Sectoral concentration risk in Portuguese banks' loan exposures to non-financial firms

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Abstract
This article proposes a credit risk model to the Portuguese banks' aggregate loan portfolio of non-financial corporations (NFC). Using a one-period simulation-based multi-factor model, we estimate the loss distribution and several one-year risk metrics between 2006 and 2017. The model differentiates from the Basel IRB framework by explicitly incorporating interdependencies between economic sectors. The flexible nature of the model allows sectoral risk to be decomposed into different components. The results point to diversification gains in the last years thanks to a lower concentration in a specific sector, the construction sector, and not due to an allocation into sectors with lower interdependency. (JEL: G17, G21, G32)

Introduction

Concentration risk in a credit portfolio can arise from large exposures to specific borrowers relative to the size of the portfolio (*name concentration*) or from large exposures to groups of highly correlated borrowers. When two or more borrowers default simultaneously, the portfolio losses are more severe. The higher the correlation of defaults, the greater is the concentration risk. Default correlation can have several sources. Some of the most commonly mentioned are macroeconomic factors, geographic factors, corporate interrelations – arising either from common shareholders or supply chain relations – and economic sectors. The last decades were marked by several episodes where sector concentration played an important role. The concentration of bank credit in the energy sector in Texas and Oklahoma in the 1980s and the overexposure to the construction and property development sectors in Sweden in the early 1990s and in Spain and Ireland in the 2000s are examples of incidents of correlated defaults that jeopardized the health of many financial institutions.

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Since the implementation of Basel II, under Pillar 1 of bank capital regulation, banks can opt to either use a regulatory standardized approach to calculate credit risk capital requirements, or follow an Internal Ratings-Based (IRB) approach using their own estimated risk parameters. Either of these approaches aims at capturing general credit risk. However, they do not explicitly differentiate between portfolios with different degrees of diversification. Among other things, Pillar 2 in Basel II and in Basel III addresses this issue by providing a general framework for dealing with concentration risk. Nevertheless, banks and regulators have a large degree of freedom in choosing the quantitative tools to cover such risk (Grippa and Gornicka 2016).

The IRB formula is based on the Asymptotic Single Risk Factor (ASRF) model derived from the Vasicek (2002) model. The origins of this model can be found in the seminal work by Merton (1974). The ASRF model is based on two crucial assumptions, namely the existence of a single risk factor and portfolio granularity. Together, these two assumptions lead to portfolio invariance, i.e. the capital required for a loan only depends on its risk, regardless of the composition of the portfolio it is added to. From a regulatory perspective, this simplifies the supervisionary process allowing for the framework to be applicable to a wider range of countries and institutions. In the ASRF model, two borrowers are correlated with each other because they are both exposed to a unique systematic factor but with (potentially) varying degrees. In the specific case of the IRB approach the degree of exposure to the systematic factor is a decreasing function of the probability of default.[1] According to BIS (2005), this decreasing function is in line with the findings of several supervisory studies. Still, this can be a simplified way of capturing the interdependencies between the various debtholders in a portfolio where several other systematic risk factors might drive default events (Das *et al.* 2007; Saldías 2013). Keeping everything else equal, the IRB approach leads to the same capital charges for banks with different levels of sectoral concentration.

In this paper we implement a simulation-based multi-factor method to estimate the loss distribution for the aggregate loan portfolio of non-financial firms of Portuguese banks and derive several one-year credit risk metrics. This method differs from the IRB approach in two aspects: (i) instead of a single systematic risk factor we consider one risk factor for each sector, mirroring the asset returns correlations between sectors; (ii) instead of using a decreasing function of the probability of default, we explicitly estimate the degree of exposure to each sector-related systematic factor. Thus, the risk of default is not synchronized across sectors and the degree of exposure to the shocks varies according to the sector. The flexible nature of simulation-based

1. I.e., the IRB approach is a specific ASRF model where the implied correlation between borrowers are a function of their own risk.

methods allow us to evaluate the evolution of concentration over time and to decompose the credit risk into different components. This can help micro and macro-prudential authorities to detect sectoral risks in individual banks and in the banking system.

Methodology

The general framework relies on a structural multi-factor risk model evolved from the seminal work by Merton (1974). In this model set-up, a default is triggered when a firm's assets value is less than debt value. This implies that a default occurs when a firm standardized asset return, X_i, is below the threshold implied by the probability of default (PD) for that firm:

$$X_i \leq \Phi^{-1}(\mathrm{PD}_i), \tag{1}$$

where Φ^{-1} denotes the inverse cumulative distribution function for a standard normal random variable.

