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Monitoring of Banks' Risks Related to the Funding of Financial Enterprises*

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The crisis period which commenced in 2008 highlighted the fact both at domestic and international level that in certain cases financial enterprises – which operate in a more relaxed prudential regulatory framework compared to banks – accumulated substantial credit risks that generated major losses for the financing credit institutions. This paper presents a simple, straightforward tool for monitoring banks' risks related to the funding of financial enterprises operating in Hungary. This tool can be reproduced based on the balance sheet and income statement data of corporate databases, and at the same time its performance is stable and as such it can be widely utilised, it facilitates close, automated monitoring and can be used as a financial warning model, which permits the allocation of a relative risk level to financial enterprises either in the medium term or 2 years ahead. It can be concluded that, based on the foregoing, prior to the major world economic crisis that commenced in 2008, it would have been possible to identify risky financial enterprises and banks could have closed or amortised their exposures to risky financial enterprises earlier, as necessary. To our knowledge, at the time of the publication this type of risk measurement methodology is unprecedented in the Hungarian literature in respect of banks' risks in relation to lending to financial enterprises.

Journal of Economic Literature (JEL) codes: G23, C53

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1. Features and supervision of Hungarian financial enterprises

1.1. Hungarian regulation and supervision

In this paper, we examine financial enterprises – as specified in Section 9(1) of Act CCXXXVII of 2013 on Credit Institutions and Financial Enterprises (Credit Institution Act) – which are not owned by a banking group.

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Based on the Credit Institution Act, financial enterprises may essentially perform similar activities as credit institutions – both types of institutions qualify as financial institutions (Section 7(1)) and according to the Credit Institution Act, financial services activity may be performed on a professional basis solely by financial institutions (Section 7(2)) – and thus their regulation is also similar in many respects. On the other hand, the most important difference between the two types of institutions is that financial enterprises may not collect deposits and render payment services, and thus any loss they may incur can only represent a risk for clients through the credit institutions which finance them. Consequently, the potential liquidation of a financial enterprise has a substantially smaller negative effect on the (household, corporate) clients using the financial services than in the case of a bank. In line with this, compared to credit institutions, financial enterprises may be established with much smaller initial capital (HUF 50 million), and furthermore, the capital requirements specified in the European Union's capital requirement regulation (CRR[1]) are also not applicable to them. Exceptions to the latter include financial enterprises owned by a credit institution, which are thus subject to consolidation.

The crisis which commenced in 2008 drew attention to the crucial importance of macroprudential regulation and to the fact that microprudential regulation can be circumvented in certain cases. One of the related risks, relevant for this paper, is the financing of financial enterprises, since in this way the financing credit institutions (seemingly) did not undertake the risk of clients which – according to their own lending policy – probably would not be eligible for financing. At the same time, during the years of the crisis – not only in Hungary – credit institutions suffered major losses on the financing of financial enterprises which did not manage client funds and were thus less strictly regulated.

With a view to addressing the problem, the European Banking Authority (*EBA 2016*)[2] regulated the measurement and reporting of the exposures of regulated credit institutions to not only financial institutions, but also to the shadow banking system, and formulated minimum requirements with regard to the related risk management processes. The Hungarian regulation adopted the EBA directive in the form of a recommendation, with effect from 1 January 2017 (*MNB 2016a*).

Both the EBA and the Magyar Nemzeti Bank's (MNB) shadow banking regulation, and particularly the part thereof related to financial enterprises, identify as a key risk

[1] *CRR (Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012): Article 395 (5)* In: Official Journal of the European Union, 27.6.2013. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32013R0575&from=EN. Downloaded: 3 January 2017.

[2] EBA (2016): *Limits on exposures to shadow banking entities which carry out banking activities outside a regulated framework under Article 395(2) of Regulation (EU) No. 575/2013.* EBA/GL/2015/20 https://www.eba.europa.eu/documents/10180/1310259/EBA-GL-2015-20+GL+on+Shadow+Banking+Entities_EN.pdf. Downloaded: 3 January 2017.

that in the case of financial enterprises – partly due to the less strict regulation – the use of short-term funds and vulnerability arising from high leverage are typical; there also may be a partial overlap of ownership with the financing credit institutions, while crisis situations are characterised by the fast withdrawal of the provided funds and the closing of the credit lines. With a view to managing the aforementioned risks, the EBA directive and the MNB recommendation expect the institutions to take into consideration the assumed risks in the course of their Pillar 2 risk management processes and capital planning, and the management board of the supervised credit institutions should be aware of the assumed risks, and take responsibility for such by their approval (of the related risk appetite and limit breach). Finally, depending on the maturity of the internal risk measurement and management, the institution may either set limits on its own or it must comply, at all times, with the large exposure limits specified in the international regulation (*CRR 2013*).[3]

The EBA prepared a report (*EBA 2014*),[4] which provides information on the national regulatory frameworks related to institutions pursuing similar activity as banks, but falling outside the scope of the EU laws applicable to credit institutions. Based on that, it can be established that the licensing and oversight practices applicable to institutions pursuing similar activity as Hungarian financial enterprises vary to a great degree from country to country; the regulation largely depends on what the individual authorities regard as risky activity and what kinds of bad practices and processes they identified as a result of the crisis.

Based on the Hungarian laws, financial enterprises are supervised both in prudential and consumer protection terms. In view of the fact that, pursuant to the laws, financial enterprises may not collect customer deposits, in terms of their individual, institution-level supervision – primarily with the customers' interest in mind – the focus has shifted mainly to the forecast and management of consumer protection risks in the past period. In addition, prudential supervision of financial enterprises may be realised the most efficiently – in accordance with the foregoing – through the banks they are owned or financed by.

Although the weight of this sector in Hungarian credit institutions' exposures is not so great that we can talk about the build-up of a shadow banking system, as we mentioned before, in the years of the crisis banks realised significant losses as a result of the deterioration in the financial situation at the refinanced financial enterprises. Accordingly, the purpose of this paper is to call the attention of domestic credit institutions to the possibility of developing a rating system operating

[3] CRR 2013 In: Official Journal of the European Union, 27.6.2013. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32013R0575&from=EN. Downloaded: 3 January 2017.
[4] EBA (2014): *Report to the European Commission on the perimeter of credit institutions established in the Member States*. http://www.eba.europa.eu/documents/10180/534414/2014+11+27+-+EBA+Report+-+Credit+institutions.pdf. Downloaded: 3 January 2017.

based on similar principles as the model presented here, which may foster the prudent financing of the financial enterprises sector. In line with this, the financial enterprises owned by banking groups registered in Hungary, fall outside the scope of this analysis in view of the fact that their financing and risk monitoring may be implemented in a different framework, and due to the reasons detailed in *Section 2.2.2,* negative events are less likely to arise in their case.

