Improved own funds levels: effects on banks' "problem probability"

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This study investigates the empirical relationship between banks' own funds levels and their probability of entering financial difficulties or "problem probability." Because many micro- and macroprudential tools used in modern banking supervision focus on own funds requirements, knowledge about this relationship is essential for effectively assessing own funds requirements in the context of supervision and financial stability. A key contribution of our study is the use of a broad definition of "problem." While standard literature takes the perspective of debt investors, harm to financial stability can emerge earlier, i.e. without losses to such investors. Our definition of a "problem" therefore also encompasses instances such as government support or aid by the banking sector and is thus more suitable from a socio-political perspective. As a case in point, dealing with the issue of "too big to fail" might require a good understanding of how additional own funds reduce the problem. We find the relationship to be economically and statistically significant. Our results suggest that a bank that increases its own funds ratio from 10% to 11% reduces its one-year problem probability by more than 50 basis points. The effect is stronger for banks with a higher risk profile or with a lower initial level of own funds.

JEL classification: G21, G32, G33, G34
Keywords: problem probability, own funds, bank rating model, too big to fail

Aside from liquidity requirements, own funds requirements are the main anchor for modern banking regulation. The causal link is clear: better capitalized banks maintain a larger cushion of capital that can absorb loss before they fail, thus reducing the rate of bank failure. In turn, a lower rate of bank failure increases financial stability. We introduce the term "problem probability" to designate the probability of a given bank failing.

For several questions in applied banking supervision, the relationship between problem probability and own funds levels is of central importance. As an example, macroprudential impact analysis quantifies the costs of a given increase in minimum own funds levels, e.g. foregone credit growth (and thus foregone short-term GDP growth), and nets these costs against the benefits from the measure, e.g. improved financial stability (longer-term growth).

A second case in point are the capital surcharges on systemically important banks. Large banks give rise to high social costs upon failure ("social loss given default," SLGD). For systemically important banks, SLGD might be so high as to severely limit the government's options, a phenomenon that has been described as "too big to fail." These banks, it is argued (see e.g. FRS, 2015), should compensate for this by an appropriately lower problem probability (PP). The idea of assigning each bank in a financial system a maximum Equal Expected Impact (PP · SLGD) was used by the Federal Reserve System (FRS, 2015) to calibrate the capital buffers for global systemically important banks (GSIBs) in 2015. Such calibration requires a sound understanding of how additional own funds reduce the problem probability. A third example corroborating the importance of knowing the relationship between

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own funds and problem probability is the recent attempt to calibrate optimal own funds requirements in a financial system (see e.g. Brooke et al., 2015).

The OeNB has developed, and maintains, bank rating methods that can quantify the problem probability of any individual bank. The Austrian Banking Business Analysis (ABBA) model – the core model – uses a selected set of bank-specific risk indicators to assess the riskiness of banks. Microprudential supervisors use the output of these models to prioritize their resources and to identify problem candidates at an early stage. As a byproduct, this model also showcases the dependence of problem probabilities on own funds levels. This sensitivity reveals by how much the problem probability of a given bank decreases when own funds levels increase by 1 percentage point. In turn, the magnitude of this effect depends on (1) the bank's initial own funds position, i.e. an increase in own funds from 8% to 9% results in a larger decline in problem probability than an increase from 24% to 25%, and (2) the level of other risk parameters, i.e. whether, given an initial level of own funds, the bank is considered "risky" or "safe." This study aims at quantifying the sensitivity of problem probability to own funds level changes and the dependence of this effect on other risk parameters.