Adding on Merton's model further consider that the standardized asset return X of a firm i belonging to sector s is a linear function of an industry specific risk factor, Y_s, and an idiosyncratic risk factor, ε_i:

$$X_{si} = r_s Y_s + \sqrt{1 - r_s^2}\varepsilon_i, \tag{2}$$

$$\varepsilon_i \sim N(0,1) \quad Y_s \sim N(0,1).$$

In the above equation $r_s \in [0,1]$ is the factor weight (or factor loading), which measures the sensitivity of the asset returns to the risk factor. The standardized asset return X_i is a function of an idiosyncratic component – the risk that is endemic to a particular firm – and a sector-specific systematic component. Dependencies between borrowers arise from their affiliation with the sector and from the correlation between Y_s.[2] The risk factors dependencies are usually estimated using market sector indices. Those indices are not available for Portugal. Therefore, we use observed default frequencies to compute, under the Merton model assumptions, the implicit normalized asset returns and estimate correlations between sectors – Table B.2 in the Appendix B.[3]

A critical parameter in this exercise is the factor loading r_s. Small changes in this parameter can produce significantly different results. In Düllmann

2. For further details see Appendix A.

3. This procedure guarantees monthly frequency data offering greater consistency. Data is available between 2005m1 and 2017m12.

and Masschelein (2006) and Accornero *et al.* (2017) the factor weight is set exogenously as equal to 0.5. This value is chosen such that their benchmark portfolio capital charge equals the IRB capital charge. In the IRB approach the implied factor weight is a decreasing function of the PD and is bounded between, approximately, 0.35 (highest possible PD) and 0.49 (lowest possible PD). The objective of this study is not to evaluate the size of the Basel capital requirements but instead to recognize the likelihood of joint-defaults and how costly they are for a portfolio. Factor loadings should thus reflect by how much an extra euro borrowed by a firm i that belongs to a sector s is affected by the business cycle. We estimate the parameter endogenously with a year fixed effect regression for each sector using the implied threshold (also referred to as distance-to-default, $\mathrm{DD} = -\Phi^{-1}(\mathrm{PD}_i)$) as the dependent variable, weighted by the outstanding amount. Our goal is to capture by how much the variability of the distance-to-default is explained by time for each euro invested in sector s. The results are available in Table B.1 in the Appendix B.

The Loss distribution, L, for a given portfolio is then estimated through Monte Carlo simulations of the systematic industry specific and idiosyncratic risk factors. In each simulation/scenario, defaults are identified by comparing simulated standardized asset returns with the default threshold $\Phi^{-1}(PD_i)$:

$$L = \sum_{s=1}^{S} \sum_{i=1}^{I_s} D_{X_i \leq \Phi^{-1}(\mathrm{PD}_i)} \cdot \mathrm{EXP}_i \cdot \mathrm{LGD}_i, \tag{3}$$

where $D = 1$, when a company defaults, EXP_i is the exposure to the company i, LGD_i is the loss given default of exposure i, S is the number of sectors and I_s is the number of firms in sector s. For a given year t, the exposure of company i is the one observed in the last month of year $t-1$ and the LGD is assumed to be constant and equal to 0.5.[4] Each Monte Carlo simulation can be seen as a scenario or state of the world. Each scenario generates a particular loss for the portfolio. The frequency of various outcomes/losses after a large number of simulations generates the credit loss distribution. Figure 1 illustrates the process.

There are several risk measures that can be computed based on the portfolio loss distribution. The most commonly referred are the expected loss (EL), the value-at-risk (VaR), the unexpected loss (UL) and the expected shortfall (ES). The EL corresponds to the expected value of the portfolio loss L, which can be estimated as the mean of the simulated loss scenarios.[5] The VaR_p is the maximum possible loss if we exclude worse outcomes whose

4. In BIS (2001) the LGD is considered to be 0.5 for subordinated claims on corporates without specifically recognized collateral.

5. The EL can also be estimated as PD*LGD*EXP. The EL estimation does not depend on the model used.

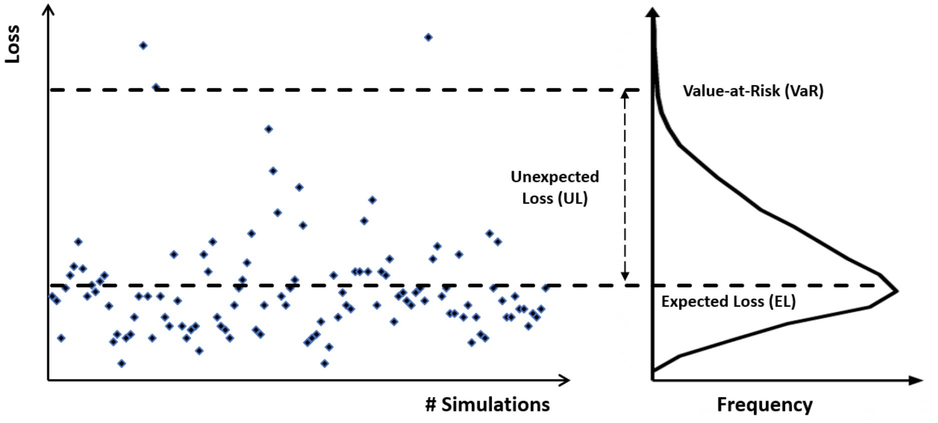


FIGURE 1: Credit Loss Distribution.

