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Supervision by robust risk monitoring – a cycle-independent Hungarian corporate credit rating system*

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International and Hungarian prudential regulation primarily tasks the supervisory authority with controlling the supervised credit institutions' lending policy and, in relation to this, the internal models used in this policy. However, the crisis period that started in 2009 demonstrated that in many cases credit institutions with the same lending policy employ models which project significantly different capital and risk costs when rating their clients. As a result, developing monitoring tools that enable comparison of individual internal models and regular monitoring of the lending practices of the individual institutions have recently gained prominence in international supervision. This study presents a possible, simple yet stable and readily applicable corporate monitoring framework which is in line with the Hungarian and international regulation and best practices.

Journal of Economic Literature (JEL) codes: C55, C53

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1. The development characteristics and goals of the monitoring tool

1.1. Internal models used in client rating

In the case of the internal models used by credit institutions in client rating for assessing creditworthiness and the probability of default (PD), it can be generally stated that the most important goal is to maximise separation power. The main regulatory requirement is to make separation power as strong as possible (*CRR, Article 174[a]*), while the requirement that the assignment to grades and the calibrated PD values should reflect the business and risk management processes of the institution (*CRR, Article 171[c]*) is only a secondary stipulation. Perhaps partly as a result of this, in many cases, institutions themselves do not clearly declare the

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goals they wish to achieve by improving their internal models, i.e. whether their aim is to give a stable rating on each point of the economic cycle or as accurate a PD estimate as possible for a given point in time. Obviously, depending on the maturity of the products offered to the client base of borrowers, both approaches may be viable and warranted, but it can be often observed that, when pricing short-term products, a through-the-cycle PD is used, and, conversely, long-term products are priced using risk factors characteristic of a given moment. "Hybrid" rating and PD calibration approach is also widely employed.

This study employs a methodology which is as close to a through-the-cycle internal risk rating system as possible and meets the following criteria:

(*1*) The number (share) of companies assigned to the individual rating categories is essentially the same at all the points of the cycle.

(*2*) Therefore, the short and medium-term migration across the rating categories can be attributed mainly to the changes in the external macroeconomic environment and, to a lesser extent, to the shifts in the financial or economic characteristics of a given company.

(*3*) The categories not only capture the relative risks of the individual companies, but do so in a way that the PD value observed in the individual categories changes as the external economic environment becomes less favourable. Of course, there is no perfect through-the-cycle or point-in-time modelling framework, but as we shall see later, a monitoring and rating methodology almost independent from the economic cycle can be achieved by choosing the right variables, at least in the segment of micro, small and medium-sized enterprises.

Therefore, the main goal and starting point of the modelling was to create a long-term rating system consistent with the aforementioned criteria, with special emphasis on ranking power and appropriate calibration with respect to the PD parameter. The secondary goal was to create a robust methodology and segmentation framework which only necessitates recalibration or revaluation under special circumstances or not even then. The qualitative and quantitative tests described below examine the compliance with these two goals.

In addition to the methodological goals, the ultimate aim of developing the monitoring tool is its practical utilisation within the framework of regular supervision. This is supported by its robust nature, which entails easy interpretability for senior management and a minimal maintenance requirement on the part of the experts operating it. Furthermore, the through-the-cycle calibration allows for detailed analysis of the long-term risks of a given financial institution's corporate portfolio, as well as the relatively smooth, modular integration of additional streams of development. Finally, it is worth mentioning that consistency with the international supervisory practices and methodology, as well as the implementation of international best practices in Hungary are also sought to be achieved. As a reference, the simplified segmentation of mortgage portfolios by loan-to-value used by the Bank of England (*2015, Subpoint 2.)* for capital requirement calculations, and the use of the reference calculations of the European Central Bank during the various Pillar 1 and Pillar 2 model reviews (*Schoenmaker–Véron 2016:130*) can be mentioned here.

1.2. Databases used

The data used for segmentation and modelling were obtained from the databases of the National Tax and Customs Administration of Hungary (NAV) and Opten (a privately held company, which maintains a corporate register database). The databases were used solely for statistical purposes, i.e. anonymously, and no unique client data was utilised during either the segmentation or the modelling steps. The NAV database was designated as the source of complete register for corporate clients, given the fact that it contains the official balance sheet and P&L figures for all Hungarian companies, and is therefore a comprehensive company register. The appropriate field in the Opten database served as the indicator of negative legal events (that are as follows: liquidation proceedings, bankruptcy proceedings, court-ordered company deregistration, completed liquidation, involuntary dissolution) as "hard" default events, i.e. as the output variable. As only a negligible portion of the companies concerned return to a clean, operating status after the initiation of a negative legal event (actually less than 1 per cent do so), in the case of all companies affected by negative events, the first negative event was taken into account during the modelling.

As can be seen from the above, the explanatory variables (balance sheet and P&L figures) are annual and "application" type data from the perspective of credit risk models. As we demonstrate later, risk segmentation can be performed with adequate accuracy using this approach.

With respect to the analysis of the NAV and the Opten databases, the available literature (*Bauer–Endrész 2016, Table 1*) gives a detailed overview about the fact that on average, 33.8 per cent of negative events occur within the first year of submitting the financial statements, 21.1 per cent occur between the first and the second year, 14.7 per cent occur between the second and the third year, while the remaining roughly 30 per cent occur later. The cited analyses are not repeated here, as no different phenomena were observed in the analysis of the databases. Nevertheless, we believe it is important to underline that the foregoing observations call for appropriate development and continuous validation. These validation analyses will be presented in the corresponding subpoints of the current study.

1.3. Segmentation and modelling approach employed

Modelling corporate default and bankruptcy risk and its methodology has a very long history. For the sake of brevity, we do not attempt to give even a modestly comprehensive overview here and only examine the most relevant international and Hungarian antecedents. The international literature is presented with respect to the motivation of the series of articles, while the Hungarian literature is examined in view of the databases and practices used.

1.3.1. Overview of the literature

In an international context, it can be stated that the methodology used for modelling corporate default and bankruptcy risk is quite varied, both from a business and a supervisory-prudential perspective. In an international supervisory survey, the Bank for International Settlements analysed the differences between the Pillar 1 risk weights applied by large banks which can be deemed "similar" from their respective risk profiles (*BIS 2013*). In the case of the corporate segment, the study mainly attributes the not fully justifiable variability in risk weights to the differences in the PD parameter. The British central bank reached a similar conclusion in its November 2012 Financial Stability Report (*Bank of England 2012*), in the third chapter of which a variability of between 50 per cent and 150 per cent was observed with respect to the risk weight of corporates, depending on the point in time. This is obviously partly attributable to the risk profile of the institutions, but it is also markedly influenced by the sample size available to the institutions for parameter estimation, as well as by the methodology employed. The latter was one of the main sources of the significant difference, even in the case of relatively large portfolios with tens of thousands of clients. This means that a supervisory reference or monitoring model not only needs to be consistent internally, from a methodological perspective, but must also cover as broad a sample as possible. Precisely because of this, the current analysis includes all non-financial enterprises registered in Hungary that use double-entry bookkeeping, employing a uniform methodology.