The use of the OeNB's ABBA model has several advantages:

- The ABBA model is grounded in long-term banking supervision experience and has been developed based on the regulatory reporting system, which supplies a large set of highly standardized input data. The model is carefully maintained and updated, and it is tested frequently by its continuous application in ongoing banking supervision.
- Even more importantly than the point above, the OeNB's ABBA model uses a suitable definition of "problem." Frequently, the literature on bank rating models uses the regulatory default definition[2]. This definition, relating to days past due and unlikeliness to pay is relevant from the perspective of external creditors. From a socio-political perspective and taking financial stability into account, costs associated with a bank's failure emerge at a much earlier stage. A bank in trouble gives rise to external social costs, e.g. by lowering the general trust in the banking system and as a result occasioning an increase in financial intermediation costs and a decrease of the value of bank liabilities. Even more evidently, government rescue programs are external social costs that are both sizeable (even from a socio-political perspective) and do not (on their own) trigger a default according to the regulatory default definition. Exactly on this point, the data definitions in the ABBA model are appropriate with respect to the questions arising from the macroprudential side. Compared to the commonly used definition of default, the ABBA problem definition includes a much broader set of "failures" and therefore considers cases where external creditors are not necessarily affected, but financial stability is. Basing our analysis on an appropriate problem definition, i.e. the one applied in the ABBA model, is the main contribution of this study. For instance, Altunbas et al. (2010) use Moody's Expected Default Frequency, which is based on a loss to external creditors,

[2] *See Article 178 of Regulation (EU) No 575/2013 (Capital Requirements Regulation – CRR), in short: "A default shall be considered to have occurred […] when either or both of the following have taken place: (a) the institution considers that the obligor is unlikely to pay its credit obligations […] in full […]; (b) the obligor is past due more than 90 days on a material credit obligation […]."*

while Berger and Bouwman (2013) track the survivability of the name of the bank[3]. The ABBA problem definition is much broader and includes, besides failing to service an obligation, e.g. support from the banking sector, rescue mergers, own funds rescue injections and state aid. The precise criteria are:

– Insolvency: This includes court-ordered initiation of bankruptcy proceedings as well as receivership proceedings ("Geschäftsaufsichtsverfahren") pursuant to Article 82 of the Austrian Banking Act (Bankwesengesetz – BWG).
– Closure (moratorium pursuant to Article 78 Austrian Banking Act): By regulation, the federal government can deny single entities the participation in the payment system and transactions with customers.
– Closure upon default – revocation or relinquishment of the banking license: The bank relinquishes the banking license, or the banking supervisors revoke it to protect customers.
– Sector aid: This is defined as aid in the form of non-symmetrical contracts in order for a bank to be rescued by other banks which share the same brand, are in an institutional protection scheme or are otherwise affiliated. Sector aid typically comes in the form of capital injections, troubled asset purchases, rescue mergers, guarantees, etc. Without that support, own funds requirements would not be met, business continuity would be questioned, and refinancing would be impossible.
– State aid: The federal government, one of its institutions or a state-owned enterprise (e.g. ABBAG) grants financial aid. The state, for instance, becomes (co)owner, provides participation capital or grants guarantees. Without that support, own funds requirements would not be met, business continuity would be questioned, and refinancing would be impossible.

For the sake of completeness, it is important to note that this study quantifies only the first of two main channels by means of which increased own funds contribute to financial stability. The first channel – and the one examined here – relies on the lower problem probability of an institution and the higher stability of that institution given increased own funds. The second effect, not studied here, is that increased own funds may help prevent the buildup of excessive credit growth and asset price bubbles. Behn et al. (2016) conclude that, depending on the parameterization of their model, up to half of the positive effects of increased own funds comes from this second indirect feedback effect.

1 Data and model

For the investigation of the relationship between a bank's own funds levels and its probability of entering financial difficulties, i.e. "problem probability," the calibration dataset of the latest ABBA calibration (ABBA 3.1) has been augmented with current quarterly data, so that the period extends from Q3 2010 to Q4 2015. The dataset ends in 2015 but includes data about the problem bank indicator from 2016, because the latter must be monitored for over a year (e.g. estimating the problem bank indicator for 2016 with data until the end of 2015). The dataset

[3] *For an overview of the literature on empirical models forecasting bank failure, see Demyanyk and Hasan (2010). The first generation early warning models were called CAMEL ratings.*

includes data from 663 credit institutions[4], which are distributed across the different banking sectors in Austria: the Raiffeisen credit cooperatives sector, the savings banks (Sparkassen) sector, the joint stock banks (Aktienbanken) sector, the state mortgage banks (Landes-Hypothekenbanken) sector, the building and loan associations (Bausparkassen) sector, and the remaining credit cooperatives (Volksbanken) sector (see table 1).

