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ESTIMATING THE WORST SCENARIO OF NET CASH OUTFLOW OF NON-MATURITY DEPOSITS BASED ON QUANTILE REGRESSION

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Abstract. The article considers models that are the most commonly used to estimate the cash outflows of non-maturity deposits: core level of deposit balances, Geometric Brownian Motion (GBM), and Cash Flow at Risk (CFaR). These models use a one-dimensional normal distribution of the probabilities of balances or cash flows. We generalize the above-mentioned cash outflow models in linear quantile regression. The properties of quantile regression are particularly attractive for assessing the liquidity risk of non-maturity deposits. Quantile regression determines quantile directly. It does not depend on the type of distributions of deposit balances or cash flows; it is resistant to outliers that are typical of outstanding deposits; captures fat tails of the underlying distribution of variables; does not assume that variance is constant. To construct a quantile regression, we use a conditional two-dimensional empirical distribution of cash outflows and deposit balances for corporate non-maturity deposits denominated in hryvnias under both normal and crisis conditions. Statistical tests confirmed the satisfactory goodness-of-fit for the model and the hypothesis of linear dependence of cash flows on the current level of deposit balances. As a result, the constructed quantile regression has no areas of the values of deposit balances in which liquidity risk would be underestimated. The developed methodology for quantile measure of deposit outflow will be useful both for banking supervision and banks.

Keywords: non-maturity deposit, cash flow, cash outflow, deposit balance, liquidity risk, quantile regression, banking

Formulas: 7; fig.: 3; tabl.: 6; bibl.: 17.

JEL Classification G17, G21, C21

ОЦІНКА НАЙГІРШОГО СЦЕНАРІЮ ЧИСТОГО ВІДПЛИВУ ДЕПОЗИТІВ ДО ЗАПИТАННЯ ЗА ДОПОМОГОЮ КВАНТИЛЬНОЇ РЕГРЕСІЇ

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Анотація. Розглянуто найбільш вживані моделі, що використовують для оцінки відпливу депозитів до запитання: незнижуваного залишку, геометричного броунівського руху (GBM) і грошового потоку під ризиком (CFaR). Ці моделі базуються на використанні одновимірного розподілу (зазвичай припускають, що розподіл є нормальним) імовірностей залишків або грошових потоків. Вони визначають найбільший відплив коштів опосередковано через оцінку найменших залишків. Модель грошового потоку під ризиком визначає відплив коштів безпосередньо.

Для узагальнення наявних моделей запропоновано модель відпливу, що базується на лінійній квантильній регресії. Властивості квантильної регресії особливо привабливі для оцінки ризику ліквідності депозитів до запитання. Квантильна регресія дає змогу визначити квантиль безпосередньо; не залежить від виду розподілу, якому підкоряються залишки або грошові потоки; є стійкою до викидів, наявність яких характерна для депозитів до запитання; підхоплює товсті хвости в розподілі змінних; вільна від припущення, що дисперсія є постійною.

Для побудови квантильної регресії використано умовний двовимірний розподіл грошових потоків і залишків для корпоративних гривневих депозитів до запитання за нормальних і кризових умов. Статистичні тестування підтвердили добру достовірність моделі та гіпотезу щодо наявності лінійної залежності грошових потоків від рівня залишків. У результаті побудована квантильна регресія не має областей значень залишків депозитів до запитання, у яких ризик ліквідності був би недооціненим. На противагу розробленій моделі, модель незнижуваного залишку завищує ризик ліквідності як у звичайних, так і у кризових умовах. Моделі GBM і CFaR завищують ризик ліквідності в області низьких значень залишків депозитів до запитання і недооцінюють в області їхніх високих значень.

Ключові слова: депозит до запитання, грошовий потік, відплив, залишок, ризик ліквідності, квантильна регресія, банківська діяльність.

Формул: 7; рис.: 3; табл.: 6; бібл.: 17.

ОЦЕНКА НАИХУДШЕМУ СЦЕНАРИЮ ЧИСТЫЙ ОТТОК ДЕПОЗИТОВ ДО ВОСТРЕБОВАНИЯ С ПОМОЩЬЮ КВАНТИЛЬНОЙ РЕГРЕССИИ

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Аннотация. Рассмотрены наиболее употребительные модели, использующие для оценки оттока депозитов до востребования: неснижаемого остатка, геометрического броуновского движения (GBM) и денежного потока под риском (CFaR). Для обобщения существующих моделей предложена модель оттока, основанный на линейной квантильной регрессии. Для построения квантильной регрессии использовано условный двумерное распределение денежных потоков и остатков для корпоративных гривневых депозитов до востребования при нормальных и кризисных условиях. Статистические тестирования подтвердили хорошую достоверность модели и гипотезу о наличии линейной зависимости денежных потоков от уровня остатков. В результате построена квантильная регрессия не имеет областей значений остатков депозитов до востребования, в которых риск ликвидности был бы недооцененным.