1.2. Characteristics of the financial enterprises sector

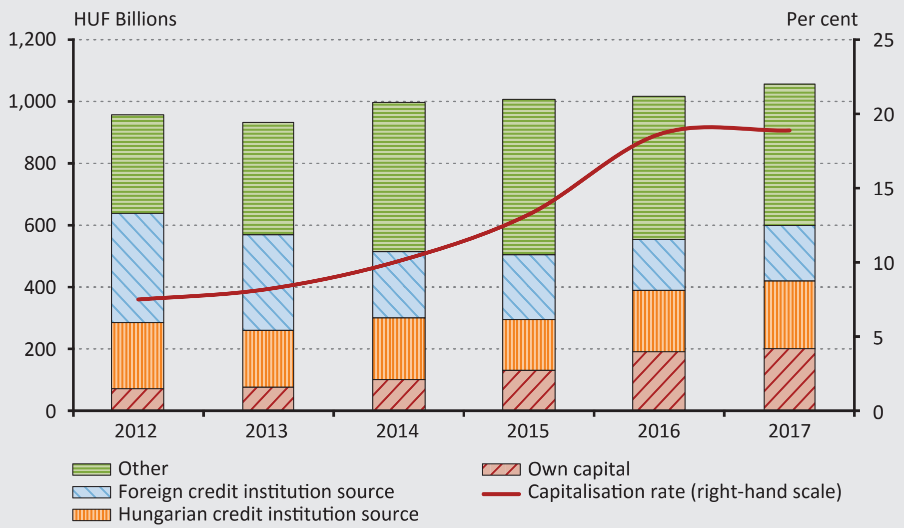
The most typical activities of financial enterprises operating in the Hungarian market include lending, financial leasing, factoring and distressed debt management, and the enterprises often mix these activities (*MNB 2016b, 2017, 2018*). Since the end of the 1990s, the sector has been characterised by rapid growth both in terms of the number of institutions and the aggregated balance sheet total, as a result of which, after 2005 the entirety of the sector reached the size of the middle-sized banks in Hungary in terms of its balance sheet total and outstanding receivables. However, as a result of deepening crisis in 2009 the earlier growth came to a halt (*Table 1*).

As regards the breakdown of gross outstanding receivables, the activity of financial enterprises is still dominated by lending, followed by leasing (*MNB 2018*). At the same time, it is a remarkable trend that, when examining the entire sector of financial enterprises not belonging to a banking group, both types of receivables declined and the portfolio of purchased non-performing receivables shows major growth since the crisis (*MNB 2016b, 2017, 2018*).

Due to the losses suffered by the financing institutions as a result of the crisis, the credit institution sector tends to be gradually withdrawing from the financing of financial enterprises, thereby making it more difficult for these institutions to raise funds. In parallel with this, within the scope of the portfolio cleansing process, credit institutions make efforts to sell their non-performing receivables, and thus the financial enterprises established in recent years usually submitted activity licence applications for the purchase of non-performing receivables (*MNB 2016b*), and the number of institutions pursuing solely this activity also rose (*MNB 2017, 2018*). It is partly attributable to the aforementioned developments and to EU transfers that the number of financial enterprises did not decrease dramatically even as a result of the crisis; the sector is rather characterised by stagnation and in the past few years – following consolidation in the sector – once again by moderate growth.

Examining the liability structure of financial enterprises not belonging to a banking group, it can be established that bank financing essentially followed the general lending trends, with substantially decreasing placement of funds during the crisis period, followed by an increase in the past year (*MNB 2016b, 2017, 2018*). It is also evident from *Figure 1* that in line with the general economic recovery, financing by credit institutions in Hungary already moved on an upward trend in the past two years, which primarily affected financial enterprises pursuing workout activity (*MNB 2018*). In terms of magnitude, the loans placed with financial enterprises cannot be deemed high at the sector level, but in view of its increasing trend, the process deserves attention both in terms of business and risk. The changes in other liabilities show that in the post-crisis years financial enterprises were only partially able to compensate for the lost credit institution funding (mostly through financing by the owner). However, in the past two years the sector's balance sheet total was able to expand even in conjunction with a decrease in other liabilities. Although the equity balance rose since 2012, and in parallel with that the capitalisation level also improved, this was mostly attributable to the profitable operation of certain larger institutions (pursuing household lending and workout activity).

Figure 1
Developments in the liability structure of financial enterprises not belonging to a banking group



Source: MNB 2018

As regards the breakdown by size, the financial enterprise sector is very heterogeneous not only in terms of the activities pursued, but also in terms of the institutions' balance sheet total: the 10 largest institutions – not belonging to any banking or other institutional group – have a market share of roughly 50 per cent. The largest market participants are typically financial enterprises with well capitalised, non-resident owners, accompanied by several smaller institutions, usually owned by residents (*MNB 2017*). The structure of the market, including a few larger and several smaller institutions, is well illustrated by the fact that at the end of 2017, the 5 institutions realising the highest balance sheet profit accounted for 80 per cent of the profit of the sector under review (*MNB 2018*). Due to the composition of the market and its negligible size compared to the overall Hungarian banking sector, one-off movements (e.g. the withdrawal of a larger institution from the market, the sale of a larger package of bank receivables, or of a financial enterprise which formerly belonged to a banking group) can generate major changes in the entire balance sheet total and often also in the financing extended by the banking groups.

It follows from the heterogeneity of the sector that risks also vary greatly, depending on the size and activity type of the institutions. At smaller financial enterprises, it can be observed that upon the exhaustion of owner financing or failure to attract financing institutions, they are often unable to reach the size of operation necessary for their profitable functioning and thus they opt to leave the market, or their activity licence is withdrawn, because they are unable to comply with the legislative requirements related to equity or other conditions applicable to prudent operation. Furthermore, after the financial crisis, we saw several examples when financial enterprises operating with high leverage and without adequate control by the financing institution did not pursue sufficiently prudent lending policy and were liquidated due to the losses incurred. It is difficult to compare the risks of financial enterprises purchasing non-performing receivables with institutions pursuing lending activity, as in their case profitability primarily depends on the proper assessment of the defaulted portfolios, the employment of properly skilled collection experts and the development of a cost-efficient operational model.

Based on the foregoing, it may be worth considering the development of different risk monitoring models for institutions with different risk features; however, we rejected this idea primarily due to the substantial decrease in the number of elements in the sample. At the same time, it should be noted that – despite the reliability of the model to be presented below – in view of the occasionally substantially different business model of the institutions, we deem the monitoring tool to be an efficient instrument for monitoring the refinancing risks primarily as a supplement to individual expert ratings.