probability is less than p. The VaR is a quantile of the distribution. The UL_p is the difference between the VaR_p and the EL. In the IRB approach, it is considered that banks should have enough capital to sustain a loss with probability less than $p = 99.9\%$. The UL can thus be interpreted as the required capital to sustain such losses. In turn, the ES measures the expected loss beyond a specified quantile, the expected loss on the portfolio in the worst $p\%$ of cases. The ES is not considered under the IRB approach. However, it can be intuitively interpreted as the amount of capital required on average to sustain losses with probability above p. From now on we will consider $p = 99.9\%$, the value used in the IRB model.

The ES can be decomposed in marginal contributions of each economic sector s. According to Puzanova and Düllmann (2013) marginal contribution measures have a desirable full allocation property, i.e. they sum up to the overall ES. The marginal contribution is interpreted as the share of ES attributable to a sector, an approximation of its systematic relevance. It combines the assessment of sector risk, its weight in terms of credit exposure and its interdependency with other sectors:

$$\mathrm{MC}_s = E[L_s | L_{tot} \geq \mathrm{VaR}_q(L_{tot})]. \tag{4}$$

Data

This article uses a unique dataset with series for non-financial corporations operating in Portugal between 2006 and 2017. This dataset includes: individual credit exposures and observed sectoral default frequencies captured from the national credit register (CRC); NACE[6] groups available from IES (*Informação Empresarial Simplificada*), and one-year probabilities of default available from Banco de Portugal in-house credit assessment – SIAC (*Sistema Interno de Avaliação de Crédito*).[7]

The initial sample covers roughly the population of non-financial firms that have at least one loan granted by a resident financial institution. Nevertheless, only firms whose loans are considered to be performing are included in the analysis because only those are in risk of default in the next year. Thus, when a firm defaults at year t it is excluded from the analysis at $t+1$ and for as long as the firm is considered as in default.[8] Therefore, we analyze approximately 77% of firms – 85% of total exposure.

The economic groups are divided based on the aggregate levels of NACE into thirteen sectors. Ideally, firms in a given group should be as homogeneous as possible in the variability of PD over time, but heterogeneous between groups. In other words, they should react in a similar way to the same factors. One possibility to increase group homogeneity would be to further divide the groups using lower levels of NACE. However, when using lower levels of NACE we could not guarantee a reasonable number of observations in each group to consistently estimate the model parameters. Thus, each firm was assigned to one of the thirteen industry groups. Figure 2 shows that more than half of the credit exposure of performing loans is concentrated in four sectors: wholesale and retail trade, manufacturing, construction and real estate activities. While the first two sectors maintained a relatively constant weight between 2006 and 2017, the aggregate exposure to the other two declined from 40% to 25% of the total portfolio. This decrease in weight was roughly equally offset by the remaining sectors, although more prominently in the transporting and storage and accommodation and food service activities.

6. Statistical classification of economic activities in the European Community.

7. See Antunes *et al.* (2016).

8. A firm is considered to be "in default" towards the financial system if it has 2.5 per cent or more of its total outstanding loans overdue. The "default event" occurs when the firm completes its third consecutive month in default. A firm is said to have defaulted in a given year if a default event occurred during that year.

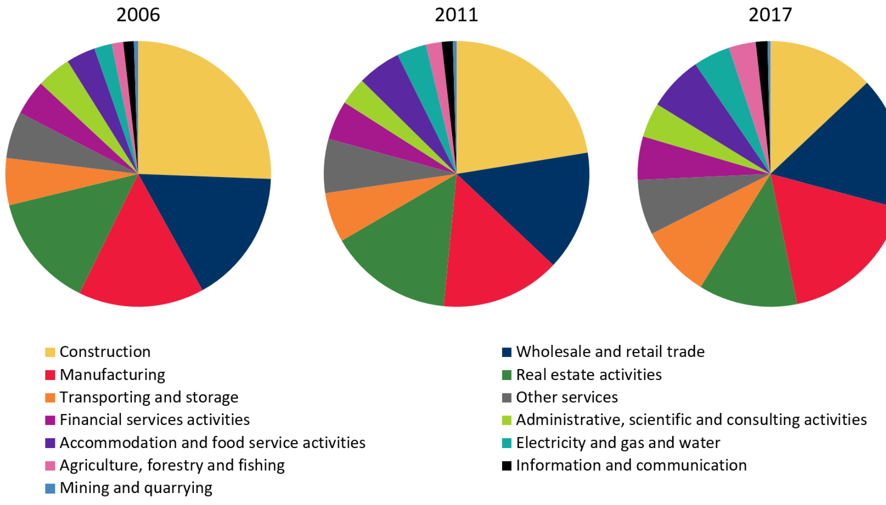


FIGURE 2: Portuguese credit portfolio of performing loans to non-financial firms – weights by activity sector.