Similar to the international literature, the Hungarian literature is considerably varied. Two studies by *Hajdu and Virág* (*1996 and 2001*) are among the first publications that attempted to estimate the default risk of Hungarian SMEs. MNB experts have also examined several approaches in the context of corporate credit risk in recent years, and their work is slightly similar to this study in terms of methodology and approach (*Banai et al. [2013], and Bauer–Endrész [2016]).* The latter can be regarded as the closest "relative" to our study, since it is based on the same scope of data (NAV and Opten databases), and its estimates and calibration hinge on the same output variable, i.e. negative legal events. Furthermore, in line with business processes in banking, it presents forecasting models for the corporate sub-segments (micro, small and medium-sized enterprises). Compared to Bauer and Endrész's approach, the main differences are in our system of goals and tools:

- This study is dominated by monitoring aspects, while the MNB's working paper focused more on creating a forecasting model by integrating macroeconomic variables.
- Related to this, the main goal of this study and series of articles is to implement short and long-term calibration as neatly as possible, while in the above-mentioned literature the authors only attempted to achieve the highest ranking power possible, taking no calibration aspects into account, or only to a very limited extent.
- The authors of the working paper utilised a classic logistic regression estimation and variable selection methodology, while this study employs machine learning algorithms with expert adjustments, albeit it also uses logistic regression as the base learner.
- Bauer and Endrész used bankruptcy proceedings, liquidation and dissolution as negative events, while the present study includes a somewhat wider scope of negative events, as presented earlier, i.e. liquidation proceedings, bankruptcy proceedings, court-ordered company deregistration, completed liquidation and involuntary dissolution. This disparity does not cause a marked difference either in the rate or dynamics of the negative events.

In summary, while Bauer and Endrész, using a wide range of variables and integrated macroeconomic variables into their model, set out to create a model for forecasting negative events with strong predictive power, this study shows a "minimalist", low-maintenance intense segmentation and modelling framework that can also be used for monitoring purposes if necessary.

1.3.2. Data generation and modelling methodology

In line with the principles detailed in the previous subpoints, the aim during segmentation and modelling was to create a through-the-cycle, low-maintenance, intense and stable monitoring tool. In view of the fact that companies with a financial focus (credit institutions, insurance corporations, financial enterprises, etc.) have a unique risk profile different from that of non-financial enterprises, this study developed a segmentation tool for non-financial enterprises using double-entry bookkeeping. The overview of the international modelling practices based on large databases features several approaches, out of which we employed the data-driven approach (*Norvig 2009*). This means that after compiling the large databases we chose the simplest, low-maintenance models possible, with minimal expert adjustments. The advantage of this is that although the use of additional variables and more complex models can result in stronger, better client quality separation performance, the longer-term stability of this is questionable, and according to experiences, in the case of credit risk models, there may not always be substantial relative performance enhancement.

During the development, i.e. during the in-sample parameter estimation and the out-of-sample and out-of-time validation, a time frame of 1 year was used from the balance sheet date of the financial statements (typically and in most cases 31 December). The available literature cited previously in Subpoint 1.2 (*Bauer–Endrész 2016*) used a time frame of 2 years during the development, because on average 55 per cent of negative events are concentrated in the first two years after the reference date of the financial statements. In contrast to this, but in line with the annual tax return cycle, the present study developed the model with a 1-year outcome time frame, and we examined whether the assignment to rating categories was stable for the medium-term time-excluded sample (i.e. over 1¼ years) and over the long term (i.e. several years after the submission of the given year's financial statements).

In summary, for the risk segment of non-financial enterprises using double-entry bookkeeping, we employed a data-driven, stable, readily interpretable and low-maintenance segmentation and modelling approach, which was driven by the negative event signal of the Opten database as the output variable, and by the companies' balance sheet and P&L figures as explanatory variables. (In a later study, it may be worth examining the possibility of fine-tuning segmentation models by including additional data.)

Finally, it must be pointed out that the companies established with a special financing purpose (i.e. project finance) were not filtered from the database, given the fact that the accurate delineation and separation of these companies from a company group is by no means of clear-cut undertaking in many cases. Since the modelling was performed on the basis of the number of companies, keeping these firms in the sample does not cause a significant change (as there are only about tens or hundreds of such companies overall in Hungary, depending on the definition), and, if necessary, they can be removed from the sample after they are precisely identified.

2. Corporate monitoring

2.1. Segmentation

According to the expectations of the regulatory authority, the portfolio must be divided into homogeneous risk segments during risk modelling (*CRR, Article 170 [4]).* In the case of the corporate segment, the economic rationale behind this expectation is that a micro or small enterprise employing a handful of people is much less diversified – from the perspective of its revenue sources – than a medium-sized or large enterprise, and its capital and liquidity reserves are also relatively more limited than those of a mature company. This is supported by the statistical analysis of the databases cited above, based on the 2014 financial statements (*Table 1*).

Table 1
Summary of the characteristics of corporate segments (non-financial enterprises)

	Segment boundary applied (HUF bn)	Number of companies	Total net turnover (HUF bn)	Share Capital / Total Assets	Proportion of profitable companies	Average FTE	Average size of Balance Sheet (HUF bn)
Large Corporate	>15	576	43,305	11.8%	82%	840	63.86
Mid-sized Corporate	2 – 15	3,525	16,860	8.0%	88%	121	5.17
Small Enterprise	0.3 – 2	18,268	12,791	2.9%	89%	25	0.70
Micro Enterprise	0 – 0.3	345,959	9,191	0.5%	67%	2	0.03

Source: Own calculation based on NAV database

The segmentation based on net sales revenue and used in the table is partly consistent with the segment limits stipulated by international standards (*EU SME regulation 2005; CRR, Article 174*). Nonetheless, when separating the segment of medium-sized and large enterprises, the segmentation was primarily based on Hungary's characteristics, taking into account expert segment limits, and the net sales revenue-based segment limits that can be consistently determined for 2000-2016 by quantitative tools (decision trees) when creating the segmentation model. The overview of the headcount figures attests that even if they were analysed in more detail and given more weight, it would not result in a substantially different segmentation.

2.2. Modelling practice employed

As suggested earlier, the modelling within the individual corporate segments was performed in a data-driven manner, using expert adjustments, in the following steps:

(*1*) Separation of the segment with the given net sales revenue was based on the final financial statements (corrected, where applicable) for the given year. During modelling, only those companies were taken into account that filed a tax return in the given year. Those that did not were not included in the calculations, since they were basically "dormant" companies, typically operating with losses for several years, the higher risk of which was already captured by the financial statements from earlier years.

(*2*) Using the balance sheet and profit and loss account variables, a group of financial variables was chosen for each year (between 1999 and 2013) which had the strongest predictive power with respect to the negative legal events within one year after the financial statements. These variables were used to create complex financial indicators based on expert assessment (see below). In order to filter out outliers, the variables' "pseudo" logarithm was derived (in the case of variables with negative values, the logarithm of their absolute value was multiplied by –1).

(*3*) Using logistic regression, the coefficients of the chosen complex financial indicators were estimated for each year, and then the parameters derived for the individual points of the cycle (1999–2013) were averaged out. Essentially, the applied approach described here is "bagging" (*bootstrap aggregating*), which is a well-known technique in machine learning, i.e. the values of the parameters estimated for the subsamples created by the bootstrap method were averaged out (*Breiman 1996*), and all the base learner models were logistic regression models. During practical application, this method produces demonstrably more stable results with all learning algorithms, logistic regression included, and based on the results presented later, this is true in this case as well.

(*4*) Within the segment with the given net sales revenue, the "cycle-independent" model determined in Step (3) was used for assigning a score to each company, and then the firms were grouped into risk categories by establishing the thresholds.

Naturally, an iterative approach was used in Steps (2)–(4) in the modelling, and the variables that did not prove to be stable – either due to data quality or other reasons – were not used in modelling the given, final subsegment defined by the net sales revenue limits.

Step (2) covered the variable selection step compulsory in modelling. As a first step in variable selection, before embarking on the iterative process described above, the ranking power of the individual variables was assessed in the case of the individual financial (balance sheet and P&L) figures, for all years and segments. After this, the variables the coefficients of which proved to be unstable or volatile in the modelling sample were removed. Finally, the complex variables were derived from the stable variables with strong ranking power in the manner already described. In all cases, these complex variables proved to be stronger than the variables' individual ranking power.