1.3. Arguments for the risk monitoring of the segment

At present, due to its size and based on former experiences, the financial enterprises segment represents no systemic risk or at least not to the degree seen in some of the Western European economic regimes – the Netherlands can be mentioned as a European example (*Broos et al. 2012*). Nevertheless, as also mentioned in the introduction, in the past decade financial enterprises have gained increasing importance both in terms of their number and risk assumption. The risks built up earlier were highlighted in this sector primarily by the financial market crisis which commenced in 2008, as follows:

- referring back to the lending processes described in the previous subsection, medium-sized and large banks registered in Hungary often financed financial enterprises with inadequate risk management, pursuing household and corporate lending or factoring and suffered major losses on such transactions;
- in several sub-markets – e.g. in the household mortgage and lease credit markets – financial enterprises often appeared with inadequate skills and background, and insufficiently prepared business models and lending processes, thereby contributing to the spread of the bad lending practices observed before the crisis;
- finally, in connection with the previous point, bad practices – often also in terms of consumer protection – started to be spread by certain financial enterprises.

The risks outlined in the foregoing declined substantially in the past few years, partly due to the macroprudential regulation by the MNB, which prevented excessive household lending (i.e. payment-to-income ratio and the regulation limiting the loan-to-collateral ratio, which are also mandatory for the financial enterprises), and partly due to consolidation of the sector.

Nevertheless, it should be examined whether the risk monitoring tool calibrated during the crisis for financial enterprises not belonging to a banking group also performs properly under a clearer regulatory framework and stronger oversight. If so, it may serve as an additional tool for surveying and monitoring the risks, economic strength and viability of financial enterprises which may potentially be refinanced. Accordingly, in the following we present a simple, yet stable monitoring tool, which allocates non-banking group financial enterprises operating in Hungary to risk segments.

2. Monitoring model for Hungarian financial enterprises

2.1. Risk features of the segment

As presented in *Subsection 1.2*, the rapid spread of financial enterprises, as a financial institution segment, commenced at the end of the 1990s and peaked in the middle of the decade thereafter. During the subsequent crisis years, financial enterprises – similarly to the credit institutions active in Hungary – implemented major deleveraging, partly due to the compulsion arising from the contraction of funding from credit institutions.

In parallel with the strong growth in the receivables of financial enterprises, the risks of the segment also rose significantly (*Table 1*). It can be observed that the negative event ratio (i.e. liquidation, bankruptcy proceedings, removal by the court, completed liquidation, forced dissolution within one year after the balance sheet date of the respective annual report), increased substantially in parallel with growth in the segment's balance sheet total and receivables, due to the deterioration in the quality of receivables after the deepening crisis in 2009. Then, after the consolidation of the economic policy in 2012 and the liquidation of financial enterprises with unsustainable business model, the risk of the entire sector gradually decreased.

Table 1
Overview of the segment of financial enterprises not belonging to a banking group and of their risk features

Year of the Tax Authority (NTCA) report	Number of financial enterprises (non-banking)	Negative events	Negative event ratio (1-year, per cent)	Balance sheet total (HUF billions)	Outstanding receivables (HUF billions)
1992	8	0	0.00%	3	1
1993	10	0	0.00%	21	2
1994	11	0	0.00%	28	3
1995	11	0	0.00%	36	5
1996	15	0	0.00%	52	24
1997	38	0	0.00%	70	35
1998	49	0	0.00%	107	68
1999	83	0	0.00%	122	88
2000	106	0	0.00%	142	112
2001	118	0	0.00%	177	137
2002	123	0	0.00%	224	165
2003	135	0	0.00%	325	250
2004	157	2	1.27%	464	325
2005	166	1	0.60%	562	459
2006	184	1	0.54%	724	545
2007	201	4	1.99%	940	730
2008	211	1	0.47%	1,273	980
2009	213	1	0.47%	1,146	850
2010	212	4	1.89%	1,302	1,006
2011	212	6	2.83%	1,224	938
2012	213	4	1.88%	1,225	774
2013	220	4	1.82%	1,146	717
2014	223	2	0.90%	1,192	881
2015	215	0	0.00%	1,339	816
2016	220	1	0.45%	1,370	788

Note: Brown shading denotes the development sample (NTCA reporting years of 2004-2011), while light blue denotes the validation sample (NTCA reporting years for 2002–2014). Finally, green denotes the time-barred test sample (NTCA reporting year 2016).

Source: Calculated based on the databases of the National Tax and Customs Administration (NTCA) and Opten

As presented in the previous subsections of this paper, according to our expectations, due to the regulatory and operating environment, it is not primarily the capital, but rather the liquidity, refinancing and rollover risks that strongly explain the operating difficulties of financial enterprises. An additional risk, following from the regulation, is the risk of business models with a limited possibility of diversification, since the ban on managing client funds permits the transformation of the structure of funding resources to a limited degree. Finally, financial enterprises are marginal, "niche" players in almost all modern financial systems, i.e. they have to run major credit risk due to the fact that, apart from a few exceptions, they are compelled to finance clients rejected by the larger actors. Later on, we present in detail how and to what extent these economic expectations were confirmed by the primarily data-driven development.

2.2. Applied segmentation and modelling practice

2.2.1. Overview of the literature

The supervised institutions and the international credit rating agencies usually assess the refinancing and credit risks of financial enterprises by closely followed rating systems developed on a shared sample of banks, insurers and perhaps of investment funds. The inevitable result of this practice is that finally the model is calibrated separately for the individual sub-segments or, simplifying it, aiming at the most general approach possible, it is developed on the basis of a few key balance sheet and income statement variables. These modelling approaches include the Moody's model (*Hill – Auquier 2014*), where in addition to the macroeconomic variables, the independent variables include, among other things, the return on equity, return on assets, balance sheet total and various liquidity indicators. The rating system of Standard and Poor's developed for financial institutions and insurers is similar in terms of the variables used, but has a different structure (*Tripolitakis et al. 2015*), which weights three modules together, i.e. the business risks, the financial risks and the credit, market and liquidity risks into one final rating. Finally, it is worth mentioning that the Basel-based Bank for International Settlements (BIS) also paid special attention to the difficulties of the rating of credit institutions in several analyses, emphasising the role of the macroeconomic environment and the regulatory circumstances, and thus e.g. support by the state or lack thereof (see e.g. *Packer – Tarashev 2011*).