Results

Figure 3 reports the loss distribution for the aggregate loan portfolio of non-financial firms of Portuguese banks between 2006 and 2017, presented as a percentage of the total exposure.[9] The distribution is not symmetric, being more concentrated in small losses and with a reduced frequency of large losses. The distribution is limited to the left since its best scenario is when there are no losses. It has a heavy tail and so losses can be quite extensive. Using the information from the loss distribution estimated for each year, Figure 4 shows the expected loss and the three tail credit risk measures – value-at-risk, unexpected loss and expected shortfall – at 99.9% between 2006 and 2017. In order to allow comparisons between different years, all credit risk measures are presented as a percentage of the total exposure. All measures display a similar pattern: a continuous increase between 2006 and 2013, followed by a decline until 2017. $\mathrm{VaR}_{99.9\%}$ and $\mathrm{ES}_{99.9\%}$ move in a parallel way because loss distributions are strictly monotonically decreasing in the tail. During this period the EL ranged from 1.6% to 5.3%, while the $\mathrm{UL}_{99.9\%}$ ranged from 5% to 8.8%. In 2017, the EL was approximately at levels of 2009/2010, while the UL was close to the minimum value reported in 2006. In fact, the difference between EL and UL has decreased over time. This issue will be addressed later on.

9. See dynamic graph on the PDF file.

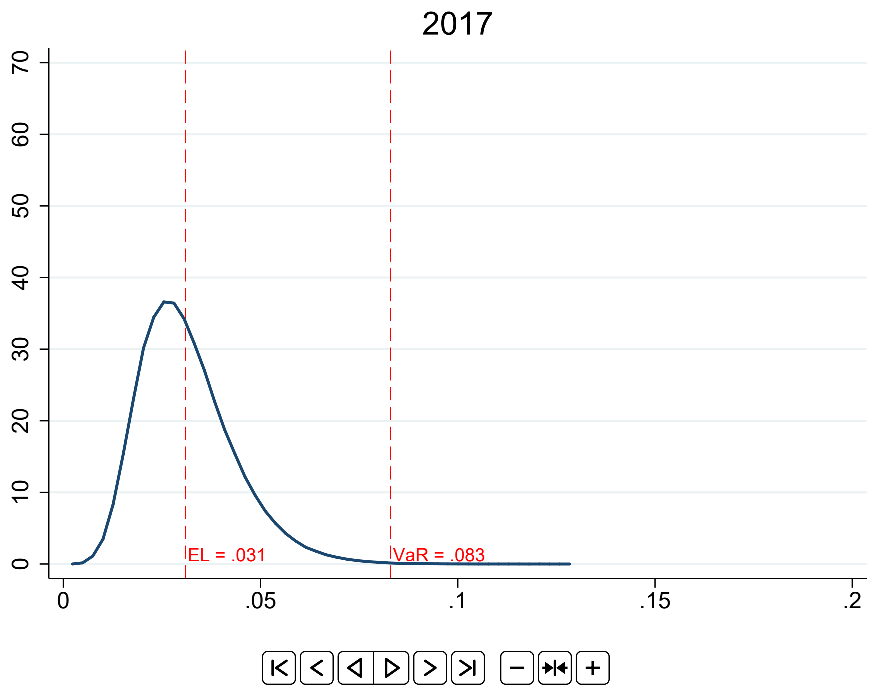


FIGURE 3: Portfolio Loss Distribution 2006-2017.

