MODELS OF CENSORED PANEL REGRESSION IN THE QUANTIFICATION OF OPERATIONAL RISK. NEW CHALLENGES IN RISK MANAGEMENT

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Abstract: *Operational risk, as one of the main sources of risk in financial institutions, has recently been estimated in accordance with the Basel Committee guidelines related to Banking supervision. After several years of using AMA solutions, the initially proposed methods were ultimately rejected. At present, the main focus is on taking macroeconomic variables into internal bank. One of the new solutions is modelling using panel data models. The purpose of the conducted research is to indicate those internal processes of the bank that are important from the point of view of quantification and operational risk management, and which may be a potential source of uncertainty and may make it impossible to construct correct models. One of the important but often overlooked aspects of research is the risk of the model itself. In the case of a poorly defined process that generates data, i.e., without a proper understanding of the data and processes that create them, the construction of econometric models is doomed to failure. One of such elements is the process of censoring data. This problem has been analysed at the level of simulation research. First, we show how correct consideration of the specificity of the data can improve the quality of the model. On the other hand, the problem was considered at the level of the censored panel regression model. Also in this case, it was pointed out that incorrect incorporation of the data specificity and omission of significant elements characteristic of the operational risk problem will be a significant problem related to the uncertainty of model. In this context, supervisory authorities and other entities responsible for the creation of new regulations in this area should, in particular, take into account the specificity of operational risk so that the new solutions will not share the old fate.*

Key words: *censoring, panel data, operational risk, uncertainty*

JEL codes: *C15,C33,C34,C63*

1. Introduction

Over the past few years, a dynamically changing approach has been observed in relation to the estimation of operational risk in banks. The Basel Committee guidelines on Banking Supervision (BCBS), as well as solutions implemented in practice, forced a complete change in approach to this problem. The solutions proposed by BCBS based on the AMA method and information on external and internal losses as a basis for the quantification of operational risk are not always sufficient. Currently, the AMA method is no longer the basis for estimating regulatory capital. Other research directions are indicated, which without a correct analysis of how to implement them and assess the risks and imperfections associated with them can share the fate of 2006 solutions.

Due to the fact that operational losses are the one of the major sources of risk in banks, understanding the key factors that determine them, estimation of their influence and stability in terms of specific character of existing process is crucial, both for risk estimation and future process of decision making. In such a sense, macroeconomic environment may be a key source of risk. Changes in macroeconomic area may imply occurrence of losses and may be responsible both for their dynamics and severity. Consideration of external factors in risk estimation or, in a broader perspective, estimation of stability of financial institutions, expressed in the form of various macroeconomic variables in relation to the features from a given institution is particularly important for effective banking supervision. Estimation of potential losses in relation to internal processes as well variability and unpredictability of macro environment is imposed by regulatory requirements and a need to carry out stress tests (Kaspereit et al., 2017).

In case of operational risk, mutual relations between a real economy area and banking sector are poorly recognized and existing surveys in this subject seem to be insufficient. The model risk itself is an additional source of uncertainty. A wrongly defined process which is responsible for mechanism of loss occurrence or adoption of too large simplifications in descriptions of occurrence cause that initially accepted assumptions are unreal and risk estimation are characterized by a huge uncertainty (Tamas-Voneki and Bathory, 2017; Yu and Brazauskas, 2017). An additional factor that should be considered, is reaction of financial institutions in case of periods with increased uncertainty in macroeconomic area. The expected reaction of financial institutions can be a decreased number of transactions, which will imply a reduced amount of operational loss. In such a context, from economic point of view, the profit to loss account is a key element in decision making and accurate depiction of problem and direction of solutions towards reduction of uncertainty source, at least the level of model itself, is significant ("Amendments to the Capital Plan and Stress Test Rules", www1; "FRB: Press Release--Federal Reserve Board invites public comment on proposed rule to modify its capital plan and stress testing rules for 2017 cycle--September 26, 2016", www2).