As for the antecedents in Hungary, it can be stated that to date no rating systems dedicated to credit institutions and financial enterprises have been published, and thus this paper – as mentioned in the introduction – can be regarded as pioneering work in this respect. Consequently, here we only briefly review the publications in Hungary dealing with the analysis and modelling of corporate bankruptcy and default risks, since these models and approaches were developed specifically for non-financial enterprises, and their applicability to financial enterprises and credit institutions fell outside the scope of our analysis; thus, presumably they would not be suitable for a really precise analysis of financial enterprises' risks. Without intending to be comprehensive, *Hajdu – Virág* (*1996, 2001*) presented their methodology developed for the estimation of the default risk of Hungarian small and medium-sized enterprises. Of the Basel 2 requirements, achieving as accurate as possible a separation effect was analysed as an objective in the publication of *Kristóf* (*2008*). Finally, in recent years the MNB's experts presented several approaches on the topic of corporate credit risk; of those, we would mention the publications by *Banai et al.* (*2013*), and *Bauer – Endrész* (*2016*).

In view of the fact that – in terms of regulation, operation and business model – the financial enterprise segment can be described by features which substantially differ from credit institutions in many respects, the authors of this paper developed the monitoring tool presented in detail below, solely on the sample of non-banking group member financial enterprises.

2.2.2. Model applied to the Hungarian financial enterprises segment

The exclusion of banking group member financial enterprises from the model is based on the economic consideration and observation that – due to reasons of reputational risk – a financial-credit institution group can far less afford for a persistently loss-making subsidiary – particularly if it operates in the market of the same country – to be subjected to liquidation or other legal proceedings with negative connotations than a financial enterprise operated by other type of owner. In addition, financial enterprises belonging to a credit institution group are often established with a view to optimising the capital and liquidity management of the respective group of institutions, i.e. for a completely different purpose than non-banking group member financial enterprises. Finally, in the past few years, mostly with a view to achieving cost synergies, several banking groups opted for the merger of the group-member financial enterprises with the group-leader institution, i.e. a reorganisation, essentially independent of the risk features, can be observed in this segment.

Prior to building the model, we contemplated the direct measurement of the quality of the loan portfolio underlying the financial enterprises, as an option, but we rejected this idea for several reasons. On the one hand, the regular reports of financial enterprises to the MNB essentially contain aggregated data on the receivables managed; detailed data are available only for shorter periods and do not contain the information necessary to assess portfolio quality. On the other hand, in most of the cases this information is not available to the financial institutions financing the financial enterprises; such information is typically not disclosed regularly, only within the scope of portfolio due diligence preceding acquisition. Finally, such model would be unsuitable for measuring the risks of financial enterprises pursuing workout activity.

In addition, consideration may be given to using the data of the balance sheet and income statement data included in the data supply to the MNB for the development of the rating model, in view of the fact that – compared to the structure of the reports included in the databases of the National Tax and Customs Authority (NTCA) and Opten – they reflect the nature of the financial services activity pursued by the institutions being reviewed. However, in developing the model our objective was to demonstrate that it may be also possible to build a reliable monitoring model based on the balance sheet data available to the credit institutions to support the measurement of refinancing risks.

Accordingly, in developing the monitoring tool we used the balance sheet and income statement of the NTCA database, and – as an output variable signalling risks and negative events – the negative event register of the Opten database. As presented in *Table 1,* the development sample included the NTCA reports for the period 2004–2011, while for validation purposes we used the NTCA reports for 2012–2014, since these were the years when negative legal events did occur in the segment. Finally, we included each financial enterprise in the sample until the date it submitted an NTCA report or until the occurrence of the first negative event, i.e. – in line with the actual observations – we anticipated no recurrence of liquidation / bankruptcy / etc. proceedings, i.e. negative legal event. An additional important modelling step, described later, was that upon assigning the rating, in the case of those financial enterprises that still existed in the respective year but failed to submit a report to the NTCA until their termination by a negative event, we allocated the occurrence date of the negative event to the last year of their existence (i.e. one year from the date of the last NTCA report). By contrast, when calibrating the probability of default and assigning the rating, financial enterprises with no NTCA report received the worst performing rating. As is demonstrated, neither procedure caused any distortion during the development (and use) of the monitoring tool; the latter, i.e. downgrading the rating due to a missing report, is in line with the practice of rating allocation to the supervised institutions (i.e. the "override" practice when negative information comes to light in respect of the enterprise).

In developing the monitoring tool, we used logistic regression based on the consideration that the intuitive measurement of the economic (log)linear risk, i.e. rising monotonously by variable, and the reliable measurement of the effects differing from them is not permitted by the low number of elements in the sample. The estimation of the weight of the variable selection and the logistic regression was performed in full on the development sample, i.e. on the NTCA reports for the period 2004–2011; we used the validation sample solely for time-barred backtesting. In this way, the ratio of the development and the validation samples is roughly 70–30 per cent, which – in terms of model validation – complies with the best practices described in the literature (*Hastie et al. 2008*).

Frequentist parameter estimation

During modelling, which was performed in the manner described in the previous subsection, we estimated the logistic regression parameters on the development sample (NTCA reports for 2004–2011) using the maximum likelihood method, known in the literature, by maximising the following expression (*Agresti 1990*):

$$L\left(data|\theta\right)=\sum_{i=1,y_i=1}^{N}\log P\left(x_i\right)+\sum_{i=0,y_i=0}^{N}\log\left(1-P\left(x_i\right)\right), \tag{1}$$

where $\log P(x_i)$ is the logarithm of the likelihood of the occurrence of the respective category attribute as a function of the acquired value of the independent variable, (N) summarised for all observations.

Upon variable selection, in the first step we examined the ranking strength of each variable of the NTCA reports (balance sheet and income statement) in the development sample, and then in the second step, we generated from the variables strongest in development sample the variables corresponding to the economic logic and best covering the risks to be measured. Upon generating the compound variables, it was a key consideration that the performance of the model created by the compound variables should not be weaker than the ranking power obtained with strongest individual variables. Finally, in the case of the compound variables we managed the outliers – similarly to the corporate monitoring tool – by logarithmisation,[5] and using the appropriate method (*Liao – McGee 2003*) we also standardised the variables (*Hong – Ryu, 2006*), i.e. established their relative strength. *Table 2* presents the model estimated on the basis of these criteria and procedures.

[5] In the case of all compound variables (x), we performed the following transformation: asinh(x/2), which is approximately similar to the logarithmisation.

