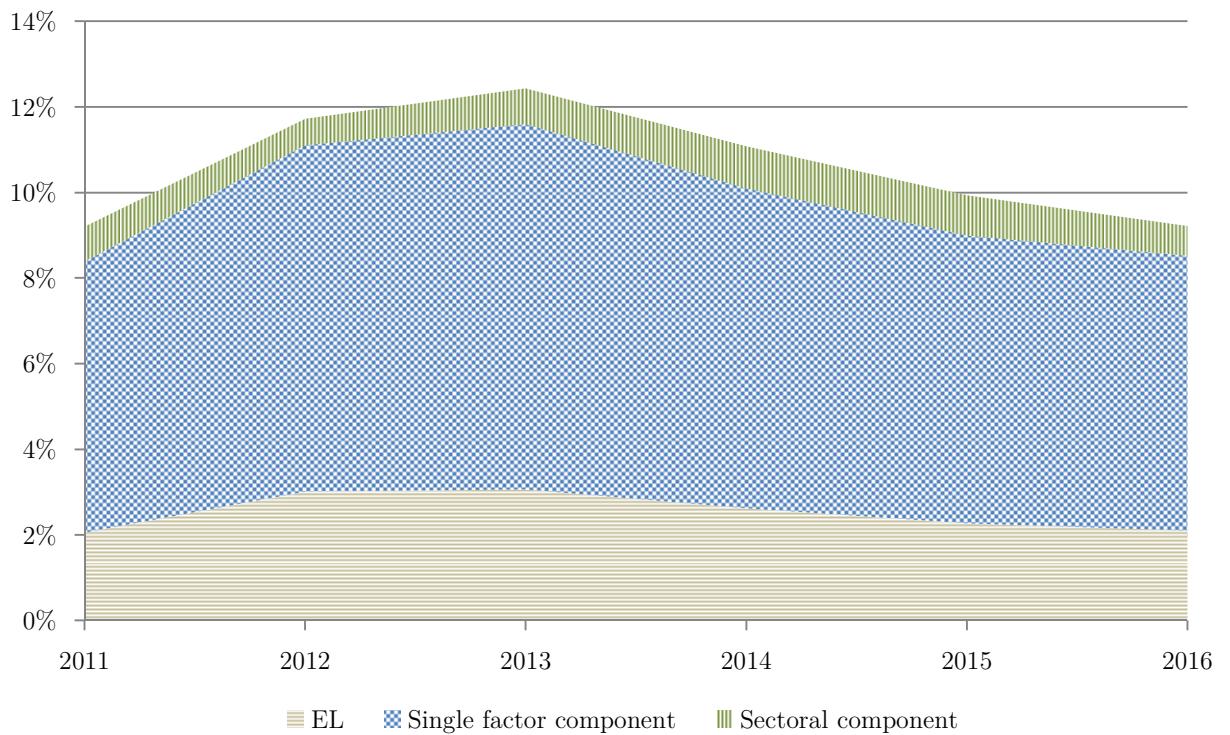
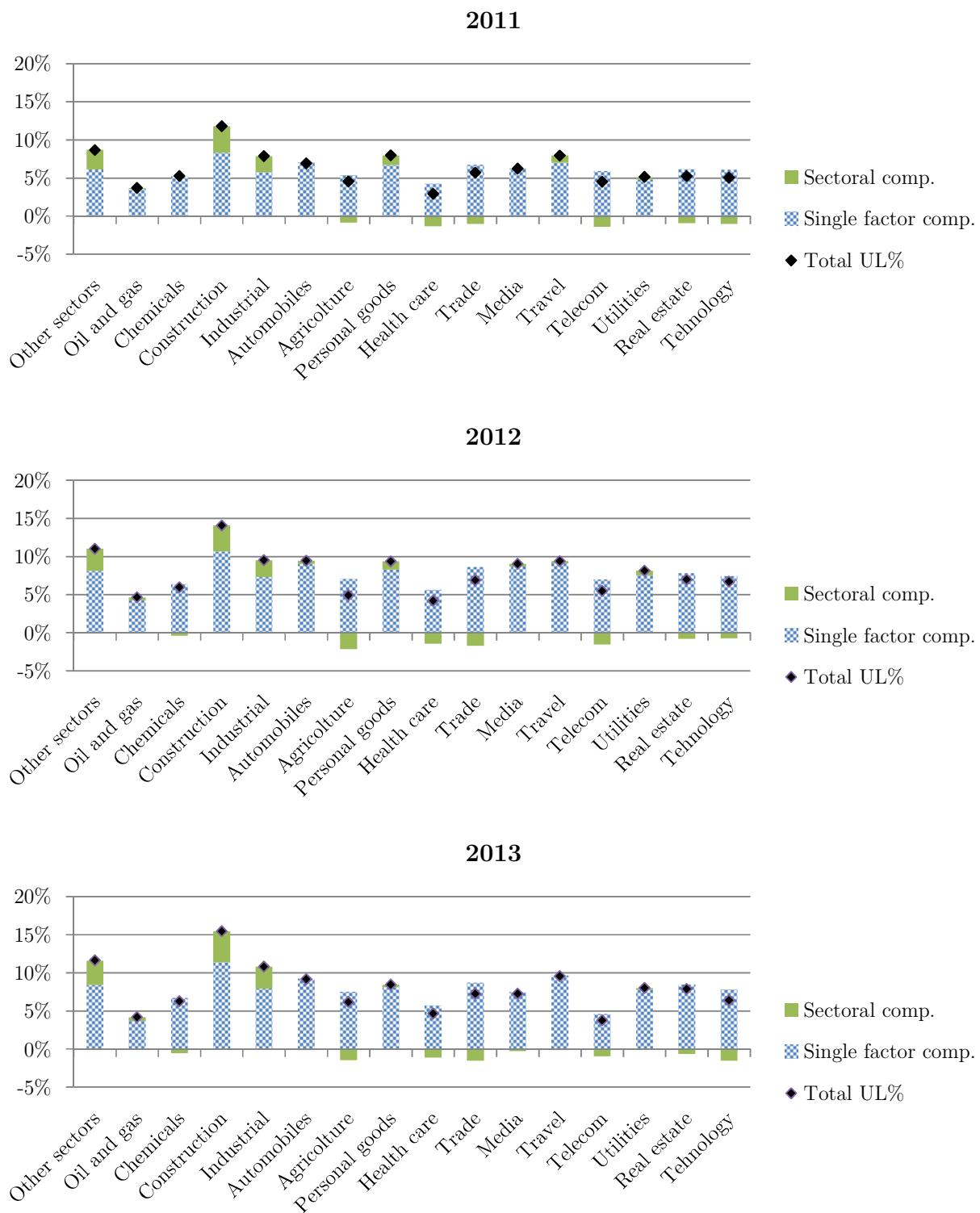