Due to imperfection of existing solutions, banking supervision increased its interest in relation to both estimation and management of operational risk. For instance, supervising entities in the United States of Northern America put the emphasis on operational risk management practices and obliged financial institutions to implement CCAR process (Comprehensive Capital Analysis and Review). They key element of this process is stress test. A particular significance of stress tests is emphasized also in solutions proposed by European supervisory entities. A very important factor that is verified in these solutions is the possibility of operational risk quantification at various macroeconomic scenarios and various prognostic horizons.

Data related to operational losses are specific for financial institutions and their direct connection to macroeconomic factors can be difficult to prove. To meet the requirements set for financial institutions in the context of stress tests, potential relations between considered variables shall be verified. Due to the fact that operational losses in banks are mostly classified according to Basel Matrix (matrix of business lines and types of risk) initial hypotheses about mutual relation between types of operational events (or business lines) and macroeconomic factors should be elaborated for their future testing. Interconnection of these areas may have various backgrounds, for instance such as the following hypotheses:

1. Internal frauds – for example, the risk of the so called Rogue trading is higher when financial markets are at the stage of growth.
2. External frauds – operational losses resulting from illegal credit card transactions are more widespread when consumer’s expenses are higher. In practice, such a behaviour may have various causes. The periods of increased expenses may be seasonal, e.g., festive seasons, or may be directly related to such factors as unemployment rate or increase in society’s debt.
3. Internal processes – in such a case, rapid drops or a high changeability at financial markets often imply increased volume of transactions, what consequently may result in losses caused by malfunctions in processes.
4. Customers, products, business processes – in case of such events, economic factors are often compared to losses implied by legal risk. In case of legal risk and generated events concerning operational losses, one should consider certain time shifts related to occurrence and actual discovery of operational losses as well as factors related to legal service of those processes.

In existing solutions, capital requirements were estimated only on the basis of historical data that concerned severity and frequency of losses. Financial institutions should pay particular attention to delays between the occurrence and macroeconomic factors that may influence their existence (Many interesting solutions may be derived from the estimation of reserves in insurance companies, where the problem of the actual occurrence of an event and its detection or claims from its title may be different).

2. Operational risk modeling – possible solutions

To meet the requirements concerning supervisory norms, financial institutions are obliged to implement models in order to consider potential relationships between losses and macroeconomic factors. In this area, two major solutions are based on regression model and LDA loss distribution models (Loss Distribution Approach), which are compared with the approach based on historical simulations (Kato, 2017; Kelliher et al., 2017; McNulty and Akhigbe, 2017).

Regression models

Regression models enable the creation and verification of functional dependence between a target variable and a set of explanatory variables. In case of model approach, both the frequency and severity of events can be a target variable. Taking into consideration the fact that the nature of potential target variables is totally different, one should apply various model concepts.

- **Severity of events – continuous target variable**
  In case of creation of model for events severity, target variable has two key features. First of all, it is a constant variable. Secondly, it belongs to $\mathbb{R}^+$ area. Additional elements that may be potential characteristic are related to the process of observation censoring. The processes of information censoring are common in case of application of data for construction of LDA models. There, information censoring adopts a specific form, which is omission of data below defined limits. Such a process is called observation truncation (description of data censoring may be found in Klein and Moeschberger (2003)). In reality, those data are available at bank level, however their practical application at the stage of modelling is slight. An additional element which characterizes data that belong to bank operational loss area is connected with their adherence to various categories of risk. That is why, the character of data and frequency of their collection or aggregation will force the application of methods relevant for panel data analysis.
- **Frequency of events – discrete target variable**
  In case of modelling of event's frequency, the information about the existing losses in specified periods is aggregated. In such a case, it is proper to use such methods as Poisson regression or general models for discrete stochastic process with constant time, which enable consideration of various dynamics of event's frequency with additional external information.