Table 2
Parameters and descriptive statistics of the logistic regression estimated on the development sample, and the standardised weights

Variable	Estimated parameter	Standard error	Significance	Expected sign	Risk	Standardised weight of variables
ROA = Balance sheet profit / Balance sheet total	–0.3276	1.0614	0.7575	–	Profitability	4.80%
Long-term return = ((Retained earnings – Impairment recognised on receivables) / (Book value of receivables)	–0.4150	0.1024	5.09e–05	–	Profitability, Credit risk	27.69%
Short-term liquidity = Short-term liabilities / Liquid assets	0.2292	0.0671	0.0006	+	Liquidity	26.98%
Average operating P&L per FTE = Operating P&L / Headcount	–0.0598	0.0308	0.0519	–	Profitability, Credit risk	18.25%
Net depreciation rate = (Value of investments deployed in the reporting year – Depreciation recognised in the reporting year) / (Intangible asset + Tangible assets)	–0.3964	0.1285	0.0020	–	Operational risk	22.29%
Intercept	–5.6751	0.4493	2.00E–16			

Source: Calculated on the basis of the samples from the NTCA database (years 2004–2011) and the Opten database (years 2004–2012)

As is evident, the monitoring tool measures almost all relevant risks of the financial enterprises by a proper index. As presented in *Annex 1,* there is a weak cross correlation between the variables, i.e. the selected indicators cover different risks.

Table 3
Ranking power of the monitoring tool on the development and the validation sample

			1-year forward-looking negative event ratio				
Year of the NTCA report (reference period: 31 December)	**Number of financial enterprises (not belonging to a banking group)**	**Negative events**	**Negative event ratio (per cent)**	**AUC (sample)**	**AUC/year**	**AUC 95 per cent bootstrap confidence interval**	**Sample**
1992	8	0	0.00%				
1993	10	0	0.00%				
1994	11	0	0.00%				
1995	11	0	0.00%				
1996	15	0	0.00%				
1997	38	0	0.00%				
1998	49	0	0.00%				
1999	83	0	0.00%				
2000	106	0	0.00%				
2001	118	0	0.00%				
2002	123	0	0.00%				
2003	135	0	0.00%				
2004	157	2	1.27%	0.8285	0.7774	0.7379–0.9190	development
2005	166	1	0.60%		0.6242		
2006	184	1	0.54%		0.9727		
2007	201	4	1.99%		0.9201		
2008	211	1	0.47%		0.6857		
2009	213	1	0.47%		0.9717		
2010	212	4	1.89%		0.7115		
2011	212	6	2.83%		0.894		
2012	213	4	1.88%	0.9494	0.9737	0.9182–0.9912	validation
2013	220	4	1.82%		0.9329		
2014	223	2	0.90%		0.9389		
2015	215	0	0.00%	Cannot be calculated in the absence of negative event			
2016	220	1	0.45%	0.9132	0.9132	Not calculated	teszt

Note: Risk ranking power groups based on AUC: red: weak (0.5–0.6), yellow: medium (0.6–0.7), orange: strong (0.7–0.8), green: very strong (>0.8).

Source: Calculated based on the databases of the National Tax and Customs Administration (NTCA) and Opten

Based on *Table 3*, the monitoring tool has distinctly strong ranking power, even when broken down into years, both based on the development and on the validation sample. This also means that the developed tool is stable and can be used in the short run as well.

Furthermore, based on *Table 2,* essential economic conclusions can also be drawn in the case of the various constellations of variables; e.g. it is possible that a financial enterprise realises adequate profit in a given year (or as the case may be, in the years since its establishment), but at the same time, if it manages to achieve this with low efficiency per employee and by postponing the investments, it inevitably raises doubts concerning its long-term viability, since these latter two variables will deteriorate the rating of the financial enterprise through the deterioration of its current year and long-term profitability ratio.

As the very last step, we also examined whether the allocation to the risk categories, defined on the development sample with the help of the decision tree (*Joopia 2016*) was also stable on the validation sample. Based on *Table 4*, which – as mentioned before – in the case of missing NTCA report manages the increased risk by reclassification, after the date of the NTCA report the risk classification by rating categories is stable both for the one-year and the two-year output window.

Table 4

Risk categories created on the basis of the monitoring tool and the 1-year and 2-year negative event ratio in the individual risk categories

2-year negative event ratio	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015 (not a full year)	Average 2004-2014 (# weighted)
1	0.00%	0.93%	0.83%	0.00%	0.00%	0.79%	3.36%	1.54%	0.00%	0.69%	0.65%	0.00%	0.79%
2	2.04%	0.00%	2.22%	3.70%	2.04%	2.00%	3.85%	2.17%	0.00%	4.76%	5.41%	0.00%	2.58%
3	0.00%	7.14%	0.00%	0.00%	0.00%	0.00%	4.17%	5.26%	9.09%	0.00%	9.52%	0.00%	3.45%
4	14.29%	0.00%	25.00%	33.33%	0.00%	16.67%	17.65%	23.53%	21.43%	22.22%	10.00%	0.00%	18.02%
5	0.00%		100.00%		100.00%	100.00%	100.00%	100.00%	100.00%	50.00%	100.00%		81.82%
Sector	1.27%	1.20%	2.70%	1.99%	0.94%	2.34%	5.16%	4.23%	3.29%	2.73%	3.13%	0.00%	2.71%

1-year negative event ratio	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015 (not a full year)	Average 2004-2014 (# weighted)
1	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2	2.04%	0.00%	0.00%	3.70%	0.00%	0.00%	1.92%	2.17%	0.00%	0.00%	0.00%	0.00%	0.99%
3	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.17%	5.26%	0.00%	0.00%	9.52%	0.00%	1.97%
4	14.29%	0.00%	12.50%	16.67%	0.00%	8.33%	5.88%	23.53%	21.43%	22.22%	0.00%	0.00%	12.61%
5	0.00%		100.00%		100.00%	0.00%	100.00%	100.00%	50.00%	50.00%	100.00%		63.64%
Sector	1.27%	0.00%	1.08%	1.49%	0.47%	0.47%	1.88%	3.29%	1.88%	1.36%	1.34%	0.00%	1.35%

Note: The coloured cells indicate the risk reclassification in the case of those 5 financial enterprises that failed to submit NTCA report for one or two years. Risk categories: green: moderate, orange: low, yellow: significant, red: high. Brown: development sample, blue: validation sample.

Source: Calculated based on the databases of the National Tax and Customs Administration (NTCA) and Opten

During the development of the monitoring tool, another important criterion, which was not mentioned before, was that the rating system should respond to the current risk status of the institutions as sensitively as possible, i.e. map the changes in the risks of the individual institutions as much as possible. Since the tool may be used within the scope of continuously monitoring institutions, the goal is to capture the current situation of the institutions, i.e. to create a cycle-dependent rating system.