Ключевые слова: депозит до востребования, денежный поток, отлив, остаток, риск ликвидности, квантильная регрессия, банковская деятельность.

Формул: 7; рис.: 3; табл.: 6; библ.: 17.

Introduction. Non-maturity deposits are an important and cheap funding source for traditional banking. «A non-maturity deposit (NMD) is, as the name suggests, a deposit that does not have a predetermined maturity, i.e. the deposit can be withdrawn at any time. Examples of NMDs are savings accounts, demand deposits, and current accounts» (Kördel, 2017). Such deposits expose banks to increased liquidity risk. Therefore, to effectively manage liquidity risk, the banks need to correctly estimate the worst net cash outflow of non-maturity deposits. So, Basel's principle 5 of sound liquidity risk management says that «a bank should be able to measure and forecast its prospective cash flows for … liabilities over a variety of time horizons, under normal conditions and a range of stress scenarios, including scenarios of severe stress» (BIS, 2008).

The worst net cash outflow is usually evaluated through quantile measure. This downside risk measure of liquidity risk shows how much cash can run off from deposit accounts over a given period at a pre-defined confidence level. It allows determining the size of a bank's liquidity cushion and «can be directly compared to the bank's risk tolerance and used to guide corporate risk management decisions» (Yan et al., 2011). Such estimates are also valuable for banking supervision as a part of the Supervisory Review and Evaluation Process (SREP) (EBA, 2014). This measure is also used to estimate potential outflows from the entire banking system (Vento & La Ganga, 2009). Therefore, it is useful to monitor financial stability risks.

Note, that the net cash outflow means the same as a reduction in deposit balances below their current level over a given period:

$$cf_t = (B_{t+1} — B_t) / \Delta t, \qquad (1)$$

where cf_t is cash flow, B_{t+1} and B_t are deposit balances at $t + 1$ and t moments of time, Δt is a given period (for instance, daily).

This study aims to analyze empirical data regarding the behavior of banking non-maturity deposits and to construct a quantile regression to find the worst net cash outflows under normal and crisis conditions.

This article is outlined as follows. A brief review of the literature about methods to estimate the worst net cash outflow is given in Section II. Section III presents an empirical study of non-maturity deposits balances. Fitting and testing quantile regression are given in Section IV. Section V concludes.

Methods to estimate the worst net cash outflow. There are indirect and direct methods to estimate the worst net cash outflow (further for brevity «the worst cash flow»). The indirect method uses a univariate distribution of deposit balances to find the worst deposit balance. Knowing the worst level of deposits, we can immediately get the worst cash outflow as a difference between the worst and current deposit balances:

$$cf_{worst}(\tau) = B_{worst}(\tau) — B_t \text{ at } B_t \geq B_{worst}(\tau), \qquad (2)$$

where $cf_{worst}(\tau)$ is the worst cash outflow of deposits, $B_{worst}(\tau)$ and B_t are the worst and current deposit levels, τ is confidence level.

In a simple case, assuming as usual that the probability distribution of daily deposit balances is Gaussian, the worst cash flow is equal to (Vozhzhov & Lunjakova, 2009):

$$cf_{worst}(\tau) = [\mu_B — k(\tau) \cdot \sigma_B] — B_t, \qquad (3)$$

where expression in square bracke $t\mu_B — k(\tau)\cdot\sigma_B$ is the worst and core level of deposit balances $B_{worst}(\tau)$, μ_B and σ_B are the mean and the standard deviation of deposit balances, $k(\tau)$ is τ-th quantile of standard normal distribution. It should be noted that the formula (3) is true only under a weak trend or absence of a trend. Further, we will this model as the model of the core level. In this model, the core level does not depend on the current level of deposits. Besides, the balances never fall below the core level. The disadvantage of this model is the fact that the worst level does not depend on the current balance of deposits. As a result, the cash outflow of deposits may be overestimated.

A more advanced approach to deposit modeling is to use the Geometric Brownian Motion (GBM) (Voloshyn, 2004; Vento & La Ganga, 2009; Bank of Japan, 2014). It employs a logarithmic growth rate as a key variable that links cash flows with deposit balances taking into consideration formula (1):

$$R = \frac{1}{\Delta t} ln\left(\frac{B_{t+1}}{B_t}\right) \approx \frac{cf_t}{B_t}.$$

In this case, the growth rate is assumed to obey the Gaussian law of distribution. **Guessing again** that a current deposit balance always falls down to the worst level of deposits, the worst cash flow is equal to (Voloshyn, 2004; Vento & La Ganga, 2009; Bank of Japan, 2014):

$$cf_{worst}(\tau) = [\exp(\mu_R \cdot \Delta t — k(\tau) \cdot \sigma_R \cdot \sqrt{\Delta t}) – 1] \cdot B_t, \qquad (4)$$

where μR and σR are the mean and the standard deviation of a growth rate of deposit balances.