LDA models

LDA models are commonly applied in case of defining economic and bank regulatory capital at basis of AMA assumptions. Interesting characteristics are defined on the basis of aggregated loss distribution, which most often comes into existence basing on Monte Carlo simulation, with defined assumptions concerning the processes of loss frequency and severity. The practice showed that in relation to operational risk LDA models are nor stable and often unpredictable (Szkutnik, 2016). It is caused by many factors, including problems connected to data availability and a way the process that generates data is perceived. The mentioned aspect related to observation censoring may have a key significance in case of LDA model. As shown in surveys, no consideration of observation censoring causes that risk estimation are loaded and additionally burdened with large variability. To modify the approach based on LDA method, some concepts, mostly related to variable frequency process, are applied. In case of modified LDA approach, frequency is understood in the categories of heterogeneous Poisson or is expressed as a function of macroeconomic variables in a relevant model.

Aim of the study

The given study focuses in the issue of operational risk estimation, especially in relation to stress tests and examination of result's stability in terms of initially adopted assumptions. Due to the increasing interest in panel data models in relation to operational risk (BGFRS, 2017), it is important to pay attention to specific process which are common in case of operational loss data. The previously mentioned problem connected with observation censoring may be also interesting in relation to regular regression and panel data models.

Standard Tobit model and censored regression model.

In standard Tobit model proposed by Tobin in 1958, dependent variable y is a censored variable at point zero, i.e. the model assumes the form:

$$y_i = \boldsymbol{x_i}\boldsymbol{\beta} + \epsilon_i, \tag{1}$$

where:

$$\begin{cases} 0\ ;\ y_i \le 0 \\ y_i\ ;\ y_i > 0 \end{cases}. \tag{2}$$

Values y are left-sided censored; vector $\boldsymbol{x}$ is a vector of explanatory variables with relevant vector of parameters and ϵ is a random component.

In a general case, the mechanism of censoring is not limited to the case defined by equation (1). Considered cases may concern situations of left-sided, right-sided or interval censored dependent variables, ie., situations when:

$$\begin{cases} a;\ y_i \le a \\ y_i;\ a < y_i < b \\ b;\ y_i \ge b. \end{cases} \tag{3}$$

In special cases, i.e., one-sided censoring, upper and lower limit, i.e., parameters a and b, assume the value of minus or plus infinity.

In case of censored regression, parameters of model (1) are estimated by means of LME method. If a random component is $\epsilon_i \sim N(0;\sigma^2)$, the optimized likelihood function will be as follows (Bruno, 2004; Henningsen, 2010):

$$logL = \sum_{i=1}^{N} \left[I_i^a \log \mathrm{F_N}\left(\frac{a - \boldsymbol{x_i\beta}}{\sigma}\right) + I_i^b \log \mathrm{F_N}\left(\frac{\boldsymbol{x_i\beta} - b}{\sigma}\right) + (1 - I_i^a - I_0^b) \cdot \left(\log \mathrm{f_N}\left(\frac{y_i - \boldsymbol{x_i\beta}}{\sigma}\right) - \log\sigma\right)\right] \quad (4)$$

where f_N, F_N is density function and normal distribution, respectively; elements $I_i^k(for\ k \in \{a, b\})$ are binary variables assuming, respectively, the value of 1 for left-sided or right-sided observation and value of 0 for other cases.

3. The influence of observation censoring on stability of regression model parameters

To present the influence of observation censoring on the values of regression model parameters, a simulation study, in which one simulation scenario includes three types of data and four possible methods of estimation, has been created. The scenario of simulation is repeated 1000 times in order to average the results and to verify the basic characteristics for interesting areas of the study. It should be taken into consideration that the proposed division into various types of data and future application of various methods of estimation for considered variants satisfies directly the problems that may occur in terms of operational risk and mechanisms related to registration, aggregation of internal data and combination of those data with information about operational loss in banks.

Three stages that are realized within one simulation scenario are described below:

Stage 1. Creation of data structure

Step 1. Full data. At this stage dependent vectors y, x are generated. They will be perceived as variables in regression models (each of 200-observation-length). Dependence is introduced as a linear dependence with correlation coefficient $r_{xy} = 0.9$

Step 2. Empirical quantile. Quantile value, defined as $K(q_i)$ for $q \in \{0,0.1, \ldots, 0.7\}$ is determined for data from vector y.