In order to assess the fulfilment of the aforementioned criteria, we compared the distribution between the individual rating categories, and the forecast and the actually incurred negative event ratios. *Table 5* presents the distribution of the financial enterprises between the individual rating categories. The analysis shows strong migration between the rating categories, which, however – as presented in *Table 4* – does not reduce the ranking power of the 2-year forward-looking classification. That is, although from one year to the next the migration between the rating categories is strong, this takes place in line with the increase and decrease in the short- and medium-term risks of the individual institutions and financial enterprises, mapping such changes. Consequently, this means that, based on the rating of the monitoring tool, an accurate relative view (risk of the financial enterprises compared to each other) and absolute view (degree of the risks at the individual and sector levels) can be obtained every year on the riskiness of the individual enterprises and the entire financial enterprise sector. In addition to this, since the rating is built solely on compound indices, based on balance sheet and income statement data, the additional, arbitrary sub-segmentation of the financial enterprises is also possible, e.g. assessing the risks by the licensed scope of activity; selecting the deteriorating enterprises, with continuously downward migrating rating and the deeper analysis of the risks inherent in their processes, etc.

Table 5

Distribution of financial enterprises between the rating categories based on the classification by the monitoring tool

Number of financial enterprises (not a banking group member)	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total (total NTCA reports)
1	88	108	121	123	137	127	119	130	136	145	155	161	1.389
2	49	41	45	54	49	50	52	46	39	42	37	37	504
3	12	14	10	18	17	24	24	19	22	22	21	10	203
4	7	3	8	6	8	12	17	17	14	9	10	7	111
5	1		1		1	1	1	1	2	2	1		11
Total	157	166	185	201	212	214	213	213	213	220	224	215	2 218

Distribution	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
1	56%	65%	65%	61%	65%	59%	56%	61%	64%	66%	69%	75%
2	31%	25%	24%	27%	23%	23%	24%	22%	18%	19%	17%	17%
3	8%	8%	5%	9%	8%	11%	11%	9%	10%	10%	9%	5%
4	4%	2%	4%	3%	4%	6%	8%	8%	7%	4%	4%	3%
5	1%	0%	1%	0%	0%	0%	0%	0%	1%	1%	0%	0%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Note: The coloured cells indicate the risk reclassification in the case of those 5 financial enterprises that failed to submit NTCA report for one or two years. Risk categories: green: moderate, orange: low, yellow: significant, red: high. Brown: development sample, blue: validation sample.

Source: Calculated based on the databases of the National Tax and Customs Administration (NTCA) and Opten

As a supplement to the table above, *Annex 2* presents the negative event ratio forecast for 1 year ahead, shown in *Table 5*, weighted by the rating distributions of the respective year, comparing it with the negative event ratio actually incurred within 1 year from the date of the NTCA report. Based on *Annex 2*, not only is the cycle-dependent nature of the monitoring tool shown repeatedly, but it is also shown that no further calibration is necessary in respect of the likelihood of the negative event, since it properly maps the actually incurred negative events both in terms of their level and dynamics, and the ratio thereof in the case of the non-banking group financial enterprises failing to submit the NTCA report. Nevertheless, in view of the low ratio of negative events, combining the risk monitoring into 3 categories, e.g. it is worth using 3 risk categories created logically from category 1, categories 2–3 and categories 4–5, since in this case, already on the 2-year forward looking horizon we obtain monotonous risk ranking in each year, with the exception of one year (this is illustrated visually by *Tables 4 and 5*).

Bayesian parameter estimation

When there is a low number of events (the less frequent category, in this publication the legal negative event) the frequentist parameter estimation is knowingly uncertain, because it is difficult to quantify it. Based on the relevant literature there are several rules of thumb. *Peduzzi et al.* (*1996*) deem necessary to have a minimum $t_n = \frac{10k}{p}$ sample size for the proper estimation of the parameter, where n is the sample size, k is the number of the independent variables and p is the event ratio. In our case, p is 1.28 per cent on the development sample (NTCA report sample for 2004–2011), while 10k is 50, that is, in the opinion of the authors a set of n = 3,890 elements would be necessary for reliable estimation of the parameters, and the set of 1,556 elements in the development sample only amounts to roughly 40 per cent of this. At the same time, in a more recent publication, *Vittinghoff et al.* (*2007*), based on wide-ranging simulation tests, find the aforementioned rule overly strict, and they mentioned primarily the too frequent occurrence of the Type II error as a problem, even when, in accordance with the above $k < 5$. Due to the foregoing, and the excellent performance of the model on the already described time-barred validation sample, the model risk is immaterial.

In summary, as mentioned here as well, the international literature also highlights the problems of the frequentist parameter estimation, which include the significance-related issues (Type I and II errors), the uncertainty arising from the point estimate nature of the parameters and the lack of their predictive distribution, and other related philosophical questions – whether it is right to define probability as a frequency in such cases when samples cannot be created through reproduction even in theory (*Jaynes – Bretthorst 2003*). The discussion of these problems is well beyond the scope of this publication; however, as the economic time series and databases – and thus, particularly the data range used in this publication – are unique, with a relatively low number of sample elements and events, it is worth also using the Bayesian estimation commonly applied in cases of this nature. This procedure captures the uncertainty inherent in the estimated parameter values through credibility intervals rather than through the significance level; it allocates predictive distribution to the parameters and through this to the forecast values of the output variable. In addition, by channelling the already available knowledge into the estimation, it provides a more accurate representation of the probabilities that can be defined based on the sample and the expert knowledge (probability of the model compared to the alternatives, predictive distribution of parameters, etc.).

As is well-known, the Bayesian parameter estimation provides the posterior distribution of the parameters based on the parameter's given distribution on the basis of our preliminary knowledge ($P(\theta)$) and the model specified in the respective manner ($P(adatok|\theta)$):

$$P\left(\theta|data\right)=\frac{P\left(data|\theta\right)p\left(\theta\right)}{\sum_{\theta'}^{\Theta}P\left(data|\theta'\right)P\left(\theta'\right)}, \qquad (2)$$

i.e. according to the Bayesian procedure, we update our preliminary knowledge of the world, based on the newly received evidence and information (*MacKay 2003*). In this case, in respect of our knowledge prior to the development sample we assume that it is essentially non-informative – for the intercept of the logistic regression and weight parameters we determined normal distribution still allocating substantial probability to a wide range of the parameters, assuming the multidimensional independence upon defining the prior distribution:

$$P\left(\theta\right)\sim N\left(0{,}10\right). \qquad (3)$$

Based on (1), (2) and (3), eliminating the normalising constant from equation (2) and using the Markov chain Monte-Carlo method (*MacKay 2003*), we obtain the prior parameter distribution under (3) and the posterior distribution, which may be simulated on the basis of the development sample, by applying logistic regression and the variables already presented above:

$$P\left(\theta|development\ data\right) \propto L\left(development\ data|\theta\right)\ N\left(0{,}10\right). \qquad (4)$$