Table 1

Distribution of the calibration data (Q3 10–Q4 15) across the different banking sectors

Sector	Number of observations
Raiffeisen credit cooperatives	10,885
Savings banks	1,034
Joint stock banks	804
State mortgage banks	124
Building and loan associations	66
Remaining (Volksbank) credit cooperatives	39

Source: Authors' compilation.

Note: Each observation represents a credit institution at a quarterly reference date.

The logit model underlying the ABBA model estimates the problem probability of a bank as a function of observable ratios

$$\hat{p} = \frac{1}{1 + e^{\hat{\beta}^T x}},$$

where $\hat{p}$ represents the estimated problem probability, x the ratios and $\hat{\beta}$ the estimated coefficients that represent the relationship of the ratios with the problem probability. Section 1.1 deals with the data basis of the key ratios x, while section 1.2 deals with the problem indicator $\hat{p}$.

1.1 Risk factors, exogenous variables

The calibration data contain the four most relevant key ratios from the ABBA Model 3.1 for each credit institution and quarterly reporting date. Together, these cover over 83% of the explanatory power[5] of the ABBA model and thus the key risk categories (see table 2). The other three ratios of the ABBA model 3.1 only play a subordinate role for the explanatory power.

Table 2

The four key ratios

Ratio	Description	Hypothesis	Risk type
RoA	Profit of common business operation (expected) / total assets (average)	Decrease	Profitability
VaR credit risk	Relative 95% VaR credit risk / own funds	Increase	Credit risk
Own funds ratio	Own funds / (own funds requirements · 12.5)	Decrease	Own funds
Own funds requirements for operational risk	Own funds requirements for operational risk / own funds requirements (total)	Increase	Operational risk

Source: Authors' compilation.

Note: RoA = return on assets; VaR = value at risk.

[4] *These include major banks, regional banks and decentralized banks. Only special purpose banks are removed from the sample.*

[5] *Measured by "beta weights," i.e. transformation of the estimated coefficients $\hat{\beta}$ into weights.*

In turn, to estimate the ABBA model 3.1, a statistical variable selection was conducted from all 51 ratios available for the calibration dataset under the following objective function: Find a model that

- has a high accuracy ratio,
- does not contain too many input variables,
- is as robust as possible against the data sample,
- covers all seven Risk Assessment System (RAS) risk modules with at least one ratio, and
- produces output that is as similar as possible compared to that of the previous ABBA model.

1.2 Problem indicator, endogenous variables

The problem bank indicator completes the calibration dataset. It indicates whether a credit institution meets at least one problem criterion according to the definition above (see section 1) in the four quarters following a quarterly reference date (problem bank indicator = 1). Table 3 shows the absolute frequency of both expressions per quarter (0 = non-problem bank, 1 = problem bank). Where one of these institutions meets the problem criteria at least once, the remaining data (with problem bank indicator = 0) are also excluded from the calibration dataset (outlier adjustment). For example, in the fourth quarter of 2010, 591 banks do not have any problems, while 20 fulfill at least one criterion according to the definition above (see section 1).

Table 4 shows descriptive statistics of the calibration dataset[6]. For example, the average (unweighted) own funds ratio is 18.75% and the average operational risk percentage of the total own funds requirements is 9.78%.

Table 3

Problem indicator

Reference date	Problem indicator = 0	Problem indicator = 1
	Number of observations	
Q3/2010	592	24
Q4/2010	591	20
Q1/2011	590	18
Q2/2011	586	18
Q3/2011	584	19
Q4/2011	582	18
Q1/2012	582	18
Q2/2012	582	18
Q3/2012	576	14
Q4/2012	575	11
Q1/2013	574	14
Q2/2013	571	13
Q3/2013	566	12
Q4/2013	563	16
Q1/2014	563	20
Q2/2014	561	29
Q3/2014	557	31
Q4/2014	552	31
Q1/2015	551	24
Q2/2015	552	16
Q3/2015	544	16
Q4/2015	543	15
Total	12,537	415

Source: Authors' compilation.