Stage 2. Estimation of parameters for scenarios of information loss according to value K (eight variants).
For each of variants i, ie., for each value of quantile K, the following steps are realized for $i \in 1, \ldots, 8$.

Step 1. For a given value of i, the limit $cens = K(q_i)$ is adopted

Variable y_{cens} is created. For $y_{cens} < cens$ this variable assumes value $cens$, i.e., it exchanges left-sided censored values into the value of considered quantile.

Step 2. Estimation of parameters according to 4 variants:

- Basic variant, complete data used, standard estimation model, dependent variable y
- Censored variant, censored data used, censored regression model, dependent variable y_{cens}
- Truncated variant, incomplete data used; data for which $y_{cens} \neq cens$, and dependent variable y_{cens}
- Naïve variant, complete data used, standard estimation method and dependent variable y_{cens}

Each of estimation variants corresponds to a certain real situation which may occur in practice. Basic variant corresponds to an ideal situation, where a complete knowledge about the event has no consequences in a right selection of estimation method. It shall be emphasized that in spite of simplification of the problem related to dependence towards the easiest possible linear regression, the consequences of information loss even for the considered situation may be significant. Censored variant concerns a situation where a certain part of data related to explanatory variable was subjected to censoring, according to accepted variant that is a specific case of problem defined by relation (3). Next variant is a case of information loss related to its truncation, which, in practice, means loss of both variable y and respective independent variables. In such a case, classic OLS method will be applied for sub-set of data for which information about variable y are above truncation limit. Naïve variant shows the problem, where the fact of censoring, meaning the registration of events below the limit that consists in a simple replacement of unknown value by censoring limit, has no reflection in selection of estimation model.

Due to the fact that cases for various information loss limits have been considered, it is possible to observe also tempo at which relevant characteristics, which describe particular structural parameters of the model, will change within accepted variants of model estimation and available scope of data.

The following tables show a collective summary of simulation results. Table 1 and table 2, respectively, include information about the average value of parameter and standard deviation of parameter in relation to a given variant type and for a given degree of information loss. In particular, column named variants informs about the summary of one of the 4 estimation variants, where each variant depicts information related to two parameters (column parameters informs about a type of parameter). The other columns inform about a given characteristics (expected value or standard deviation) in relation to a degree of information loss, understood as a percentage of lost data (increasingly, according to value of variable y).

Tab. 1 Expected values of simulation results

Variants	Parameters	0%	10%	20%	30%	40%	50%	60%	70%
Base variant	α_0	0.0007	-0.0004	-0.0002	-0.0009	-0.0004	0.0005	-0.0007	-0.0014
	α_1	0.9011	0.9001	0.9007	0.8999	0.9010	0.8985	0.9006	0.8997
Censored variant	α_0	0.0002	-0.0001	0.0001	-0.0009	-0.0010	-0.0006	-0.0011	-0.0029
	α_1	0.9027	0.8996	0.9000	0.9001	0.9018	0.8995	0.8999	0.9011
Truncated variant	α_0	0.0022	0.0479	0.0993	0.1585	0.2279	0.3122	0.4135	0.5406
	α_1	0.8976	0.8359	0.7932	0.7528	0.7163	0.6738	0.6327	0.5890
Naïve variant	α_0	0.0007	0.0471	0.1114	0.1893	0.2833	0.3968	0.5377	0.7100
	α_1	0.9011	0.8102	0.7197	0.6297	0.5416	0.4500	0.3595	0.2703

Source: Own work. Simulation study

In analysis of simulation results included in the above table (table 1), we can observe that for a sample of size 400 observations, even a significant level of censoring enables to keep results concurrent with basic variant. In case of observation truncation and especially in case of naïve variant we can observe a progressive change in expected values of the parameters. Here, the rate of changes is noticeably more intensive for naïve variant. In particular, values of parameters α_1 are highly significant because the differences in relation to values for basic variant will evidenced to a change in slope of regression line, and as a result, the nature of described event.