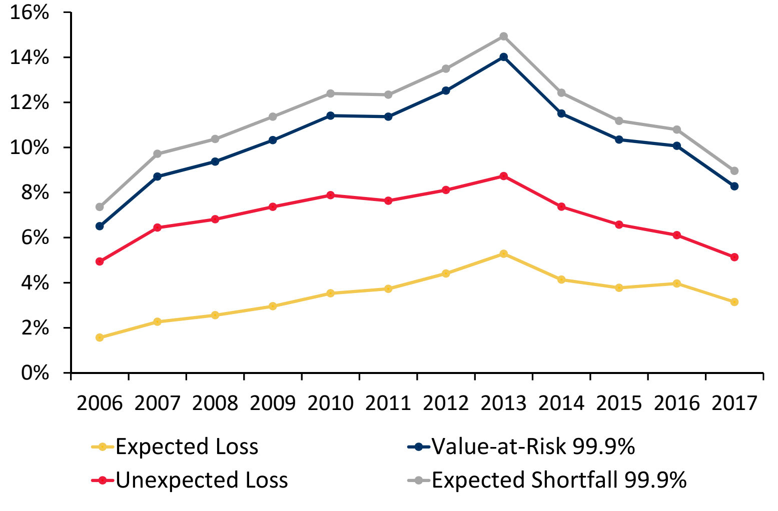


FIGURE 4: Credit risk measures based on Loss Distribution for the Portuguese loan portfolio.

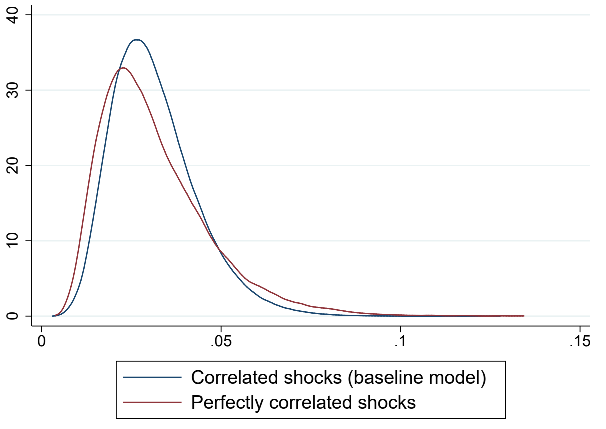
The measures presented so far are useful to assess the credit risk in a loan portfolio but they fail to quantify the role of sector concentration for portfolio credit risk. As such, we will rely on two different exercises that try to establish meaningful measures for the evolution of concentration risk. The first compares the results of our general framework (baseline model) with an ASRF model, while the second decomposes the unexpected loss. The values that are going to be presented should be interpreted with caution since they are sensible to the interdependency structure considered and to the factor weight r_s.

For the first exercise, Figure 5 (A) reports the portfolio loss distribution for 2017 under two different assumptions for the industry specific risk factor Y_s in equation (3). The model with correlated shocks (baseline model, in blue) refers to the loss distribution generated using the correlation structure presented in Table B.1 in the Appendix B, the same distribution as in Figure 3. Whereas the model with perfectly correlated shocks ignores diversification issues and can be treated as an ASRF model. The distribution in this second case (in red) is slightly to the left but it has also a heavier tail. This result is somehow expected since positive (negative) scenarios will now materialize simultaneously for all sectors. By construction the distribution in red produces higher (or equal[10]) values for the $\mathrm{VaR}_{99.9\%}$. In 2017, the unexpected loss is approximately 54% higher under this hypothesis (8.0% instead of 5.2%). In other words, if default risk was perfectly synchronized across sectors the UL for the Portuguese loan portfolio in 2017 would be 54% higher *vis-à-vis* a scenario where default risk is only partially synchronized. By repeating this exercise for all periods, the results indicate that in the last years the difference in the unexpected loss between the baseline model and the one with perfectly correlated shocks increased – Figure 5 (B). In the pre-crisis period the difference was around 40% and has increased since 2014 to approximately 50%, suggesting that the portfolio has become more diversified. But what drove this change?

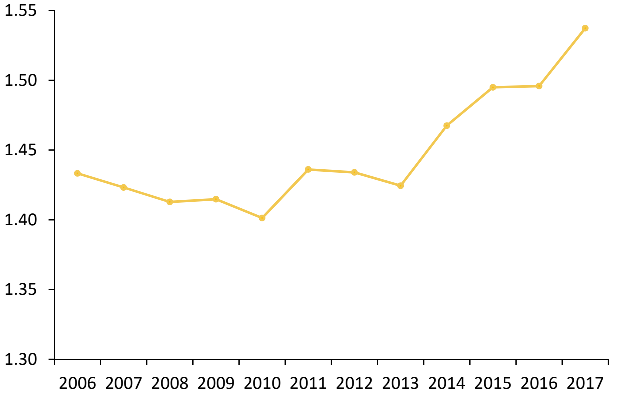
To try to answer the question we will perform a second exercise. Again, let us consider the industry specific risk factor, Y_s, in equation (3) and define three different auxiliary models: (i) a model with only idiosyncratic shocks, where all firms are independent and so each one suffers from a specific shock Y_i; (ii) a model that imposes only correlation within-sector by simulating a different Y_s for each sector s but assumes that all Y_s are independent; (iii) our baseline model that imposes both intra and inter-sector correlations. By construction each model has the same expected value but produces higher (or equal) values for the $\mathrm{VaR}_{99.9\%}$ and $\mathrm{UL}_{99.9\%}$:

$$\mathrm{UL}^{(i)}_{99.9\%} \leq \mathrm{UL}^{(ii)}_{99.9\%} \leq \mathrm{UL}^{(iii)}_{99.9\%} \,. \tag{5}$$

10. The portfolio exposure is concentrated in only one sector or in perfectly correlated sectors.



(A) Portfolio Loss Distribution 2017.