Figure 2 shows ES estimates under multi-factor model using Monte Carlo simulations. The overall ES is decomposed into its elementary components, i.e. EL, the product between firm-level PD and exposure-level LGD; the component obtained under the single-factor model; the sectoral component.

Figure 3. Sectoral UL% and its components



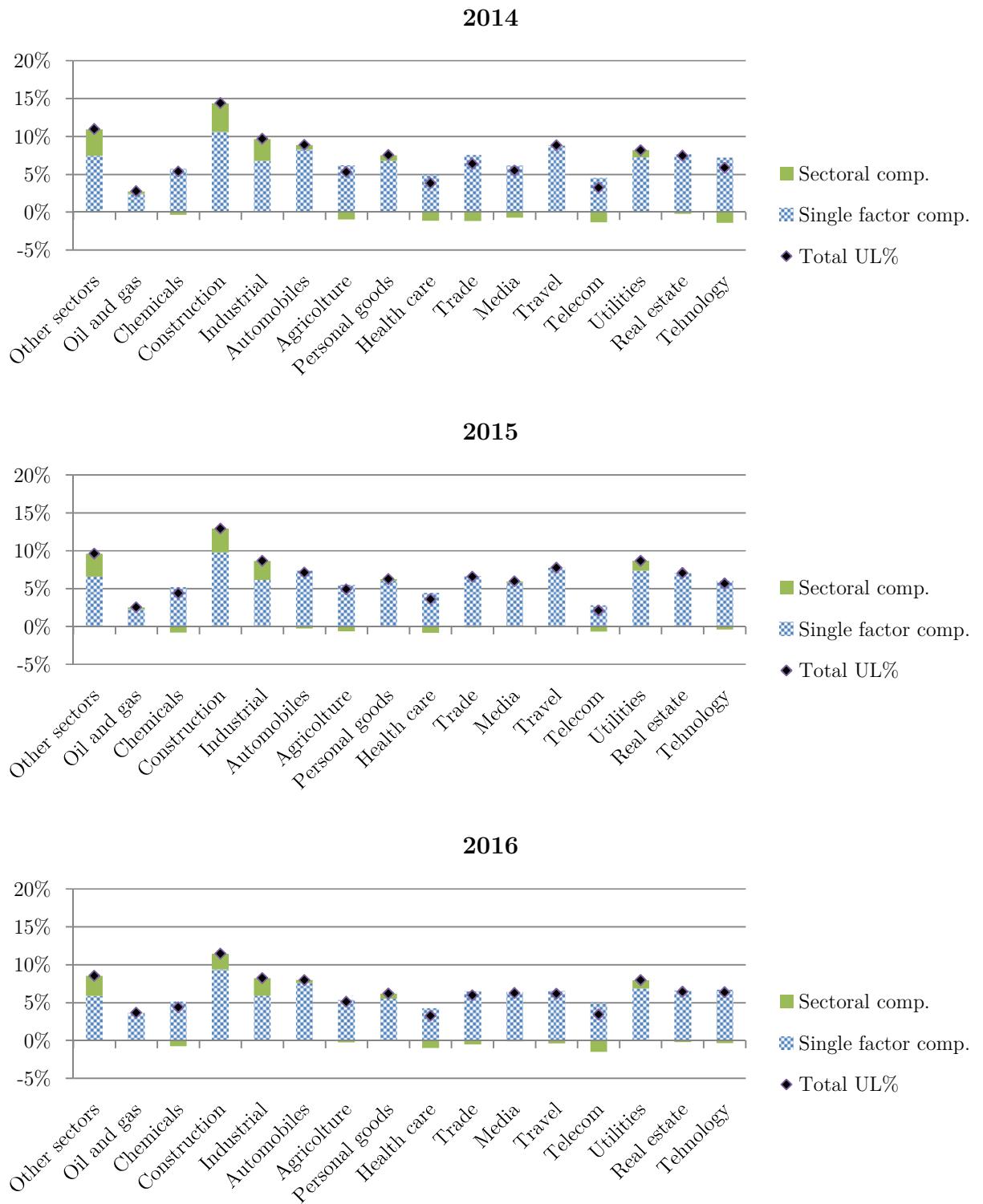


Figure 3 shows UL estimates sector by sector under multi-factor model using Monte Carlo simulations. The overall UL is decomposed into its elementary components, i.e. the component obtained under the single-factor model and the sectoral component.