During the simulation, starting from a point of the prior distribution defined by a random draw, we drew 25,000 elements from the posterior distribution, and discarded the first 2,500 elements upon the calculation of the posterior statistics (also known in the literature as "burn-in"). As the last step, in order to assess the parameters and through that the stability of the model, on the validation sample, assuming the multidimensional normality of the (4) posterior parameter distribution (i.e. using multidimensional normal distribution during the Laplace approximation of the posterior distribution), we performed the estimation on the validation sample as well, as follows:

$$P\left(\theta \middle| validation\,data\right) \propto L\left(validation\,data \middle| \theta\right)\, P\left(\theta \middle| development\ data\right). \quad (5)$$

In accordance with (5), we updated the previous information based on the newly received information base, in line with the Bayesian methodology and the related best practice. This procedure proved its viability in several practical applications, including the analysis of such extremely rare events as e.g. the detection of German submarines in the huge area of the Atlantic Ocean *(Koopman 1946)*, in the course of which the US military searched for submarines of a few ten meters lengths within cells of 200 x 50 miles. This search efficiency was significantly improved by the Bayesian methodology, also used in this publication, and the more efficient utilisation of the information as part of that.

The results of the Bayesian estimate and the comparison of those with the frequentist parameter estimation shown in *Table 2* is presented in *Table 6*.

Table 6
Parameters estimated by the frequentist and the Bayesian method on the financial enterprises' development sample (NTCA reports for 2004–2011) and validation sample (NTCA reports for 2012–2014)

	Maximum likelihood development		Bayesian estimation development		Bayesian estimation validation	
Variable	**Estimated parameter**	**Standard error**	**Estimated parameter**	**Standard error**	**Estimated parameter**	**Standard error**
Intercept	–5.675	0.449	–5.779	0.476	–5.764	0.571
ROA	–0.327	1.061	–0.659	0.922	–0.649	0.888
Long-term return	–0.415	0.102	–0.396	0.11	–0.393	0.114
Short-term liquidity	0.229	0.067	0.222	0.07	0.221	0.085
Average operating profit per FTE	–0.059	0.030	–0.064	0.034	–0.062	0.036
Net depreciation rate	–0.396	0.128	0.386	0.139	–0.386	0.143

Source: Calculated based on the databases of the National Tax and Customs Administration (NTCA) and Opten

Based on Table 6, the maximum likelihood, the Bayesian estimation performed on the development sample using the non-informative prior, and the Bayesian estimate performed with the informative priors – channelling in the former information – on the validation sample return similar results. The only exception is the return on assets (ROA) ratio, the estimated value of which significantly differs on the basis of the two methodologies. This is attributable to the fact that it is not a strong variable in either of the methodologies, which is also confirmed by the value of the standardised regression weight (4.8 per cent) shown in *Table 2.*

Nevertheless, based on both the time-barred cross validation used during the frequentist estimation and the parameter estimation according to the Bayesian methodology, a stable rating system with strong predictive power can be built. The only difference in the two approaches lies in the weighting of the return on assets – having a low weight anyway, but retained in the model due to expert considerations – which, however, obviously does not change the adequacy of the model's forecast power.

2.3. Warning model based on risk segmentation

As we mentioned in the Subsection of *Section 2.2* entitled *Frequentist parameter estimation*, the risk segmentation can be made more straightforward by applying a three-part warning system created from categories 1, 2–3 and 4–5. In this way, the 2-year negative event ratio will be monotonous in almost all years and returns a straightforward result, which is easier to interpret. The "green" category 1 contains the good- quality, low-risk financial enterprises eligible for financing, the "yellow" category 2 contains financial enterprises that will potentially become of high risk, while "red" category 3 includes particularly problematic, high-risk enterprises (*Table 7*). Based on the warning model, it may be easier for the financing entities to make decisions in a more substantiated manner which is easier to monitor – e.g. the gradual phase-out of the financing of financial enterprises with "yellow" and "red" ratings, and enhanced monitoring of financial enterprises belonging to these categories.

Table 7
Warning model for the risk monitoring of the non-banking group financial enterprises

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
1	0.0%	0.9%	0.8%	0.0%	0.0%	0.8%	3.4%	1.5%	0.0%	0.7%	0.6%	0.0%
2	1.6%	1.8%	1.8%	2.8%	1.5%	1.4%	3.9%	3.1%	3.3%	3.1%	6.9%	0.0%
3	12.5%	0.0%	33.3%	33.3%	11.1%	23.1%	22.2%	27.8%	31.2%	27.3%	18.2%	0.0%
	1.27%	1.20%	2.70%	1.99%	0.94%	2.34%	5.16%	4.23%	3.29%	2.73%	3.13%	0.00%

Source: Calculated based on the databases of the National Tax and Customs Administration (NTCA) and Opten

3. Conclusion

In view of the fact that financial enterprises manage no client funds, the risk occurs primarily at the financing or owner credit institutions; in addition, consumer protection risks may also occur in the case of these institutions.

The importance of the developed tool lies in the fact that – in the case of non-banking group financial enterprises – it presents a stop-gap monitoring model based on balance sheet and income statement data, also available to the Hungarian banks, which may be an efficient additional tool for measuring refinancing risks. All of this information may be useful and valuable both for investors and risk assessment experts.

It should be noted that the tool can also be used as an early warning system, as needed. Despite the fact that the model essentially uses *"point-in-time"* variables, combining it based on Table 4 into 3 risk categories (e.g. creating 3 categories from category 1, 2–3 and 4–5), it shows the relative riskiness of the respective enterprise on a two-year time horizon as well, and this time is sufficient for making proper risk management decisions or – upon degradation of the risk monitoring – for the review and override of those.

Finally, the future enhancement of the monitoring tool may include the channelling of additional information, such as the use of negative information related to the respective financial enterprise. Such information may include court procedures initiated against the enterprise, the queued items on the bank account or negative changes in the management of the financial enterprise. Another potential development direction may include the channelling of micro data into the risk measurement of financial enterprises. The latter would be based on the rating of the household and – primarily in the case of financial enterprises with a corporate profile – corporate transactions and clients financed by the respective financial enterprise, i.e. it would provide an additional balance sheet analysis criterion for the rating of financial enterprises, in addition to the balance sheet indicators already used.

In addition, based on preliminary surveys and calculations, the model may also support the measurement of the relative riskiness and business efficiency of banking group financial enterprises (in view of the fact that banking groups typically organise financial enterprises for a specific activity or business process, e.g. leasing, factoring, etc.), and thus it may be worth analysing this as well in more detail.