(B) Unexpected Loss – ratio between the perfectly correlated shocks model and the baseline model.

FIGURE 5: Model under the hypothesis of perfectly correlated shocks *vis-à-vis* the baseline model.

Figure 6 decomposes the UL between 2006 and 2017 based on its risk drivers, notably, an independent firm contribution, a contribution arising from within-sector correlation and a contribution arising from between-sector correlation. This is done using the three models before mentioned. From the figure, it is possible to see that, despite slightly increasing, the independent firm contribution plays a very minor role. Most of the unexpected loss is justified by within and between sector correlations. The relative contribution from each of these sources of correlations to UL has however changed during the last years. While in the pre-crisis period, the within-sector correlation explained most of the UL, this role is now played by the between-sector correlation. An interesting additional metric to understand this dynamic is the ratio between unexpected and expected loss (UL / EL). Figure 7 shows this ratio and decomposes it into the same contributes as Figure 6. Based on Figure 7 it is possible to see that the referred ratio decreased steadily from 2006 until 2015 and remained constant afterwards. This ratio is especially affected by interdependency in borrowers' defaults. The between-sector contribution to the ratio remains fairly constant over time while the within-sector contribution dictates the ratio's trend. The results indicate that the possible diversification gains in the last years are caused by a lower concentration in specific sector(s) and not due to an allocation into sectors with lower dependency *vis-à-vis* other sectors. Otherwise the between-sector contribution would have decrease. This trend is also found in the Herfindahl Index that measures the size of activity sectors in relation to the overall portfolio (normalized to 2006). So which sector or sectors are driving this result?

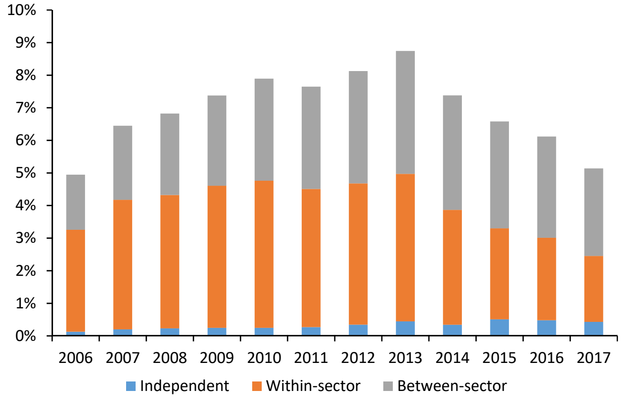


FIGURE 6: Contributions for the Unexpected Loss.

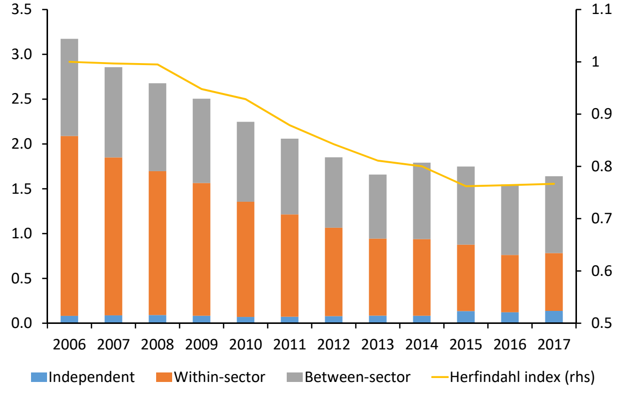


FIGURE 7: Contributions for the ratio UL/EL and Herfindahl Index (normalized to 2006).

Figure 8 reports the contributions of each sector to the expected shortfall for the baseline model in three different periods. Tail risk is significantly concentrated in two sectors, namely construction and real estate activities, which account for more than half of the ES. Still, while the contribution of the real estate sector remains fairly constant, the contribution of the construction sector decreases from approximately 55% to 30% between 2006 and 2017. Thus, the diversification gains documented before are apparently a result driven by the construction sector. Its marginal contribution for the tail risk is decreasing over time, mainly because its weight in the overall portfolio is also decreasing. This decrease results, *inter alia*, from the very significant number of defaults observed in this sector. Moreover, in Figure 9 we observe that the construction sector has, on average, the highest contribution for the EL but an even higher contribution for the ES. In contrast, sectors such as manufacturing and wholesale and retail trade, have a low contribution to the ES (approximately 13%) when compared with their importance to the EL (approximately 24%).[11] This difference suggests the existence of potential diversification gains.