Note that in the GBM model, the worst level of deposits linearly depends on its current level (Voloshyn, 2004; Vento & La Ganga, 2009; Bank of Japan, 2014):

$$B_{worst}(\tau) = \exp(\mu R \cdot \Delta t — k(\tau) \cdot \sigma_R \cdot \sqrt{\Delta t}) \cdot B_t.$$

The equation (4) has no intercept. Deposit outflow is assumed to occur at any value of the current balance of deposits, whatever low it might be. As a result, cash outflow of deposits may be overestimated liquidity risk at least in a zone of small deposit balances.

Direct methods use the concept of Cash Flow at Risk (CFaR). «The maximum shortfall of net cash … for a specified reporting period and confidence level» (Risk Metrics Group, 1999). This method developed for corporates began to be used for banks (see, for instance, Onorato, 2012).

Assuming that the probability distribution of daily net cash outflows is Gaussian, the worst cash flow is equal to τ-quantile:

$$cf_{worst}(\tau) = \mu_{cf} — k(\tau) \cdot \sigma_{cf}, \qquad (5)$$

where μ_{cf} (in practice closed to zero) and σcf are the mean and the standard deviation of cash flows. As and in the GBM model, deposit outflow is assumed to occur at any value of the current deposits balance, whatever low it might be. The worst cash flow is assumed to do not depend on the level of deposit balances at all.

Note that in more advanced approaches in order to estimate a cash outflow it is used a multivariate mean regression with relevant macro and market variables (Yan et al., 2011).

So, both indirect and direct methods usually utilize the univariate probability distributions. The indirect methods employ the probability distributions of deposit balances or logarithmic growth rate, whereas the direct methods do the probability distribution of cash flows.

It is interesting to note that according to LCR methodology the expected cash outflow of demand deposits, for instance, of non-financial corporates under a stress scenario is calculated by the following formula (BIS, 2013):

$$c_{f\exp} = b \cdot B_t, \qquad (6)$$

where cfexp is an expected cash outflow *w*, $b = 0.4$ is a run-off factor, B_t is a total amount of deposit balances. The formula (6) is similar to the formula (4).

Table 1 presents all the above-mentioned models (3—6).

Table 1

Summarizing the models for cash outflows

#	Model	Formula	Intercept, *a*	Slope, *b*
1	Core level	(3)	$\mu_B – k(\tau) \cdot \sigma_B$	-1
2	GBM	(4)	0	$\exp(\mu_R – k(\tau) \cdot \sigma_R)– 1$
3	CFaR	(5)	$\mu_{cf} – k(\tau) \cdot \sigma_{cf}$	0
4	BIS	(6)	0	*b*

Source: developed by author.

We have considered different relationships (3—6) between cash outflows and deposit balances. Some models contain the intercept, other models do not. They have different slopes. Note that the lack of intercept indicates that cash outflow is possible at any low level of deposits. But what the actual data will show?

We summarize the above-mentioned models (3—6) in the form of linear quantile regression (LQR):

$$cf_{worst}(\tau) = a(\tau) - b(\tau) \cdot B_t, \quad (7)$$

where $cf_{worst}(\tau)$ is the worst net cash outflows of deposits, $a(\tau)$ is an intercept, $b(\tau)$ is a slope, and B is a deposit balance.

To get the worst level of deposits, it needs to slightly rearrange the equation (7):

$$cf_{worst}(\tau) = [a(\tau) + (1 - b(\tau) \cdot B_t] - B_t.$$

In the above equation, expression in square bracket is the worst level of deposits:

$$B_{worst}(\tau) = a(\tau) + (1 - b(\tau)) \cdot B_t.$$

Thus, the worst deposit level is irreducible (as it has non-zero intercept $a(\tau)$. Besides, the worst deposit level linearly depends on the current deposit level B_t. The more the current balance, the more the worst level of deposits. Thus, this model has summarized the features of the core level and GBM models. So, it is more flexible and is seemed to will better explain empiric data.

So, to estimate the worst cash outflow, we will use a quantile regression introduced by Koenker and Bassett (Koenker & Bassett, 1978). Note that at present the use of quantile regressions in risk management is becoming more and more popular (see, for instance, Xiao et al., 2015; Rodriguez & Yao, 2017).