Note: Each observation represents a credit institution at a quarterly reference date, where a problem bank indicator of 1 indicates that a credit institution meets at least one problem criterion in the four quarters following a quarterly reference date.

2 Empirical analysis and results

In the ABBA model framework, a logit model is used to estimate a bank's problem probability. For the model presented here, the calibration dataset of the current ABBA model (3.1) is expanded, the explanatory variables are reduced to the four most relevant key ratios and the

[6] *Note that the ratio values of the four model ratios are winsorized both at the lower and at the upper end. During winsorization, extreme measure values are set to a statistically determined lower or upper winsorization limit to prevent bias and data quality issues caused by outliers.*

Table 4

Descriptive statistics of the calibration dataset

	Total assets (EUR thousand)	RoA (%)	VaR credit risk (%)	Own funds ratio (%)	Own funds requirements for operational risk (%)	Problem bank indicator (0/1)
Minimum	4,737	–0.93	0	0	1.92	0
1st quartile	69,640	0.36	16.18	13.87	7.77	0
Median	151,100	0.54	27.32	17.60	8.99	0
Mean	56,980,000	0.54	974.74	18.75	9.78	0.03204
3rd quartile	365,700	0.72	43.26	22.35	10.52	0
Maximum	125,100,000,000	1.47	27,402.49	39.34	30.16	1

Source: Authors' calculations.

Note: RoA = return on assets; VaR = value at risk.

up-sampling[7] usually required for a model like this is omitted. This allows a transformation of the model's estimated logit scores into probabilities[8], which is central to the relationship between capitalization and problem probability.

Table 5 shows the model result of the estimated model with the four key ratios (4-factor model). The estimated logit scores using this model have a very high selectivity (Area Under the Curve (AUC)[9] = 0.84). The correlation between the estimated logit scores from the model used here and the ABBA score for the most recent quarterly reporting date of the calibration dataset (Q4 2015) is, at 0.93, very high. This demonstrates the stability of the current ABBA model and that the four key ratios used here are the most relevant ones from the ABBA model.

The estimated problem probabilities for the entire calibration dataset range from 0.01% (one basis point) to 94.2% (see table 6). The mean value of 3.2% corresponds to the proportion of problem banks in the calibration dataset (415/12,952). The 1-factor logit model with the own funds ratio as the only explanatory variable also shows the desired relationship (see table 7) and exhibits good calibration quality even without the remaining key ratios (AUC = 0.74).

Table 5

Model result of the logit model (4-factor model)

	Estimate	Standard error	p-value	Statistical significance
Intercept	–0.471100	0.195500	0.01595	*
RoA	–3.058000	0.127000	< 2E-16	***
VaR credit risk	0.000026	0.000009	0.002714	**
Own funds ratio	–0.144300	0.011900	< 2E-16	***
Own funds requirements for operational risk	0.468100	0.012730	0.000237	***

Source: Authors' calculations.

*Note: RoA = return on assets; VaR = value at risk. Codes denoting statistical significance: *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1.*

[7] *Up-sampling duplicates the datasets with the rarer value (here: problem bank); otherwise, the datasets with the more frequent value (here: non-problem bank) would have an exaggerated influence on the estimates. In the most extreme form, all problem database records would be duplicated until the ratio of problem banks to non-problem banks is 1:1 (for ABBA 3.1, however, each problem bank was included in the estimation a maximum of ten times).*

[8] $p = \frac{1}{1+e^{-s}}$, *with probability p and logit score s.*

[9] *Measures the discriminatory power of a model: 1 stands for perfect selectivity and 0.5 corresponds to the expected value of a random method.*

Chart 1 shows a summary of the model result:

- The x axis shows the own funds ratio and the y axis the estimated problem probability. The black dots indicate the actual own funds ratio and the problem probability estimated by the 4-factor model (see table 5) for each record[10] of the calibration dataset.
- The lines represent the estimated relationship between the own funds ratio and the problem probability, assuming constant values of the other inputs (RoA, own funds requirements (total), relative 95% VaR credit risk, own funds requirements for operational risk)[11]:
  - For the blue line, the above inputs are set to their respective averages, representing banks whose risk level would typically be estimated to be average.
  - For the magenta line, the above inputs are set to values usually reported by banks whose risk level is estimated to be rather low.
  - For the orange line, the above inputs are set to values usually reported by banks whose risk level is estimated to be rather high.[12]
- There is a clear negative correlation: Banks with high own funds have substantially lower problem probabilities. The reduction in problem probability is largest for banks with poor capitalization as well as for banks which have a high degree of risk due to other risk factors.

In contrast to chart 1, chart 2 shows the relationship between the own funds ratio and the problem probability as a *change*, i.e. the decrease of the problem probability if the own funds ratio increases by 1 percentage point:

- Again, this depends on the (initial) own funds ratio (x axis) and the other input variables (color scale).
- As shown in chart 1, the lines reflect the relationship assuming constant values for the inputs (RoA, own funds requirements (total), relative 95% VaR credit risk, own funds requirements for operational risk):
  - The magenta line shows the relationship usually reported by banks whose risk level is estimated to be rather low.
  - The orange line shows the relationship usually reported by banks whose risk level is estimated to be rather high.

Table 6

Distribution of the estimated logit scores

Minimum	1st quartile	Median	Mean	3rd quartile	Maximum
0.0001	0.0052	0.0142	0.0320	0.0332	0.9420

Source: Authors' calculations.

Table 7

Model result of the 1-factor logit model

	Estimate	Standard error	p-value	Statistical significance
Intercept	-0.965800	0.178700	0.000000064	***
Own funds ratio	-0.147842	0.011554	< 2E-16	***

Source: Authors' calculations.

*Note: Codes denoting statistical significance: *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1.*

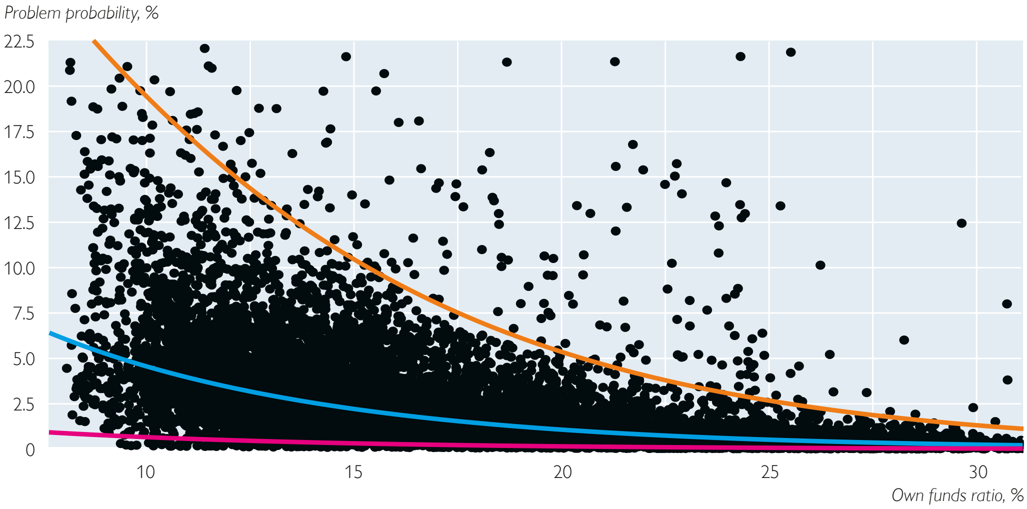
[10] *One credit institution at a quarterly reference date.*