Companies were assigned a score and grouped into risk categories in Step (4) using the long-term parameters. The latter step was performed with a decision tree, with the establishment of optimal cut-off points (*Joopia 2016*). This step was almost fully data-driven, with a single adjustment: the number of risk score thresholds determined annually was not the same across years, but their values were practically the same in each year. Accordingly, the most frequent thresholds that could be deemed stable were chosen for determining the final risk rating.

2.3. Monitoring models within the individual segments

In view of their large number, the credit risk quality of large corporates can only be assessed individually, and in their case, due to their special nature, the expert analysis-type risk assessment approach is more appropriate. Accordingly, in the following we present the further segmentation of micro, small and medium-sized enterprise segments separated based on net sales revenue as shown in Subpoint 2.1.

2.3.1. Microenterprise segment

As a result of the iteration process described in Subpoint 2.2, in the case of the microenterprise segment, the variables shown in Table 2 proved to be the indicators exhibiting a stable explanatory power and showing an appropriate performance for all points in the cycle.

Table 2
Explanatory variables chosen for the microenterprise segment and their values for the given year's financial statements

Year of Annual Report (Review date: 31st December)	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Average
Debt servicing capacity	0.085	0.070	0.090	0.100	0.089	0.100	0.085	0.094	0.092	0.080	0.069	0.053	0.088	0.084
Fixed Assets / Long term liabilities	0.065	0.081	0.050	0.043	0.044	0.039	0.066	0.065	0.071	0.060	0.077	0.086	0.061	0.062
Liquid Assets / Short term liabilities	–0.206	–0.200	–0.185	–0.166	–0.148	–0.153	–0.158	–0.155	–0.141	–0.170	–0.168	–0.144	–0.220	–0.170
Total Expenses / Net Sales Revenues	0.063	0.076	0.024	0.029	0.037	0.017	0.040	0.025	0.019	0.020	0.029	0.045	0.017	0.033

Source: Own calculation based on the NAV and Opten databases

The set of variables include the following complex financial indicators:

- indicator capturing *debt service*

$$\textit{debt burden} = \frac{\textit{pre-tax profit}}{\textit{interest paid} + \textit{short-term liabilities}}$$

- indicators capturing the *short and long-term liquidity position*

$$\textit{long-term liquidity position} = \frac{\textit{invested financial assets} + \textit{tangible assets} + \textit{immaterial assets}}{\textit{long-term liabilities}}$$

$$\textit{short-term liquidity position} = \frac{\textit{financial assets} + \textit{securities}}{\textit{short-term liabilities}}$$

- *productivity indicator*

$$\textit{productivity indicator} = \frac{(\textit{material} + \textit{personal} + \textit{other})\ \textit{expenditures}}{\textit{sales revenue}}$$

Similar to the debt coverage and payment-to-income ratio indicators in force in the household segment as stipulated by the Hungarian regulations, the indicators use the debt service capacity of corporate clients as well as the group of assets available as collateral for loan repayment as risk indicators.

Using the above variables and the averaged parameters for each year and assigning corporate clients to rating categories based on the scores derived in this manner, we arrive at the one-year negative event proportions for each rating category, as presented in Table 3. Based on this table, the model ensures monotonous risk ordering for each year in the cycle, i.e. the minimum requirement of monotonicity on each point of the cycle mentioned in Subpoint 1.1 is satisfied. Furthermore, it is worth mentioning that across the categories, in the years that were not characterised by economic slumps, the probability of companies' negative event involvement doubled in an almost linear fashion. In the periods characterised by macroeconomic stresses – i.e. in 2009 and 2010 – the relative risk between the rating categories decreases, which is not unprecedented however. This is because in better categories, the heightening of relative risks is to be expected much more, while in the case of companies of a poorer quality, a crisis is only the last straw for them before they stop operating as going concern.

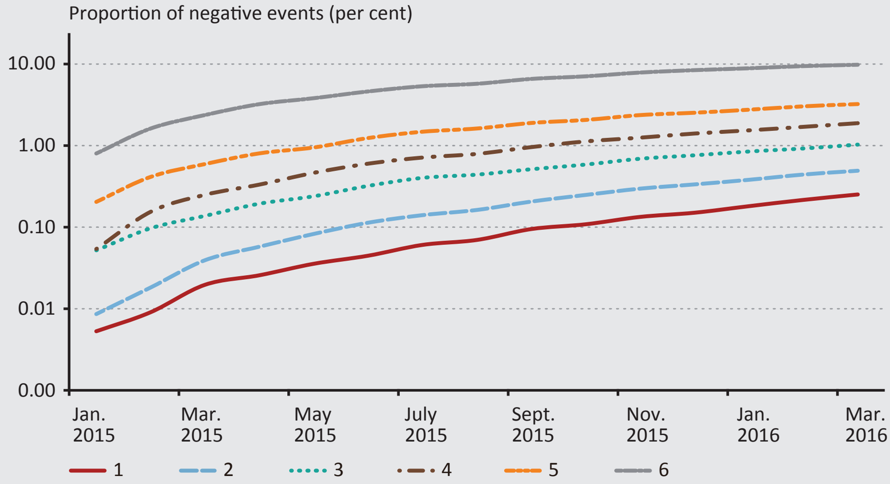
Table 3
One-year negative event proportion within the rating categories of the microenterprise segment

	Year of NAV Annual Report															
Rating	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**Average**
1	0.22%	0.25%	0.19%	0.25%	0.25%	0.26%	0.33%	0.33%	0.43%	0.47%	0.63%	0.80%	0.21%	0.23%	0.18%	0.3%
2	0.42%	0.53%	0.36%	0.45%	0.50%	0.47%	0.51%	0.48%	0.63%	0.75%	0.88%	0.92%	0.37%	0.40%	0.38%	0.6%
3	1.00%	1.35%	0.88%	0.99%	0.90%	1.05%	0.93%	0.97%	1.18%	1.39%	1.32%	1.32%	0.65%	0.76%	0.80%	1.0%
4	1.76%	2.02%	1.48%	1.78%	1.55%	1.44%	1.68%	1.65%	2.08%	2.21%	2.05%	2.08%	1.04%	1.35%	1.47%	1.7%
5	3.33%	3.84%	2.65%	2.82%	2.36%	2.54%	2.63%	2.67%	3.15%	3.43%	3.08%	3.09%	2.01%	2.34%	2.55%	2.8%
6	9.98%	11.67%	7.81%	9.02%	7.32%	7.96%	7.82%	7.85%	9.08%	9.80%	9.94%	8.82%	6.88%	7.96%	7.97%	8.5%
Segment	1.2%	1.3%	0.9%	1.1%	1.0%	1.0%	1.1%	1.1%	1.3%	1.6%	1.8%	1.8%	1.0%	1.2%	1.1%	1.2%

Source: Own calculation based on the NAV and Opten databases

In order to test the model's out-of-sample performance, the assignment to risk categories was performed based on the 2014 financial statements. Based on *Figure 1*, the model's out-of-sample performance is adequate, as it separates between the individual risk categories at all points in time.