Figure 4. Sectoral MC under single and multi-factor model

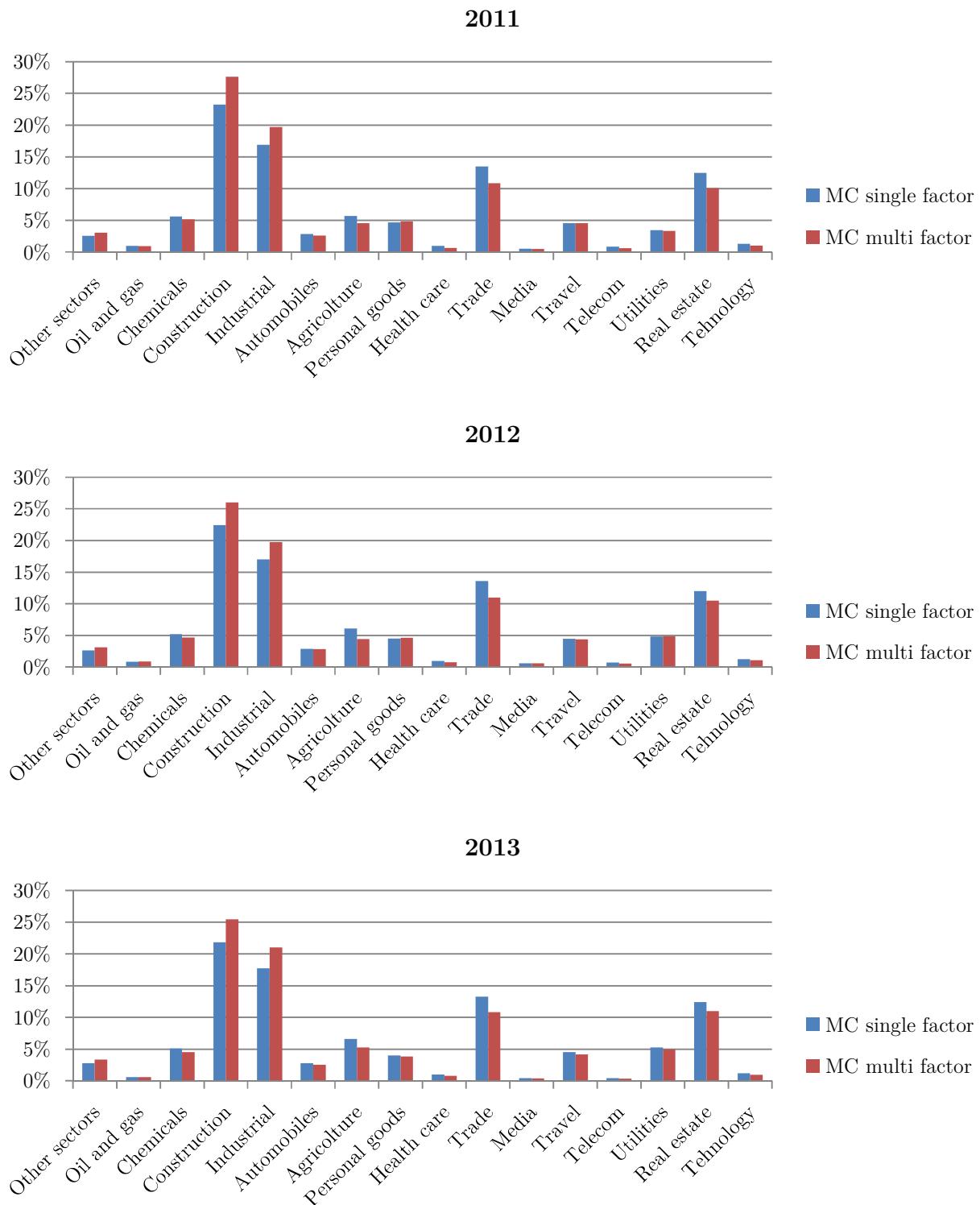




Figure 4 shows the marginal contribution (MC) of each sector to the total ES95 under single multi-factor models.

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SECTORAL RISK IN ITALIAN BANKING SYSTEM

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SECTORAL RISK AND BANKS' DISTRESS

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 for the banking system (BIS, 2006).

SECTORAL RISK AND DEFAULT CORRELATION

Default of non-financial firms display positive correlations within and across industries and sectoral (systematic) risk factors might drive their dependence structure (De Servigny and Renault, 2002; Das et al., 2007; Saldías M., 2013)

SECTORAL RISK AND THE BASEL FRAMEWORK

The IRB approach uses the Asymptotic Single-Risk Factor model whose consistency requires two key assumptions:

- Borrowers-idiosyncratic risk is diversified away in banks' portfolios;
- Macro-economy apart, there are no additional sources of credit risk at sectoral or geographical level (Gordy, 2003);

As a result, IRB risk-weights are portfolio invariant.