Tab. 2 Standard deviations of simulation results

Variants	Parameters	0%	10%	20%	30%	40%	50%	60%	70%
Base variant	α_0	0.0214	0.0218	0.0216	0.0227	0.0217	0.0221	0.0222	0.0216
	α_1	0.0217	0.0224	0.0226	0.0213	0.0217	0.0214	0.0216	0.0220
Censored variant	α_0	0.0214	0.0225	0.0237	0.0272	0.0298	0.0358	0.0435	0.0597
	α_1	0.0217	0.0248	0.0276	0.0285	0.0331	0.0393	0.0426	0.0542
Truncated variant	α_0	0.0214	0.0237	0.0256	0.0298	0.0344	0.0421	0.0502	0.0684
	α_1	0.0219	0.0265	0.0308	0.0321	0.0376	0.0448	0.0489	0.0618
Naïve variant	α_0	0.0214	0.0236	0.0264	0.0303	0.0345	0.0396	0.0464	0.0532
	α_1	0.0217	0.0260	0.0281	0.0284	0.0294	0.0296	0.0271	0.0251

Source: Own work. Simulation study.

In the summary related to the level of diversity of particular parameters shown in Table 2, we can observe that together with the progress of information loss process (excluding basic variant), the level of variability of particular parameters increases. The average results of censored variant, being practically unbiased, are characterized by much higher variability. A similar level of standard deviations is observed for truncated variant. In spite of progressive information loss in naïve variant and a high burden of results for particular parameters, the range of analyzed characteristic is not significantly different (for parameter α_1) from the analyzed levels of loss of information in relation to basic variant. In case of naïve variant we cannot observe a noticeable dynamics in this area.

On the basis of illustrative results presented by a considered simulation example, we may draw very important practical conclusions. Even in case of a simple linear model for which there is a certain information loss event, naïve and truncated variant do not allow for a reconstruction of original model structure. In case of retaining some of information in the form of event occurrence without information related to the value of feature y, the process of censoring with the application of relevant estimation structures enables the reconstruction of a part of information that characterizes the initial model. The only limitation here is the information related to event occurrence, without which the application of censored estimation results is impossible.

The model of censored panel regression

Problem specified at the beginning, which is operational risk, and the need to construct models of panel regression, which often results directly from regulations and precautionary norms set by supervisory entities (that concern mainly stress tests), indication of problems that may concern panel regression models seems to be significant. The construction of censored panel regression model itself is similar to the previous case, i.e.:

$$y_{it} = \boldsymbol{x_{it}\beta} + \epsilon_{it} = x_{it}\beta + \mu_i + \nu_{it}, \tag{5}$$

$$\begin{cases} a\,;\ y_{it} \le a \\ y_i\,;\ a < y_{it} < b\,, \\ b\,;\ y_{it} \ge b \end{cases} \tag{6}$$

where: indices i and t denote, respectively, unit, subject, or in case of operational risk, business line or also jurisdiction. Moreover, the values u_i, v_{it} denote, respectively, the values of individual effects and random disturbances.

In case when values $\mu_i \sim N(0;\sigma_\mu^2)$ and $\nu \sim N(0;\sigma_\nu^2)$ are independent, likelihood function for i is express by (Baltagi, 2005, 2013; Bruno, 2004; Henningsen, 2010):

$$L_i = \int_{-\infty}^{\infty} \left\{ \prod_{i=1}^{T_i} \left[\Phi\left(\frac{a - x_{it}\beta - \mu_i}{\sigma_\nu}\right)\right]^{I_{it}^a} \left[\Phi\left(\frac{x_{it}\beta + \mu_i - b}{\sigma_\nu}\right)\right]^{I_{it}^b} \left[\frac{1}{\sigma_\nu}\phi\left(\frac{y_{it} - x_{it}\beta - \mu_i}{\sigma_\nu}\right)\right]^{1-I_{it}^a-I_{it}^b} \right\} \phi\left(\frac{\mu_i}{\sigma_\mu}\right) d\mu_i \tag{7}$$

The value of relevant logarithm of likelihood function may be determined by means of Gauss-Hermite quadrature (a detailed description can be found in (Bruno, 2004; Henningsen, 2010).