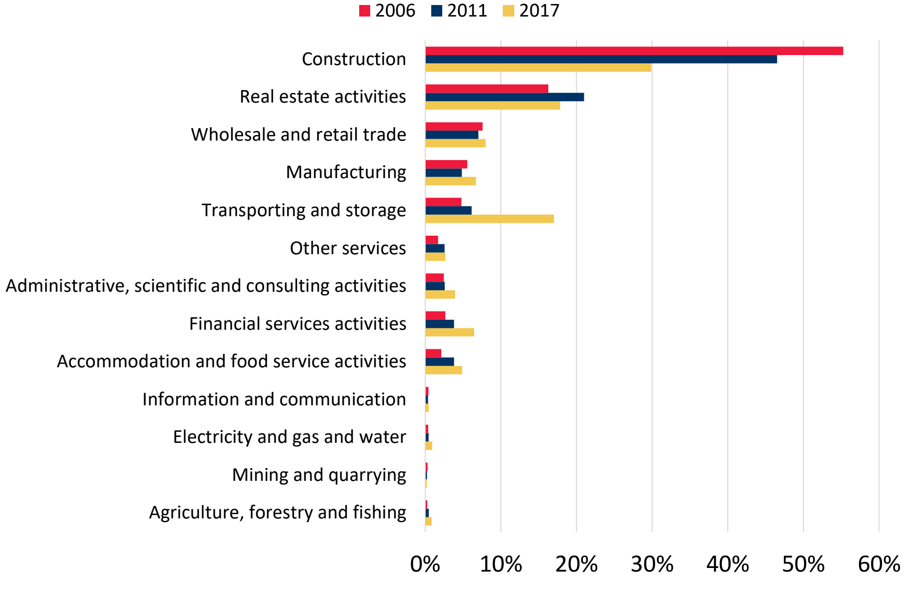


FIGURE 8: Contributions to $\mathrm{ES}_{99.9\%}$.

For each year contributions must sum up 100%.

11. The magnitude of this difference depends significantly from the factor loading parameterization. Whenever one considers r=0.5, the homogenous factor loading proposed in Düllmann and Masschelein (2006), this effect is considerably mitigated.

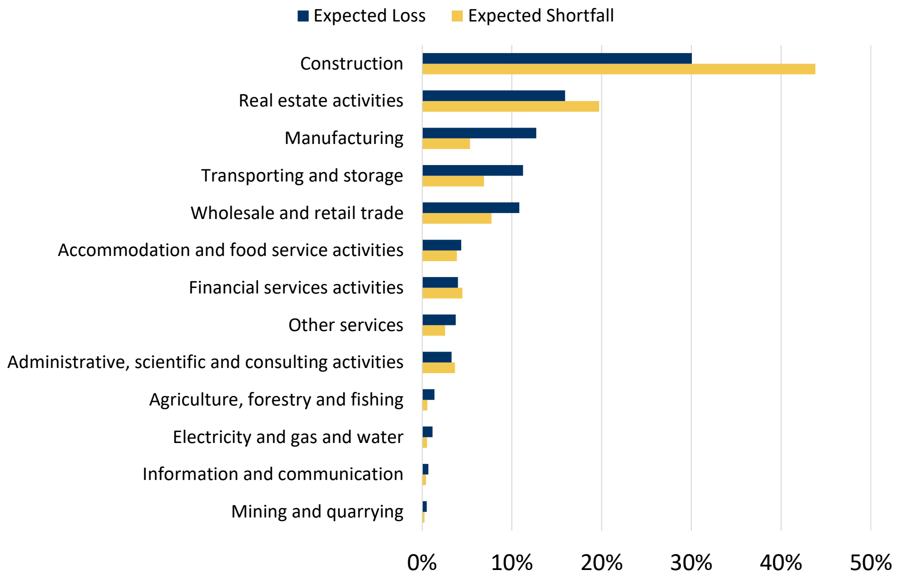


FIGURE 9: Average contributions to EL and $ES_{99.9\%}$.
For each measure contributions must sum up 100%.