To the best of our knowledge, previous works assumed homogeneous *PD* within each sector and fixed *LGD* for every exposure. We use a unique supervisory dataset and we show that significant differences exist within and between sectors.

BANKING SYSTEM LEVEL

This paper analyzes the **exposure** of the **Italian banking system** to credit risk arising from different **sectors** of the economy.

SECTORAL LEVEL

We investigate whether credit exposure towards some economic sectors is particularly **vulnerable to credit risk**, providing **estimates** of **expected** and **unexpected losses** on credit portfolios.

We obtain a measure of contribution to **systemic risk** stemming from credit **exposures** in different economic sectors.



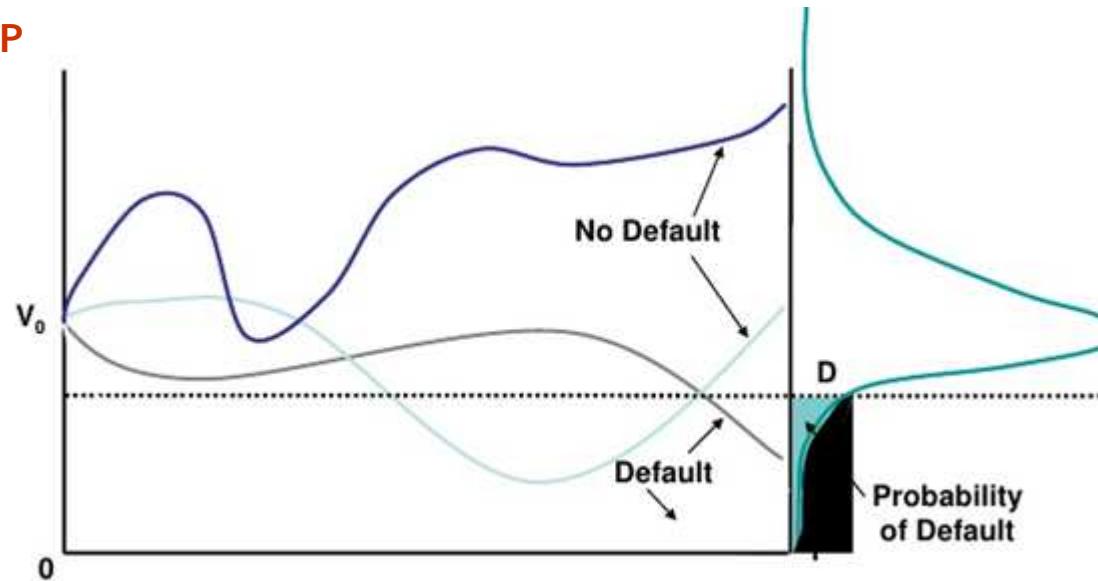
RESULTS

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 cyclical**.

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.

In terms of systemic relevance, *Industrial Goods and Services, Construction, Trade and Real Estate* are the most relevant sectors for the Italian banking system. This ranking is mainly determined by the size of the credit exposure of each sector. In some cases though, such as *Construction*, the contribution to risk is greater than that to total exposure because of relatively high default risk profile and positive correlation with other sectors.

THE MODEL SET-UP



We use a [structural multi-risk factor model](#) where a default is triggered when a firm standardized asset return falls below the default threshold implied by the PD for that firm:

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

Where: X represent firm i standardized asset return; and PD is the Probability of Default.



THE MODEL SET-UP

Default dependencies are driven by composite latent risk factors \mathbf{Y} , affecting the standardized asset return \mathbf{X} of a firm i belonging to a sector s :

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

Where: $r \in (0,1)$ is the factor loading; ε is an idiosyncratic risk component.

The composite risk factors \mathbf{Y} , one for each sector, are expressed as linear combinations of iid standard normal factors \mathbf{Z} and $\alpha\{s,k\}$ are obtained by the Cholesky decomposition of the correlation matrix of the sectoral risk factors $\rho\{s,k\}$.

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



THE MODEL SET-UP

The **Loss Distribution** is estimated via **Monte Carlo** simulations of systematic and idiosyncratic factors, and by **comparing** the simulated standardized return with the threshold to identify the individual defaults in each scenario.