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Annex

Annex 1: Cross correlation test of the used variables

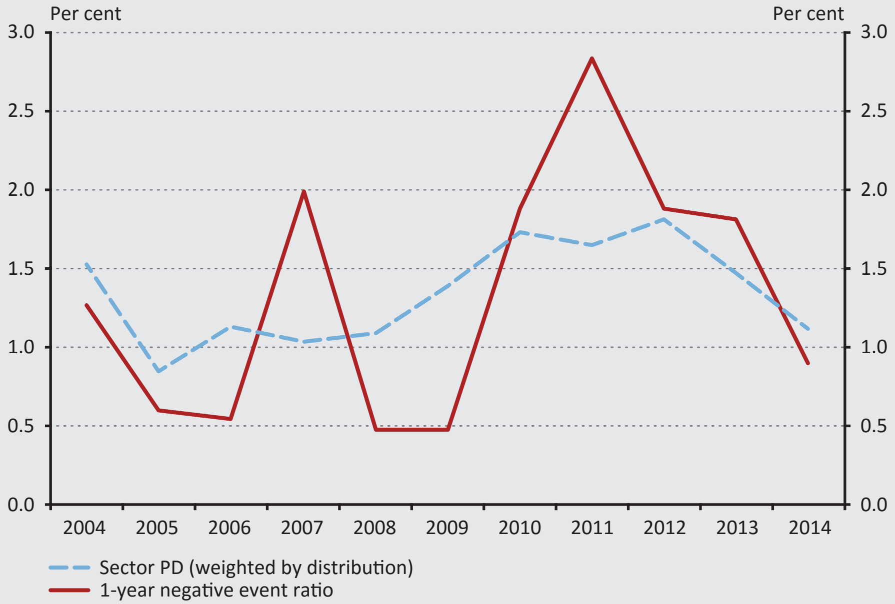
Metrics: Spearman rho

Development sample	ROA	Long-term return	Short-term liquidity	Pre-tax profit/ loss per FTE	Net depreciation rate
ROA		0.389	–0.048	0.357	0.057
Long-term return	0.389		–0.116	0.182	0.022
Short-term liquidity	–0.048	–0.116		–0.029	–0.022
Pre-tax profit/ loss per FTE	0.357	0.182	–0.029		–0.011
Net depreciation rate	0.057	0.022	–0.022	–0.011	

Validation sample	ROA	Long-term return	Short-term liquidity	Pre-tax profit/ loss per FTE	Net depreciation rate
ROA		0.245	–0.015	0.461	0.061
Long-term return	0.245		–0.070	0.120	0.172
Short-term liquidity	–0.015	–0.070		–0.029	–0.041
Pre-tax profit/ loss per FTE	0.461	0.120	–0,029		–0.048
Net depreciation rate	0.061	0.172	–0.041	–0.048	

Source: Calculated based on the database of the National Tax and Customs Administration (NTCA)

Annex 2: Actually incurred and forecast negative event ratio

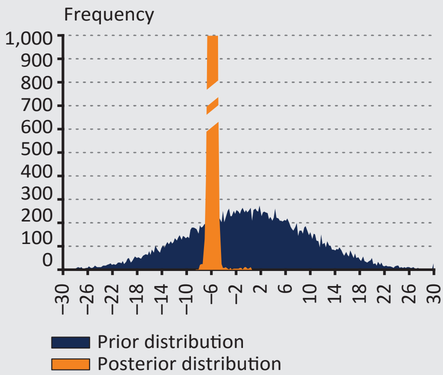


Note: The rating was allocated on the basis of the NTCA report of the given year, while the PD was allocated to the individual rating categories based on the long-term average for 2004–2014. Until 2011 the development sample, in the years 2012–2014 the validation sample and the displayed time series.

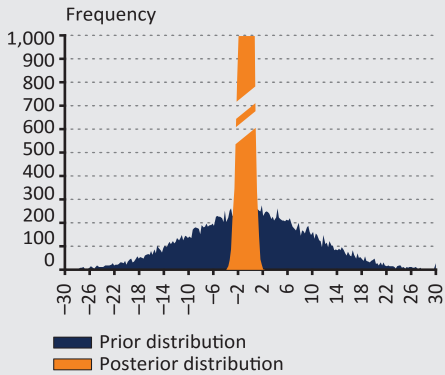
Source: Calculated based on the databases of the National Tax and Customs Administration (NTCA) and Opten

Annex 3: Prior distributions applied on the development sample and the posterior distributions obtained based on the estimation during the Bayesian estimation

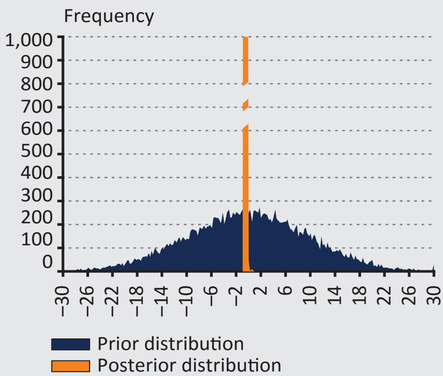
Intercept



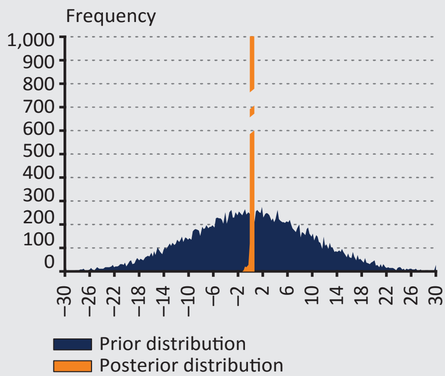
ROA



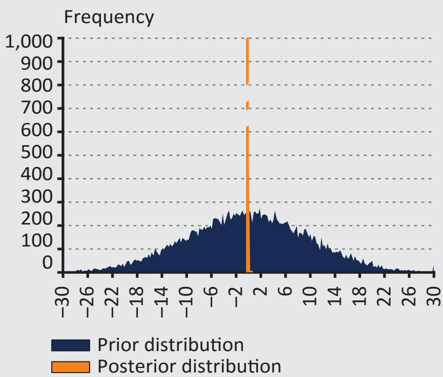
Long-term return



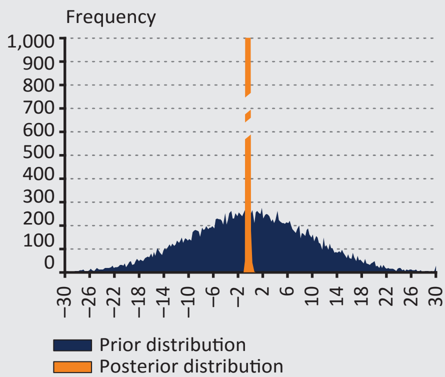
Short-term liquidity



Average operating profit per FTE



Net depreciation rate



Source: Calculated based on the databases of the National Tax and Customs Administration (NTCA) and Opten