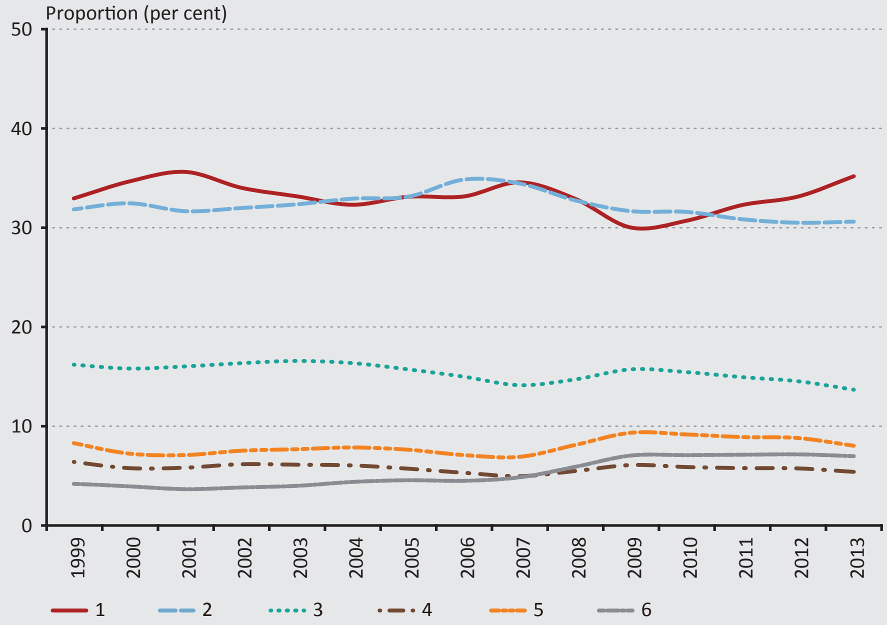
Figure 1
Cumulative monthly negative event involvement of microenterprises with financial statements in 2014



Source: Own calculation based on the NAV and Opten databases

As a second test, we examined the adequacy of the model's long-term classification through the migration of clients between rating categories. Although the data in *Figure 2* show that a slight downward migration occurred during the crisis and that after it passed, a migration in the opposite direction could be observed, overall this does not materially influence the model's through-the-cycle nature. This also means that the model primarily assigns greater risk to a given company through the higher probability of default within the category, and not through the downward migration of the company.

Figure 2
Distribution of microenterprises across the rating categories of the microenterprise segment

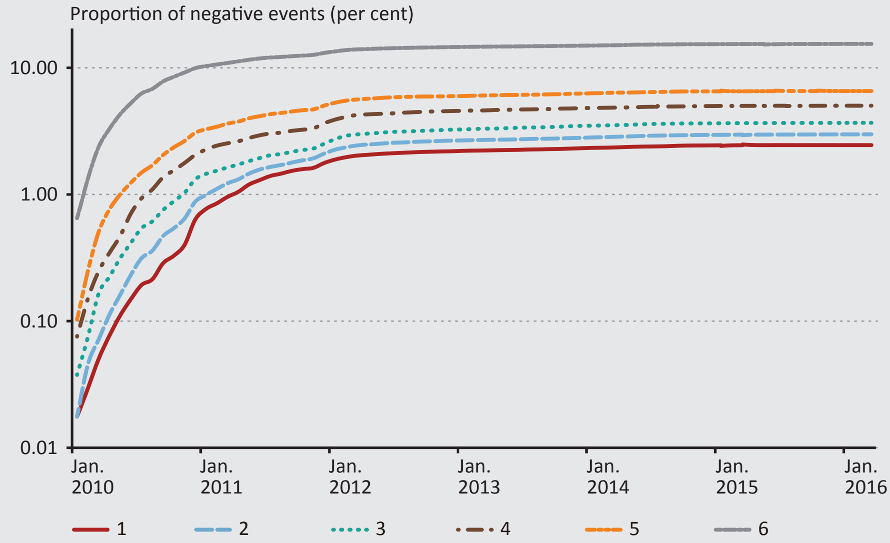


Source: Own calculation based on the NAV and Opten databases

Finally, we examined whether the risk rating provided for a long-term monotonous separation, which is not only significant from the perspective of testing the through-the-cycle nature of the model, but is also important from the aspect of the process, as detailed earlier in Subpoints 1.2 and 1.3 (missing financial statements), and from the aspect of development (relevance of choosing the output time frame). Based on *Figure 3*, it can be stated that the model has stable separation power even in a long outcome frame, and the rating derived in a 1-year time frame can be applied to very long horizons.[1]

[1] In this study, these tests are only presented for the micro, small and medium-sized enterprises that submitted financial statements on the accounting dates of 31 December 2009 and 31 December 2014. Upon request, the authors can send an analysis for other accounting dates to demonstrate the model's stability.

Figure 3
Cumulative monthly negative event proportion of microenterprises with financial statements in 2009



Source: Own calculation based on the NAV and Opten databases

All in all, in the microenterprise segment, with respect to companies' negative event involvement, strong segmentation power can be achieved by using four variables with a strong economic content. The variables are stable both from the perspective of their distribution and their ability to classify companies, and they are persistently able to separate companies with respect to their ability to survive from month to month, at all points in the cycle.

2.3.2. Small enterprise segment

Similar to the microenterprise segment, the strong and stable variables in the small enterprise segment proved to be the debt burden and the indicator capturing short-term liquidity, which is shown in Table 4 (the definitions of the variables are the same as in Subpoint 2.2.1). It is readily observable from the values of the parameters that compared to the microenterprise segment, the small enterprise segment is more sensitive to the magnitude of debt servicing and to short-term liquidity problems, provided, of course, that everything else remains the same.

Table 4
Explanatory variables chosen for the small enterprise segment and their values for the given year's financial statements

Year of the financial statements (accounting date: 31 December)	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Average
Debt burden	0.145	0.106	0.117	0.111	0.120	0.105	0.096	0.112	0.101	0.101	0.090	0.073	0.103	0.105
Liquid assets / Short-term liabilities	–0.334	–0.167	–0.201	–0.333	–0.232	–0.237	–0.202	–0.227	–0.192	–0.273	–0.256	–0.240	–0.186	–0.237

Source: Own calculation based on NAV's and Opten's database

It was impossible to create a stable model in the medium size segment due to the low number of negative events (around 10-30 a year for approximately 3,000 companies annually, depending on whether there was an upswing or a slump in the economy). Therefore the small enterprise model was used as a "shadow" model, and the same thresholds were used for assigning rating categories to the medium-sized enterprises, which, as presented below, produced an acceptable result that required only some minor fine-tuning. In the case of both the small and medium-sized enterprise segments, the detailed definitions of the debt burden, liquid assets and short-term liabilities were the same as in the microenterprise segment, i.e. the results were derived the same way as presented there.

2.3.3. Small enterprise segment

The two variables presented in the previous subpoint and used in modelling are stable and strong, however, the optimal segmentation of scoring only enabled the division into four rating categories. This also shows that – as we shall demonstrate it later – that in itself, a higher value of the AUC indicator does not necessarily indicate a stronger model, as the segmentation potential, i.e. the separation of false and actual positive cases may also be stronger in the case of model with a lower AUC indicator.

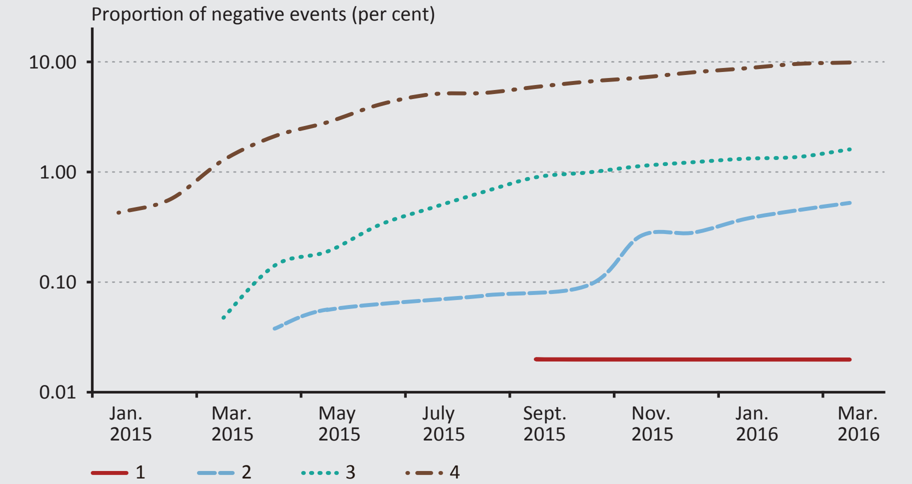
Table 5
One-year negative event involvement within the rating categories of the small enterprise segment