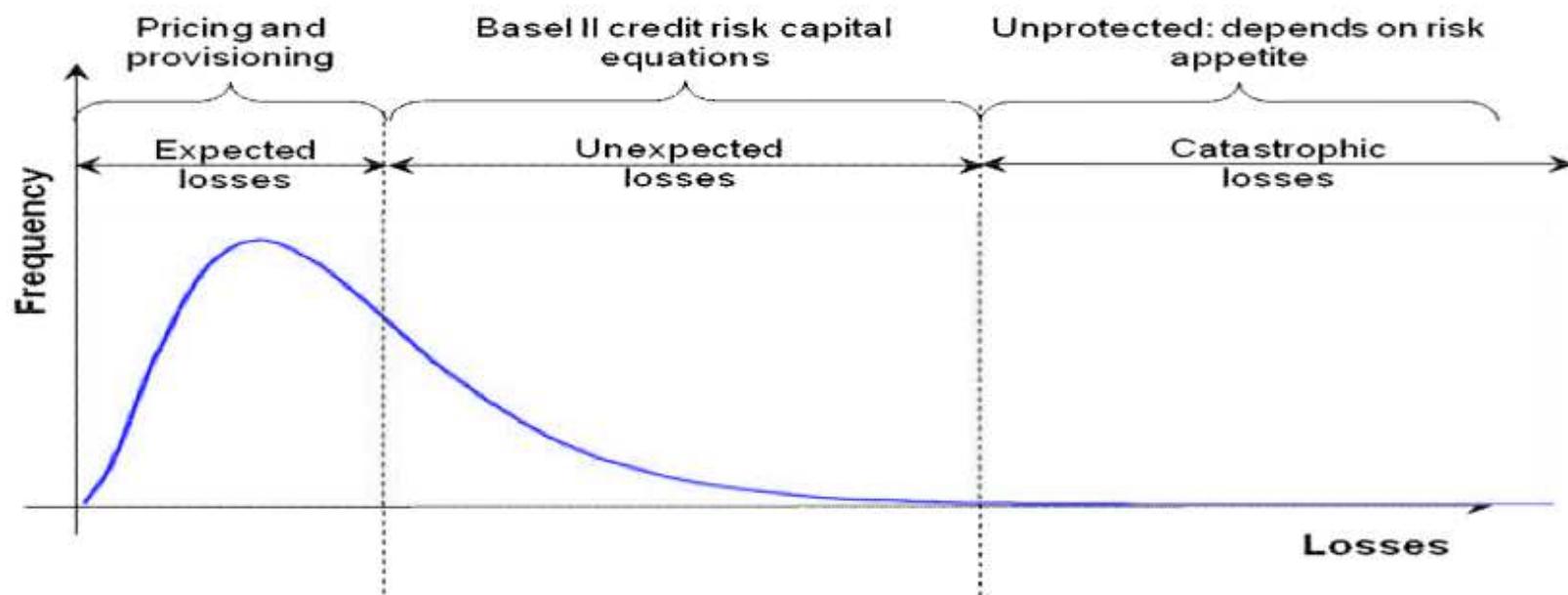
$$L = \sum_{s=1}^S \sum_{i=1}^{I_s} D_{\{X_{s,i} \leq \Phi^{-1}(PD_i)\}} \cdot EXP_{s,i} \cdot LGD_{s,i}$$

Where: **D** = 1, when a firm defaults; **EXP** is Exposure at Default; **LGD** is Loss Given Default.

CREDIT RISK MEASURES: EL - UL - ES

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

$$UL \equiv ES - EL$$





CONTRIBUTION TO SYSTEMIC RISK: MC

The Expected Shortfall for the banking system can be **decomposed** into **marginal contributions** of each sector (Tasche, 2008; Dullman and Puzanova, 2011).

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

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.



DATA AND SOURCES

Credit Data

- Exposures At Default (EXP)
 - National Credit Register;
 - Supervisory Reports on security holdings;
- Probabilities of Default (PD)
 - BI-ICAS (Bank of Italy In-House Credit Assessment System)
- Loss Given Default (LGD)
 - Supervisory Reports on loans workout ;

Market Data

- Sectoral risk factors correlations
 - FTSE sectoral indices (via Datastream).



PD, PROBABILITY OF DEFAULT

- Bank of Italy In-House Probability of Default of individual borrowers;
- > 500.000 borrowers;
- 12 - month PD estimated via a reduced form credit scoring model based on:
 - Financial statements;
 - Credit data;
 - Geo – Sectorial data;

LGD, LOSS GIVEN DEFAULT

- Model-based estimations for LGD of individual exposures
- A regression model was estimated using data from Loan Workout procedures;

$$LGD = \beta_0 + \beta_1 Log(EXP) + \beta_2 Size + \beta_3 Guarantee_coverage_ratio + \beta_4 Guarantee_type + \varepsilon,$$



SECTORAL EQUITY CORRELATIONS

Based on:

- 16 indices FTSE-Italy Supersectors indices sourced from DATASTREAM;
- 5 Years daily observations;

Lowly correlated sectors: [Chemicals](#), [Agriculture](#), [Heath Care](#) and [Trade](#).

Highly correlated sectors: [Industrial G.](#), [Oil and Gas](#), [Construction](#) and [Utilities](#).