The influence of observation censoring upon the stability of parameters in censored panel regression model

Similar to previous cases, we have a simulation study. To make it real, it was assumed that specific effects connected with value will play the role of business lines (eight cases) with the assumption that we have monthly data from the period of 8 years (96 months in total). For the needs of the study, it was assumed that the simulation scenario would be: $\mu_i \sim N(0{,}20); \nu \sim N(0{,}15); x_1 \sim N(40;8); x_2 \sim LN(2.5{,}5)$ and parameters $\alpha_0 = -1; \alpha_1 = 2; \alpha_2 = 3$. Four levels of information censoring have been accepted. They have been determined on the basis of empirical quantile from the simulated value y (representing a hypothetical loss) at the level $q_i \in \{0, 0.1, 0.2, 0.3\}$. These values shall be sufficient to present the influence of information loss related to its censoring with respect to estimation that does not take into account a fact of modified set of values.

Tables 3 and 4 include the information that summarize the results of performed simulations (in total, 1000 iterations of each scenario). A single scenario generated a sample of data of an overall length of 768 units, with a division according to previous groups and periods (8 groups, 96 months). For such a defined sample, we determined the values of empirical quantile for variable y. Next, these observations were subjected to censoring at the level of each consecutive limits q. A result of single iteration was a set of estimated parameters for two models of panel data (CPR- censored panel regression and PR- Panel Regression). The first took into consideration the fact of data censoring, while in the second case, this information was ignored and a standard estimation procedure for panel data was applied (i.e., procedure based on reconstructed linear regression model-transformed data, OLS estimation).

Tab. 3 Expected values of simulation results

Model type	Parameters	0%	10%	20%	30%
Censored Panel Regression	α_1	2.0033	2.0000	1.9955	1.9971
	α_2	3.0010	3.0005	2.9936	2.9976
Panel Regression	α_1	2.0001	1.8020	1.5955	1.3930
	α_2	2.9999	2.8517	2.6655	2.4642

Source: Own work. Simulation study.

Tab. 4 Standard deviations of simulation results

Model type	Parameters	0%	10%	20%	30%
Censored Panel Regression	α_1	0.0730	0.0773	0.0792	0.0786
	α_2	0.0747	0.0779	0.0816	0.0849
Panel Regression	α_1	0.0706	0.0735	0.0730	0.0753
	α_2	0.0750	0.0749	0.0827	0.0916

Source: Own work. Simulation study.

4. Conclusions

Bearing in mind the purpose of the study, which was the initial assessment of the proposed solutions regarding the use of the panel regression model and the inclusion of macroeconomic factors in models related to estimation of severity or frequency of operational risk problems, it can be concluded that the models are not included in the construction process (even the simplest ones related to classic linear regression models) of facts resulting from the specificity of data collection as well as the existing practice of their use in statistical models (this is the loss of information resulting from their truncation or censoring) may lead to a significant burden of estimators of individual model parameters . The variability of parameters itself is not such a problem here as biases of the estimated parameters. However, it should be considered that the problem at the level of simulations in practice would have to be extended to more real characteristics, in particular in terms of adopted distributions of individual variables or random components.

As shown in recent history related to the AMA methodology and BCBS solutions from the New Capital Accord of 2006, where initially designed and implemented solutions were rejected as not meeting the original objective only a few years later. Undoubtedly, one of the reasons was the complexity of the processes of collecting, assessing and using information in the process of building models for the needs of the AMA methodology. In case of panel data models, the problem seems to be even more complex even when the complexity of the operational risk issues is not taken into account and the elements that characterize them are significant, i.e., the loss of information in the censoring process. Therefore, the proposals of supervisory bodies, as well as entities such as BCBS, must consider the specificity of problems relevant to operational risk, so that the new proposals do not share the fate of the old ones.

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