	Year of the NAV report															
Rating	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Average
1	0.08%	0.07%	0.06%	0.05%	0.05%	0.05%	0.16%	0.15%	0.17%	0.23%	0.14%	0.27%	0.25%	0.15%	0.07%	0.1%
2	0.07%	0.39%	0.22%	0.54%	0.40%	0.63%	0.45%	0.47%	0.57%	0.78%	0.77%	0.91%	0.30%	0.23%	0.08%	0.5%
3	1.31%	1.68%	1.13%	1.76%	1.50%	2.34%	1.60%	1.33%	1.74%	2.41%	2.05%	1.78%	1.57%	1.01%	0.74%	1.6%
4	8.63%	5.27%	6.70%	11.78%	8.16%	10.31%	8.34%	10.70%	9.90%	14.78%	10.69%	9.87%	7.63%	7.34%	6.51%	9.4%
Segment	0.8%	0.7%	0.6%	1.0%	0.8%	1.1%	0.9%	0.9%	1.1%	1.9%	1.7%	1.5%	1.1%	0.8%	0.5%	1.0%

Source: Own calculation based on the NAV and Opten databases

Similar to the model validation practice employed in the case of microenterprises, the cumulative proportion of negative events for the subsequent one and a quarter of a year was also examined in the case of the small enterprises which filed a tax report with the accounting date of 31 December 2014. The separation was stable, both for a month-by-month horizon and a multiple-year horizon.

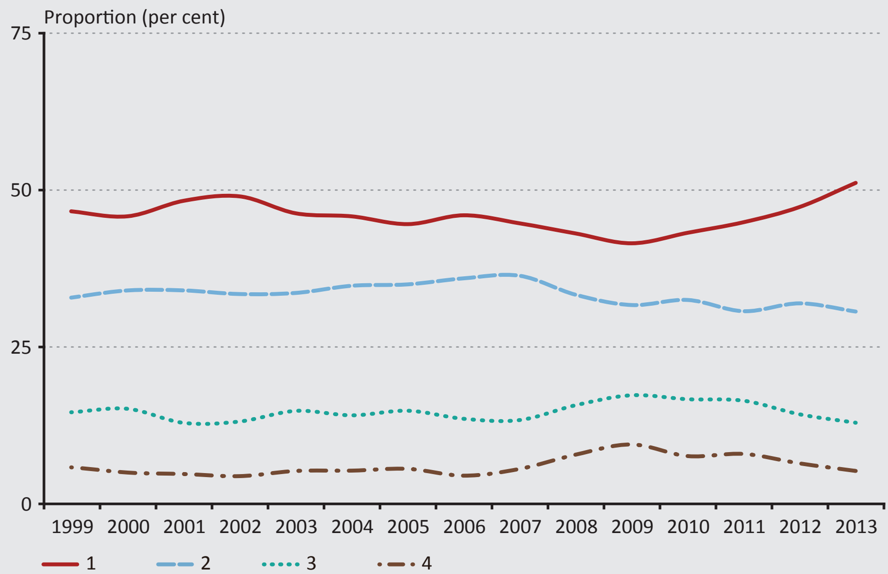
Figure 4
Cumulative monthly negative event proportion of small enterprises with financial statements in 2014



Source: Own calculation based on the NAV and Opten databases

The test presented in the case of microenterprises on the stability between the rating categories of the segment was also performed for small enterprises. The test demonstrates that there is no considerable migration risk in the small enterprise model either, however, partly due to the smaller number of variables, the risk is more pronounced than in the case of the microenterprise model. Nevertheless, it is clear that cross-category migration primarily happens between the 1st, best and the 2nd category, which does not materially jeopardise the through-the-cycle nature of the model. At the same time, going forward, the addition of further variables may be worth considering in order to ensure better smoothing of the ratings' distribution.

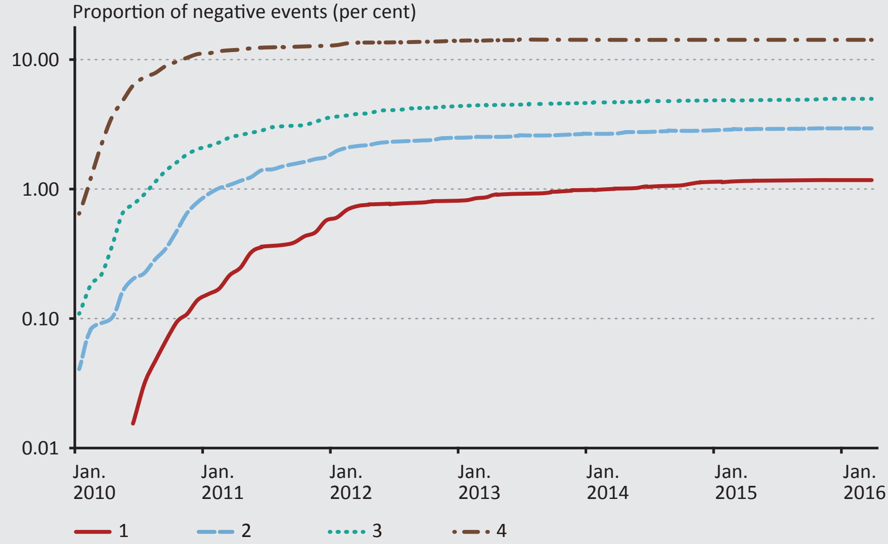
Figure 5
Distribution of small enterprises across the rating categories of the small enterprise segment



Source: Own calculation based on the NAV and Opten databases

Finally, for small enterprises it was also examined whether the risk rating provided for a long-term monotonous separation, and this test had the same significance as described in the case of the microenterprise model. Based on *Figure 6*, it can be stated that the small enterprise model has stable separating power even in a long-term outcome time frame, and the rating derived in a 1-year time frame can be applied for very long horizons.

Figure 6
Cumulative monthly negative event involvement of small enterprises with financial statements in 2009



Source: Own calculation based on the NAV and Opten databases

2.3.4. Medium-sized enterprise segment

In addition to the modelling and segmentation problems indicated in Subpoint 2.2.2, due to the small number of elements in the medium-sized enterprise segment, there is no monotonous risk separation at all points in time. This is shown in Table 6: the proportion of one-year negative events by risk categories is monotonous almost exclusively in crisis years.

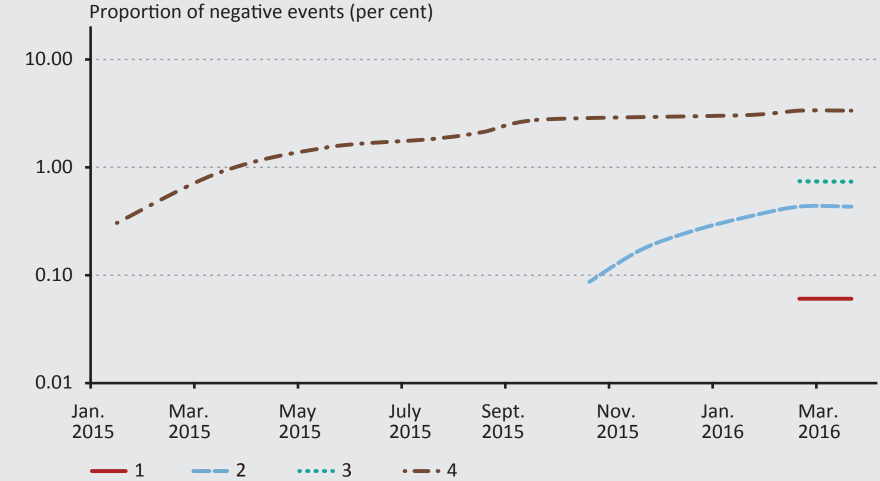
Table 6
One-year negative event proportion within the rating categories of the medium-sized enterprise segment