| | Chemicals | Automobiles | Agriculture | Technology | Health Care | Personal G. | Industrial G. | Media | Oil and G. | Travel | Real Estate | Trade | Construction | Telecom. | Utilities | Others |
|---------------|-----------|-------------|-------------|------------|-------------|-------------|---------------|-------|------------|--------|-------------|-------|--------------|----------|-----------|--------|
| Chemicals | 1.00 | | | | | | | | | | | | | | | |
| Automobiles | 0.49 | 1.00 | | | | | | | | | | | | | | |
| Agriculture | 0.41 | 0.46 | 1.00 | | | | | | | | | | | | | |
| Technology | 0.46 | 0.53 | 0.39 | 1.00 | | | | | | | | | | | | |
| Health Care | 0.38 | 0.48 | 0.42 | 0.45 | 1.00 | | | | | | | | | | | |
| Personal G. | 0.51 | 0.57 | 0.53 | 0.54 | 0.54 | 1.00 | | | | | | | | | | |
| Industrial G. | 0.59 | 0.67 | 0.54 | 0.62 | 0.55 | 0.68 | 1.00 | | | | | | | | | |
| Media | 0.47 | 0.57 | 0.43 | 0.51 | 0.47 | 0.54 | 0.65 | 1.00 | | | | | | | | |
| Oil and G. | 0.62 | 0.58 | 0.50 | 0.54 | 0.47 | 0.59 | 0.71 | 0.58 | 1.00 | | | | | | | |
| Travel | 0.46 | 0.56 | 0.46 | 0.49 | 0.49 | 0.60 | 0.64 | 0.56 | 0.57 | 1.00 | | | | | | |
| Real Estate | 0.39 | 0.49 | 0.38 | 0.46 | 0.45 | 0.46 | 0.58 | 0.53 | 0.51 | 0.48 | 1.00 | | | | | |
| Trade | 0.38 | 0.46 | 0.38 | 0.41 | 0.40 | 0.51 | 0.52 | 0.44 | 0.45 | 0.44 | 0.42 | 1.00 | | | | |
| Construction | 0.54 | 0.65 | 0.50 | 0.59 | 0.54 | 0.62 | 0.75 | 0.65 | 0.65 | 0.63 | 0.57 | 0.49 | 1.00 | | | |
| Telcom. | 0.37 | 0.41 | 0.36 | 0.37 | 0.40 | 0.42 | 0.55 | 0.49 | 0.51 | 0.48 | 0.40 | 0.29 | 0.50 | 1.00 | | |
| Utilities | 0.52 | 0.55 | 0.51 | 0.51 | 0.52 | 0.57 | 0.71 | 0.59 | 0.69 | 0.61 | 0.54 | 0.40 | 0.65 | 0.58 | 1.00 | |
| Others | 0.63 | 0.70 | 0.57 | 0.64 | 0.59 | 0.68 | 0.85 | 0.72 | 0.84 | 0.70 | 0.63 | 0.51 | 0.80 | 0.66 | 0.86 | 1.00 |



TABLE 1. CREDIT EXPOSURE

| | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|---------------------------------|-------|-------|-------|-------|-------|-------|
| Other sectors | 2.7 | 2.7 | 2.9 | 2.9 | 3.1 | 3.5 |
| Oil and gas | 2.0 | 1.9 | 1.5 | 1.4 | 1.4 | 1.5 |
| Chemicals and basic resources | 6.8 | 6.7 | 6.6 | 6.8 | 6.7 | 6.7 |
| Construction | 17.2 | 16.4 | 15.6 | 14.7 | 12.9 | 11.8 |
| Industrial goods and services | 18.8 | 19.2 | 19.4 | 19.1 | 19.7 | 20.2 |
| Automobiles and parts | 2.6 | 2.6 | 2.6 | 2.5 | 2.7 | 3.1 |
| Agriculture, food and beverages | 6.9 | 7.3 | 7.7 | 8.2 | 8.5 | 8.7 |
| Personal and household goods | 4.3 | 4.3 | 4.2 | 4.3 | 4.4 | 4.5 |
| Health care | 1.5 | 1.5 | 1.6 | 1.7 | 1.7 | 1.8 |
| Trade | 12.7 | 12.8 | 13.1 | 13.8 | 14.3 | 14.4 |
| Media | 0.6 | 0.6 | 0.5 | 0.5 | 0.4 | 0.4 |
| Travel and leisure | 4.1 | 3.9 | 3.9 | 4.0 | 3.9 | 4.0 |
| Telecommunications | 1.0 | 1.0 | 0.8 | 0.8 | 0.8 | 0.9 |
| Utilities | 4.8 | 5.4 | 5.9 | 5.6 | 6.0 | 5.7 |
| Real estate | 12.8 | 12.5 | 12.5 | 12.2 | 11.7 | 11.2 |
| Tehnology | 1.4 | 1.4 | 1.4 | 1.4 | 1.5 | 1.6 |
| Total | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 |
| Total^(b) | 870.1 | 870.0 | 800.2 | 706.2 | 681.7 | 664.4 |

(a) Percentage values; (b) Billions of euros.

Table 1 reports banks' exposure to non-financial firms by sector, as sourced from the NCR. Stock market indices and the NCR 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.