[11] *It follows from this assumption that for the model ratio VaR credit risk, own funds were simulated proportionally to the own funds ratio.*

[12] *In detail, for the orange line, the 5% quantile of the model ratio RoA and the 95% quantiles of the model ratio own funds requirements for operational risk and the model ratio own funds requirements (total) and relative 95% VaR credit risk were used, with the corresponding mirrored quantiles (95% and 5%, respectively) used for the magenta line.*

Chart 1

Relationship between the own funds ratio and the estimated problem probability (4-factor model)



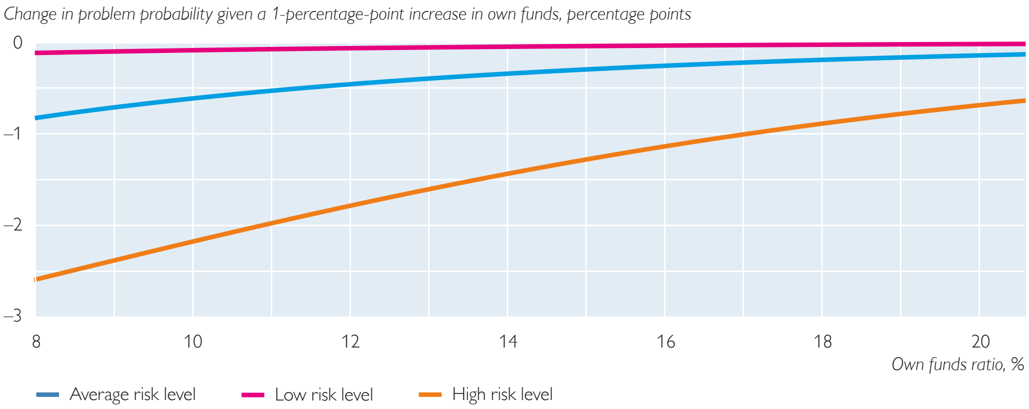
Source: Authors' calculations.

Note: Each black dot represents a credit institution at a quarterly reference date. The three lines show the estimated relationship assuming different levels of risk (low, average, high) of the other inputs.

– The blue line, which shows the relationship usually reported by banks whose risk level is estimated to be average, is of primary interest. It shows that banks with an own funds ratio of 10% can expect an increase to 11% to lead to a decline in problem probability of more than 50 basis points. Thus, the relationship is not only statistically but also economically significant: When one considers loss events where the loss makers are not the bank's direct creditors as a "problem," the reduction of the likelihood of a problem occurring with a higher capitalization is substantial.

Chart 2

Relationship between the own funds ratio and changes in the problem probability



Source: Authors' calculations.

Note: The three lines represent the different levels of risk (low, average, high) of the other inputs.

3 Summary

We quantify the dependence of problem probability on a bank's own funds levels. This relationship serves as a basis for assessing macro- and microprudential supervisory measures.

Our key contribution is the use of the OeNB's ABBA model that employs a much broader definition of "problem" compared with the definition of default commonly used that considers losses from the perspective of debt investors. The definition we use includes, inter alia, rescue mergers and state aid, and is thus much better equipped to answer questions related to financial stability. The magnitude of the effect of a better own funds position depends on the initial own funds level and the level of other risk factors. If a bank with an own funds ratio of 10% and an average level of all other risk indicators increases its own funds by 1 percentage point, its one-year problem probability will decline by 50 basis points according to our estimations. This implies a 300-basis-point reduction of the ten-year problem probability[13], which we deem an economically sizeable effect. At the same time, we emphasize that a lower problem probability of individual banks is only one aspect of the positive effect of improved own funds levels on financial stability that does not consider positive effects coming from indirect feedback, such as a reduction of excessive credit growth and asset price bubbles.

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[13] *To extrapolate from a one-year probability to a ten-year probability, we assume a constant logit score s (see footnote 8). For instance, this condition holds if the increase of own funds is permanent, there is no change in the other risk indicators and the relationship between risk indicators and problem probability is time invariant.*