	Year of the NAV report															
Rating	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Average
1	0.00%	0.00%	0.00%	0.00%	0.12%	0.00%	0.22%	0.19%	0.37%	0.00%	0.00%	0.10%	0.17%	0.08%	0.00%	0.1%
2	0.20%	0.00%	0.14%	0.25%	0.72%	0.62%	0.70%	0.94%	0.24%	0.59%	0.10%	0.38%	0.09%	0.00%	0.00%	0.3%
3	0.00%	0.00%	0.00%	0.00%	1.21%	0.36%	0.67%	1.61%	1.16%	2.61%	0.77%	0.98%	0.73%	0.00%	0.24%	0.8%
4	2.72%	1.46%	3.21%	2.43%	3.66%	6.04%	4.98%	3.68%	4.79%	7.37%	4.46%	1.90%	3.28%	2.49%	2.95%	3.9%
Segment	0.4%	0.2%	0.4%	0.3%	0.9%	1.0%	1.1%	1.0%	0.9%	1.8%	1.0%	0.6%	0.7%	0.3%	0.4%	0.8%

Source: Own calculation based on the NAV and Opten databases

Nonetheless, based on Table 6, risk segmentation exhibits a stable and monotonous classification over the long term. This can readily be judged by employing the test used for micro and small enterprises. After the first year following the balance sheet date of the financial statements, the rank ordering between the rating categories is restored and is monotonous again in the medium term, as attested by *Figure 7*.

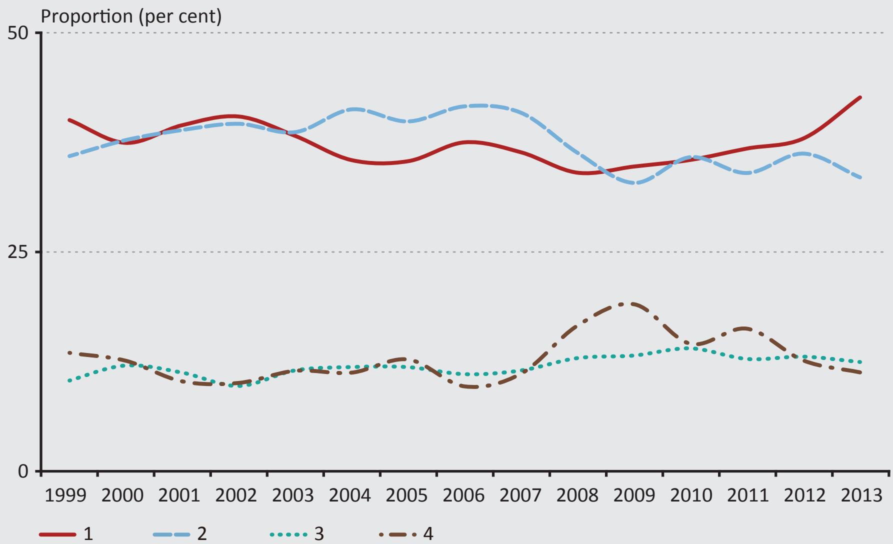
Figure 7
Cumulative monthly negative event involvement of medium-sized enterprises with financial statements in 2014



Source: Own calculation based on the NAV and Opten databases

Partly due to the small number of elements in the medium-sized enterprise segment and the extremely high explanatory power of the debt burden and short-term liquidity variables in this segment, there is a dynamic migration between the two better and two weaker categories in the case of the years characterised by poorer and better economic conditions. Due to this and the unique characteristics that are more pronounced in the case of medium-sized enterprises, this segmentation model is the weakest, and its use must be supplemented by expert opinion and other qualitative and quantitative information, just as in the case of supervised institutions. Going forward, the model should be expanded in this direction. Nonetheless, in its present form, it can be used for simpler risk monitoring analyses.

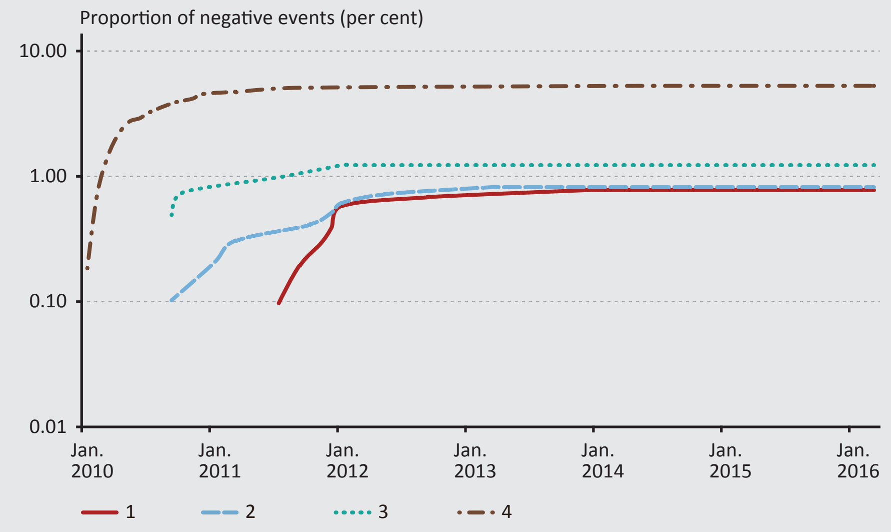
Figure 8
Distribution of medium-sized enterprises across the rating categories of the medium-sized enterprise segment



Source: Own calculation based on the NAV and Opten databases

Finally, the long-term monotonicity of the risk rating was also examined in the case of the medium-sized enterprises. Based on *Figure 9*, it can be stated that the medium-sized enterprise model has stable separating power even in a longer outcome time frame, and the rating can be applied for very long horizons, not just for a 1-year forward-looking time window. In the case of this segment, it is also worth noting that despite the low number of negative events, approximately a little over 1 year after the 2009 and the 2014 financial statements, the cumulative proportion of negative events had become monotonous again, which is consistent with the observed monotonous rank ordering by categories for the whole cycle, as presented in Table 6. This confirms the applicability of the (small enterprise) model in the case of the medium-sized enterprise segment as well, and the fact that the low number of negative events does not markedly influence the short, medium and long-term stability of the model.

Figure 9
Cumulative monthly negative event proportion of medium-sized enterprises with financial statements in 2014



Source: Own calculation based on the NAV and Opten databases

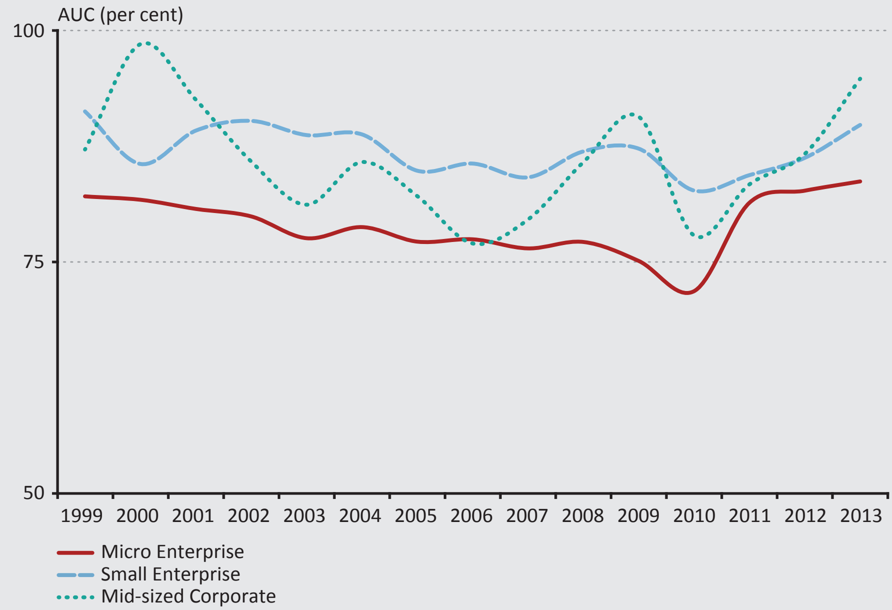
2.3.5. Further model validation tests

a) AUC indicator within the individual segments – With the score based on the given year's financial statements, rank ordering strength can also be calculated in the individual segments using a negative event within one year as an output variable. Based on *Figure 10*, when taking only the AUC indicator into account, the strongest model in the medium-sized enterprise segment is that of small enterprises, but in view of what we have seen earlier, the medium-sized enterprise ranking can only be considered stable over the medium term. This once again confirms that the AUC/Gini coefficient, although it condenses the adequacy of ranking into one number, is not suitable for the comprehensive validation of the credit risk model's adequacy in itself, i.e. the ordering performance and calibration of the rating system must be examined separately.