Conclusion

The Basel capital framework has opted for a simple and transparent model that do not to explicitly account for portfolio concentration risk. This fact is then compensated in several ways. Still, the objective of this study is not to evaluate whether the Basel capital requirements is sufficiently conservative or not. As already argued, the fact that all the usual tail risk measures are largely dependent on the factor loading assumption, whose estimation is particularly challenging, significantly affects the value of this type of exercise. Instead, this study has three objectives. The first objective is to track the evolution of tail risk in banks' portfolio of performing loans. Under the model proposed in this article, tail risk increased significantly until 2013 and then started decreasing. The decline in tail risk measures such as the value-at-risk and the expected shortfall has been considerably more pronounced than the reduction in the expected loss. The second objective of this study is to analyze the determinants behind tail risk evolution. In particular, we are interested in the ratio between the unexpected loss and the expected loss, which is especially affected by interdependency in borrowers' defaults. Under our multi-factor model, where borrowers' correlations result mostly from sector concentration and inter-sector relations, the progressive reduction in banks' exposure to the construction sector causes the ratio between the unexpected loss and the expected loss to decrease gradually. The last objective of this article is to call the reader's attention for the discrepancy between the marginal contribution of each loan to the expected loss and to the expected shortfall, depending on the borrowers' sector of activity. In particular, it is shown that the ratio between these two contributions is significantly above unity in the construction and real estate sectors while it is considerably below unity in sectors like manufacturing. This difference suggests the existence of potential diversification gains.

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Appendix A

The correlation between the systematic sector risk factors, Y_s, is referred as factor correlation and denoted by ρ_{ij}. Consider that Y_s (known as a composite factor) can be expressed as a linear combination of iid standard normal factors, Z, that impose the factor correlation structure between sectors:

$$Y_s = \sum_{k=1}^{S} \alpha_{s,k} Z_k, \quad \text{with} \quad \sum_{k=1}^{S} \alpha_{s,k}^2 = 1 \tag{A.1}$$

The matrix $(\alpha_{s,k})$ is obtained from the Cholesky decomposition of the sector correlation matrix, ρ_{ij} – Table B.2 Appendix B. To ensure that Y_s has unit variance it must hold that $\sum_{k=1}^{S} \alpha_{s,k}^2 = 1$.

The correlation between asset returns of two firms in sectors i and j is then obtained as:

$$\omega_{ij} = r_i r_j \rho_{ij} = r_i r_j \sum_{k=1}^{S} \alpha_{i,k} \alpha_{j,k}. \tag{A.2}$$

The correlation between the systematic sector factors and the sensitivity of the asset return to the composite factor determine the dependencies between firms. The intra-sector asset return correlation for each pair of firms is given by considering that $\rho_{ij} = 1$. In this case, $\omega_{ij} = r_s^2$.

Appendix B

Sector of activity	r_s
01 - Agriculture, forestry and fishing	0.229
02 - Mining and quarrying	0.303
03 - Manufacturing	0.098
04 - Electricity and gas and water	0.162
05 - Construction	0.457
06 - Wholesale and retail trade	0.199
07 - Transporting and storage	0.244
08 - Accommodation and food service activities	0.304
09 - Information and communication	0.258
10 - Real estate activities	0.363
11 - Financial services activities	0.472
12 - Administrative, scientific and consulting activities	0.422
13 - Other services	0.313

TABLE B.1. Factor Loadings.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	**1**	-0.03	0.28	0.03	0.29	0.36	0.02	-0.02	0.07	0.09	0.23	-0.12	0.16
2	-0.03	**1**	0.45	0.24	0.27	0.46	0.29	0.45	0.01	0.35	0.11	0.34	0.13
3	0.28	0.45	**1**	0.28	0.56	0.69	0.39	0.55	0.16	0.52	0.42	0.42	0.39
4	0.03	0.24	0.28	**1**	0.46	0.36	0.2	0.3	0.33	0.32	0.35	0.32	0.13
5	0.29	0.27	0.56	0.46	**1**	0.64	0.3	0.42	0.45	0.76	0.51	0.45	0.39
6	0.36	0.46	0.69	0.36	0.64	**1**	0.42	0.54	0.49	0.65	0.44	0.56	0.25
7	0.02	0.29	0.39	0.2	0.3	0.42	**1**	0.53	0.18	0.38	0.27	0.56	0.21
8	-0.02	0.45	0.55	0.3	0.42	0.54	0.53	**1**	0.05	0.42	0.5	0.45	0.51
9	0.07	0.01	0.16	0.33	0.45	0.49	0.18	0.05	**1**	0.5	0.4	0.33	0.06
10	0.09	0.35	0.52	0.32	0.76	0.65	0.38	0.42	0.5	**1**	0.32	0.6	0.28
11	0.23	0.11	0.42	0.35	0.51	0.44	0.27	0.5	0.4	0.32	**1**	0.28	0.6
12	-0.12	0.34	0.42	0.32	0.45	0.56	0.56	0.45	0.33	0.6	0.28	**1**	0.3
13	0.16	0.13	0.39	0.13	0.39	0.25	0.21	0.51	0.06	0.28	0.6	0.3	**1**

TABLE B.2. Sectoral Correlations.