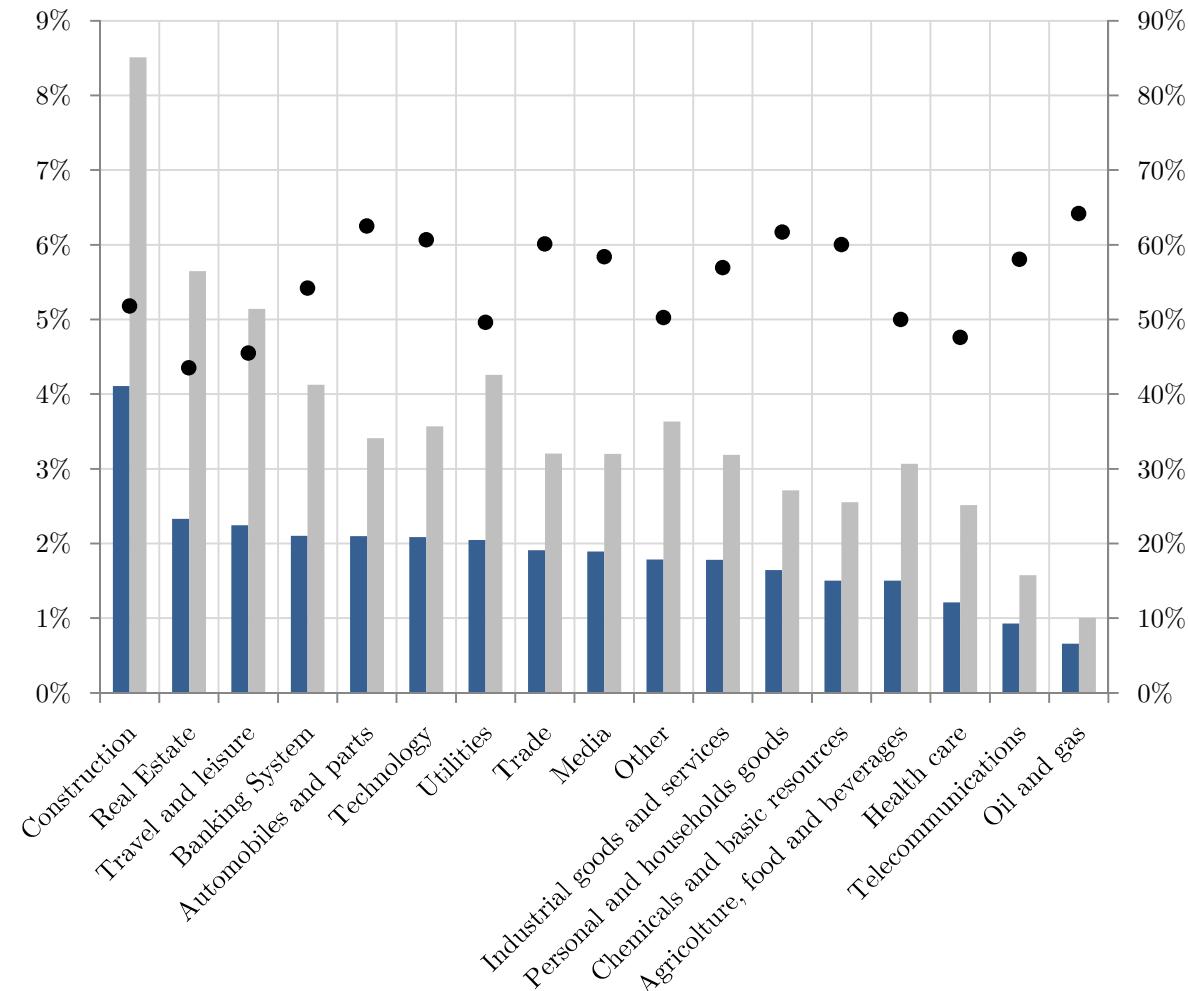
FIG 1. CREDIT RISK MEASURES: EL AND ITS COMPONENTS

Figure 1 reports average EL rate (dark blue 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 were computed as the product between firm-level PD and exposure-level LGD at Dec. 2015.

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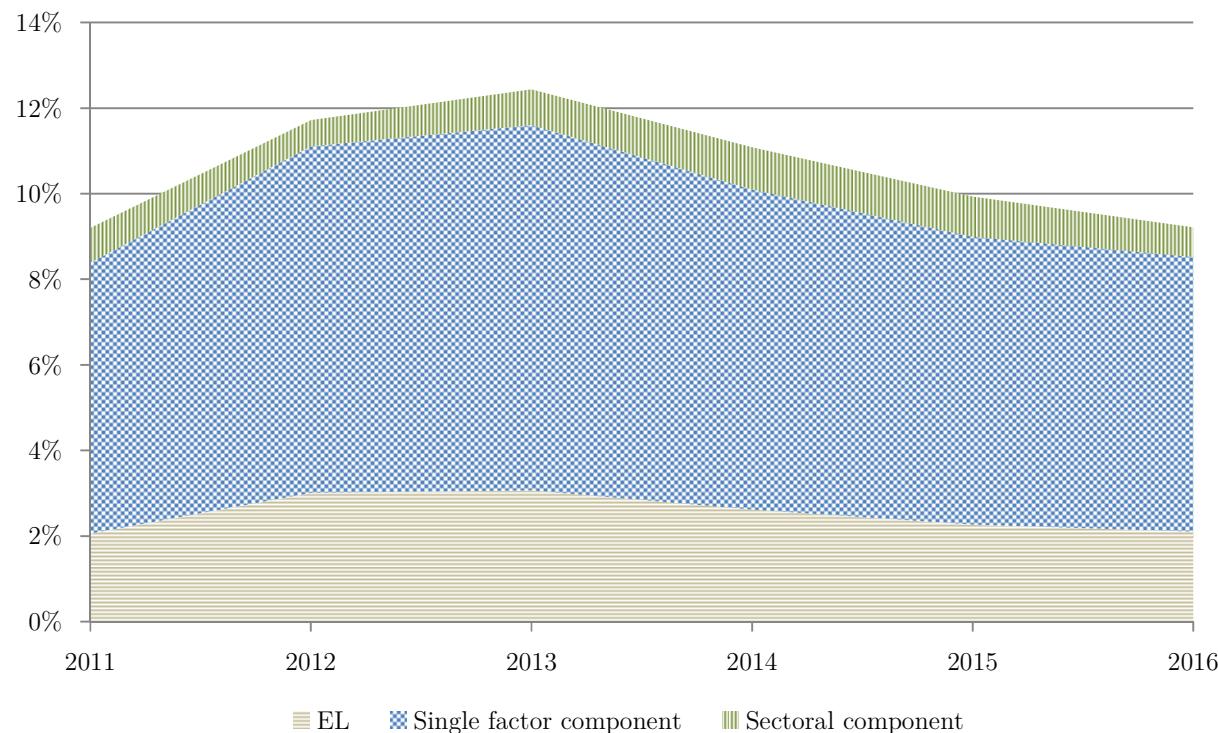
FIG 2. CREDIT RISK MEASURES: ES AND ITS COMPONENTS

Figure 2 shows ES estimates under multi-factor model using Monte Carlo simulations. The overall ES is decomposed into its elementary components, i.e. EL, the product between firm-level PD and exposure-level LGD; the component obtained under the single-factor model; the sectoral component.