b) The cross-correlation analysis of the explanatory variables within the individual segments – Taking economic aspects into account, there may be a stronger-than-average correlation between the explanatory variables, since there may be a strong trade-off between short and long-term financing.[2] In order to assess the potential

[2] We wish to thank one of the anonymous reviewers of this study that they pointed out the necessity of this analysis.

Figure 10
Time series AUC indicator in the individual segments



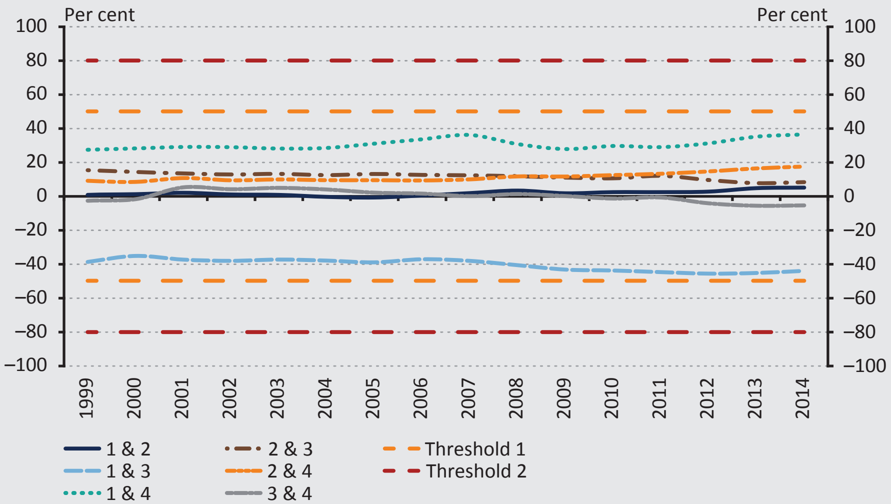
Source: Own calculation based on the NAV and Opten databases

model risk in logistic regression, we assessed the cross-correlation between the variables in pairs, for all the used variables in all the segments that were modelled.

Based on *Figure 11*, it can be stated that between the variables capturing debt servicing and the short and long-term liquidity position, there is a weaker-than-average correlation that does not materially distort and jeopardise the stability of the model and the estimates. The presence of the correlation, however, is in line with economic expectations, since a larger volume of liabilities means a weaker capacity for debt servicing.

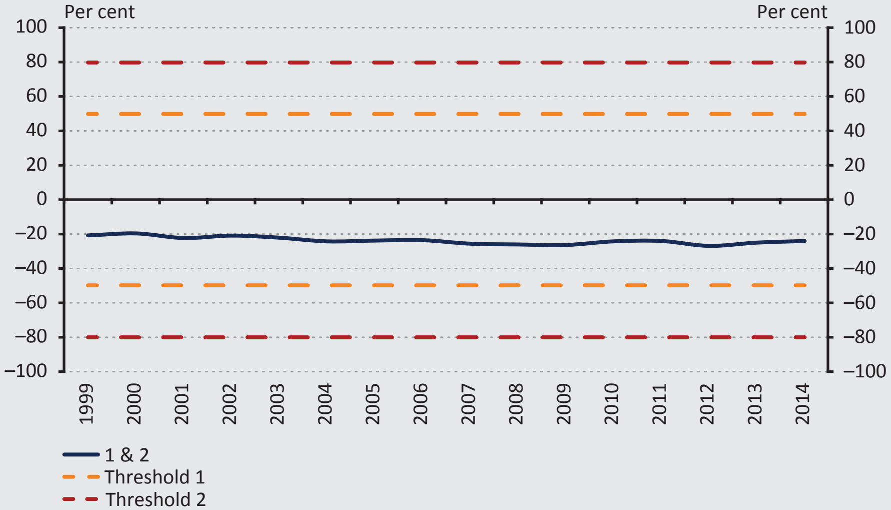
In the case of the small enterprise segment, the direction, strength and sign of the correlation tallies with economic expectations, and does not cause major problems in the model's stability or the parameter estimates.

Figure 11
Microenterprise segment – Cross-correlation between the explanatory variables in a time series view



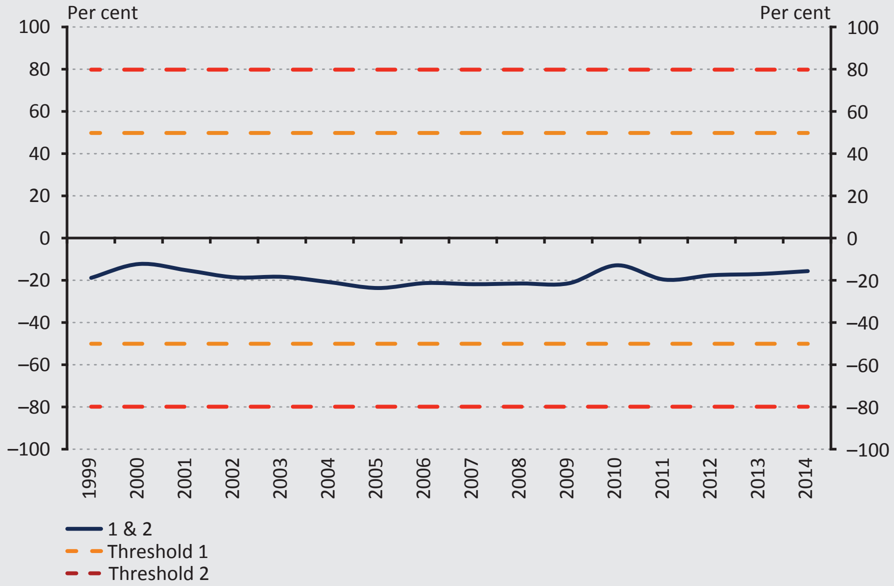
Note: Variables 1: Debt burden; 2: Fixed assets/Long-term liabilities; 3: Liquid assets/Short-term liabilities; 4: Expenses/Sales revenue.
Source: Own calculation based on the NAV and Opten databases

Figure 12
Small enterprise segment – Cross-correlation between the explanatory variables in a time series view



Note: Variables 1: Debt burden; 2: Liquid assets/Short-term liabilities.
Source: Own calculation based on the NAV and Opten databases

Figure 13
Medium-sized enterprise segment – Cross-correlation between the explanatory variables in a time series view



Note: Variables 1: Debt burden; 2: Liquid assets/Short-term liabilities.
Source: Own calculation based on the NAV and Opten databases

In the case of the explanatory variables used in the medium-sized enterprise segment, the conclusions reached in the micro and small enterprise segments can be repeated. Nonetheless, it is worth noting that the cross-correlation between the two variables is almost of same magnitude in the small and the medium-sized enterprise segments, which serves as an additional argument for the applicability of the small enterprise model in the medium-sized enterprise segment.

3. Conclusion

The monitoring model presented in this study contains several simplifications. In creating the sub-segments of enterprises, we only took into account net sales revenue, and in order to separate as accurately as possible the clients that cause actual losses (for their lenders), the risk categories determined by the monitoring tool used negative legal event categories – which can be construed as "hard" default events – as output category variables. The regulatory authority requires that clients be assigned to client groups (*in accordance with Articles 147(5) and 172(1) of the CRR*), and international definitions of default include both restructuring with a material loss and the delay in excess of 90 days (*CRR, Article 178*).

As we have seen above, even taking all these limitations into account, the tool is based on homogeneous and consistently increasing risk categories, and separates clients adequately through the whole economic cycle by their probability of negative event involvement. In case of negative events, in contrast to the softer default definitions that include either the 90-day delay or restructuring with a negative present value, recovery is not expected until closure of the legal procedure or the re-establishment of the client's solvency, it can only be resolved from the available assets of the given company. This means that the monitoring tool captures the actual credit risk losses, thereby achieving the primary goal, i.e. the establishment of an easily interpretable and usable supporting tool for microprudential supervision.

As a further step, the monitoring framework may be expanded by the integration of behavioural information, by bringing the PD calibration in line with the definition of default of being overdue for over 90 days, and, as a combination of these, the risk categories pertaining to the corporate segments may also be widened. This may be performed in a future study. In a similar vein, it is also important to create at least 7 non-default and 1 defaulted rating categories (*CRR, Article 170[1b]*) in the future with the inclusion of further information, and these categories should comply with the regulatory requirements and the expectations regarding advanced internal credit risk assessment (IRB). Of course, *the main objective was the creation of a simple, low-maintenance monitoring tool*, which was achieved. Nonetheless, striving to achieve a more precise calibration of the probability of default based on behavioural variables, our forthcoming studies must examine whether and to what extent further risk segmentation is facilitated by the incorporation of qualitative and behavioural information available in the individual corporate segments – as well as in case of the retail segment.

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Annexes

Annex 1
Microenterprise segment: Number of companies, proportion of long-term, 1-, 2-, 3-year negative events by categories.

Year of Annual Report	1	2	3	4	5	6	Total	DR1	DR2	DR3
1999	42 023	40 682	20 637	8 135	10 526	5 402	127 405	1.2%	1.7%	2.1%
2000	47 948	44 877	21 873	8 003	10 019	5 468	138 188	1.3%	1.8%	2.2%
2001	60 338	53 639	27 165	9 895	12 046	6 222	169 305	0.9%	1.3%	1.7%
2002	64 787	60 907	31 154	11 780	14 367	7 320	190 315	1.1%	1.5%	2.0%
2003	70 031	68 340	35 028	12 957	16 252	8 469	211 077	1.0%	1.4%	1.9%
2004	73 396	74 795	37 173	13 773	17 880	10 001	227 018	1.0%	1.6%	2.1%
2005	81 062	81 082	38 507	14 035	18 709	11 199	244 594	1.1%	1.7%	2.2%
2006	84 402	88 733	38 180	13 549	18 090	11 494	254 448	1.1%	1.7%	2.4%
2007	93 044	92 739	38 070	13 407	18 655	13 099	269 014	1.3%	2.2%	3.0%
2008	94 894	94 463	42 483	15 871	23 452	17 098	288 261	1.6%	2.7%	3.9%
2009	91 074	96 092	47 769	18 518	28 385	21 429	303 267	1.8%	3.2%	3.9%
2010	98 269	101 082	49 460	18 882	29 385	22 729	319 807	1.8%	2.5%	3.2%
2011	109 936	105 025	50 907	19 726	30 366	24 309	340 269	1.0%	1.7%	2.5%
2012	114 233	105 129	50 103	19 868	30 405	24 748	344 486	1.2%	1.9%	2.2%
2013	122 958	106 979	47 842	18 929	28 111	24 454	349 273	1.1%	1.5%	1.5%
DR1	0.3%	0.6%	1.0%	1.7%	2.8%	8.5%		1.2%		
DR2	0.8%	1.1%	1.8%	2.6%	4.0%	10.7%			2.0%	
DR3	1.2%	1.6%	2.4%	3.4%	4.9%	11.9%				2.5%

Source: Own calculation based on the NAV and Opten databases

Annex 2

Small enterprise segment: Number of companies, proportion of long-term, 1-, 2-, 3-year events by categories.

Year of Annual Report	1	2	3	4	Total	DR1	DR2	DR3
1999	3 904	2 761	1 226	498	8 389	0.8%	1.0%	1.1%
2000	4 509	3 347	1 492	493	9 841	0.7%	1.0%	1.1%
2001	5 274	3 715	1 411	522	10 922	0.6%	1.0%	1.1%
2002	5 711	3 898	1 532	518	11 659	1.0%	1.3%	1.5%
2003	5 816	4 223	1 864	662	12 565	0.8%	1.2%	1.5%
2004	6 097	4 626	1 880	708	13 311	1.1%	1.7%	2.0%
2005	6 198	4 864	2 066	779	13 907	0.9%	1.4%	2.1%
2006	7 135	5 577	2 106	701	15 519	0.9%	1.5%	2.1%
2007	7 102	5 776	2 125	889	15 892	1.1%	2.0%	2.8%
2008	7 260	5 615	2 652	1 326	16 853	1.9%	2.8%	3.4%
2009	6 427	4 905	2 681	1 468	15 481	1.7%	2.6%	3.2%
2010	6 705	5 044	2 590	1 185	15 524	1.5%	2.3%	3.1%
2011	7 304	4 997	2 677	1 298	16 276	1.1%	1.9%	2.8%
2012	7 575	5 117	2 287	1 036	16 015	0.8%	1.5%	1.9%
2013	8 501	5 095	2 152	876	16 624	0.5%	0.9%	0.9%
DR1	0.1%	0.5%	1.6%	9.4%		1.0%		
DR2	0.4%	1.1%	2.9%	11.4%			1.7%	
DR3	0.6%	1.6%	3.7%	12.4%				2.1%

Source: Own calculation based on NAV's and Opten's databases

Annex 3
Medium-sized enterprise segment: Number of companies, proportion of long-term, 1-, 2-, 3-year negative events by categories.

Year of Annual Report	1	2	3	4	Total	DR1	DR2	DR3
1999	547	490	142	184	1 363	0.4%	0.5%	0.5%
2000	611	616	197	206	1 630	0.2%	0.5%	0.6%
2001	718	708	205	187	1 818	0.4%	0.6%	0.8%
2002	826	809	199	206	2 040	0.3%	0.4%	0.6%
2003	820	829	247	246	2 142	0.9%	1.0%	1.2%
2004	835	971	280	265	2 351	1.0%	1.2%	1.6%
2005	889	1 003	299	321	2 512	1.1%	1.4%	1.6%
2006	1 052	1 167	311	272	2 802	1.0%	1.3%	1.6%
2007	1 090	1 225	345	334	2 994	0.9%	1.5%	1.9%
2008	1 112	1 186	422	543	3 263	1.8%	2.1%	2.3%
2009	1 023	968	389	561	2 941	1.0%	1.4%	1.6%
2010	1 030	1 039	407	422	2 898	0.6%	1.1%	1.3%
2011	1 174	1 085	409	519	3 187	0.7%	1.1%	1.4%
2012	1 204	1 149	415	401	3 169	0.3%	0.9%	1.0%
2013	1 408	1 107	412	373	3 300	0.4%	0.5%	0.5%
DR1	0.1%	0.3%	0.8%	3.9%		0.8%		
DR2	0.2%	0.7%	1.4%	4.6%			1.1%	
DR3	0.3%	0.8%	1.9%	4.8%				1.3%

Source: Own calculation based on the NAV and Opten databases