FIG. 3 SECTORAL UL% AND ITS COMPONENTS

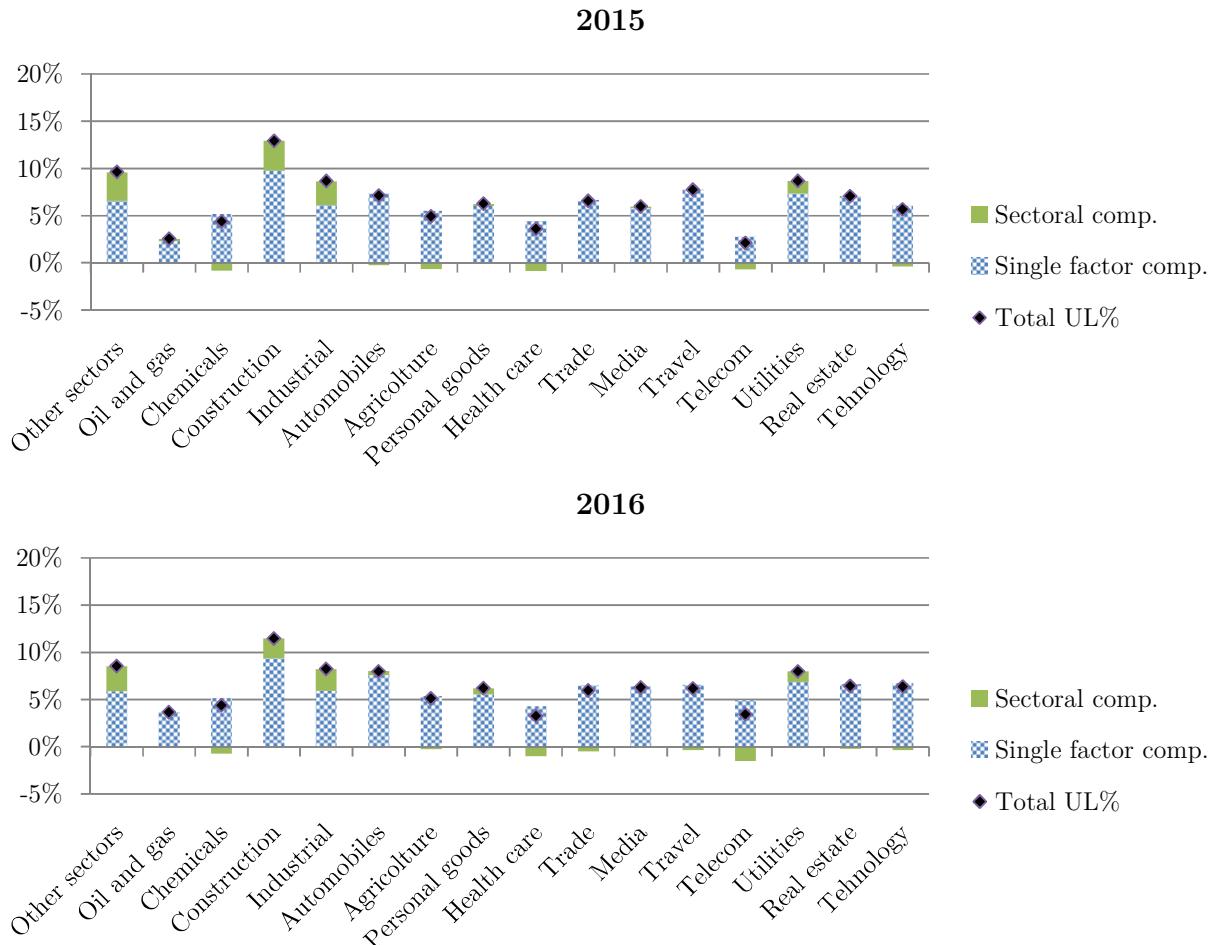


Figure 3 shows UL estimates sector by sector under multi-factor model using Monte Carlo simulations. The overall UL is decomposed into its elementary components, i.e. the component obtained under the single-factor model and the sectoral component.

FIG. 4 SECTORAL MC UNDER SINGLE AND MULTI-FACTOR MODEL

Figure 4 shows the marginal contribution (MC) of each sector to the total ES under single and multi-factor models.



FINAL REMARKS

Measuring concentration and sectoral risk can help to spot and prevent **excessive credit growth** and **concentration of credit risk** that are a **threat** to the **stability** of a single institution and for the banking system

With micro data at hand, sectoral risk analysis can adopt standard risk-management techniques used by banks risk management desks, such as VaR or ES, that enable us to consider credit risk at the bank portfolio level, to aggregate the individual bank risk measures at system level and to drill down to marginal measures of sectoral risk

Computing sectoral risk with micro data requires granular information on credit, but also balance sheet data and market data. In particular balance sheet data can be used for the estimation of individual PD and LGD.



Thank you for your attention!

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