Quantile regression allows directly estimating a quantile of a dependent variable (in our case, cash outflow) conditional on an independent variable (in our case, the current level of deposit balances). «Quantile regression meets requirements to versatile, robust, and scalable methods of building explanatory and predictive statistical models» (Rodriguez & Yao, 2017). Compared with ordinary least squares regression the benefits of quantile regression are the following (Rodriguez & Yao, 2017):

- «Quantile regression does not assume a particular parametric distribution» of residuals,
- «Nor does it assume a constant variance» for dependent variable, and
- It captures risks in tails of the conditional distribution of dependent variable.

Quantile regression «estimates are not sensitive to outlier observations» (Xiao et al., 2015; Rodriguez & Yao, 2017). It allows directly defining the desired quantile. Such properties of quantile regression are especially attractive for assessment of liquidity risk arising from non-maturity deposits.

Empirical study of non-maturity deposit balances. We will consider two historical datasets on the corporate non-maturity deposits denominated in hryvnias (UAH). The first dataset relates to the period from 01.01.2002 to 11.12.2003, during which the business conditions in Ukraine were normal. The second one relates to the period from 01.10.2008 to 13.10.2009 when the financial crisis has swept over Ukraine. This bank rapidly grew. Therefore, the levels of deposit balances for these periods are essentially different.

In the first dataset, we have 488 observations. *Table 2* presents descriptive statistics for the dataset.

Table 2

Descriptive statistics of deposits under normal conditions

Balance, UAH mln	Cash flow, UAH mln
Min.: 5.628	Min.: -23.16172
1st Qu.: 11.293	1st Qu.: -1.47161
Median: 13.298	Median: -0.05643
Mean: 14.995	Mean: -0.01807
3rd Qu.: 17.602	3rd Qu.: 1.50139
Max.: 55.684	Max.: 23.03202

Source: developed by author.

In the second dataset, we have 256 observations. *Table 3* presents descriptive statistics for the dataset.

Table 3

Descriptive statistics of deposits under crisis condition

Balance, UAH mln	Cash flow, UAH mln
Min.: 225.3	Min.: -198.560
1st Qu.: 265.6	1st Qu.: -18.289
Median: 300.5	Median: -1.612
Mean: 356.2	Mean: -1.316
3rd Qu.: 391.0	3rd Qu.: 14.379
Max.: 843.4	Max.: 193.363

Source: developed by author.

Fig. 1 presents the dynamics of deposit balances for both normal and crisis conditions.

As can be seen in *Fig. 1*, the deposit balances under crisis fell sharply down.

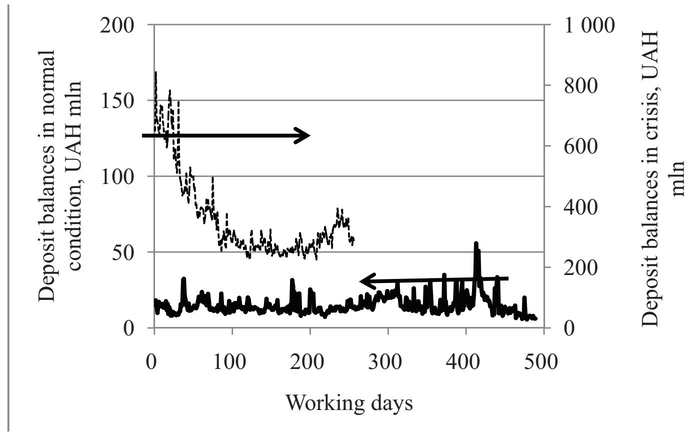

Fig. 1. Dynamics of deposit balances in UAH mln: «solid» — normal conditions (left scale), «dotted» —crisis conditions (right scale).

Source: developed by author.

Further, we selected only such a dataset that contained only negative net cash flows and respective deposits balances.

Fig. 2 and *3* present the dependencies of the negative cash flows on the deposit balances under normal and crisis, correspondently.

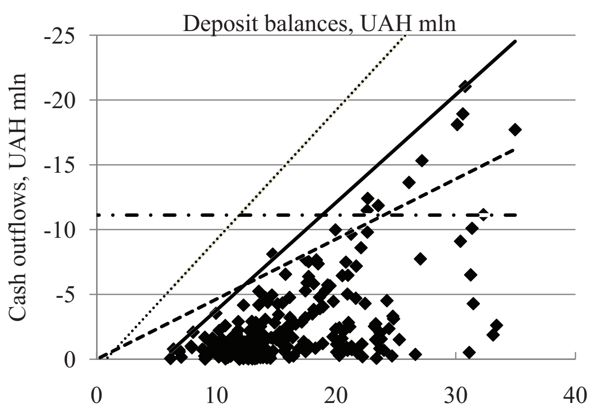

Fig. 2. Dependence of cash flows on deposit balances under normal conditions for confidence level τ = 0.01 (recommended by Basel): «dotted line» — formula (3), «dashed line» — formula (4), «dashdotted line» — formula (5), «solid line» — formula (7)

Source: developed by author.

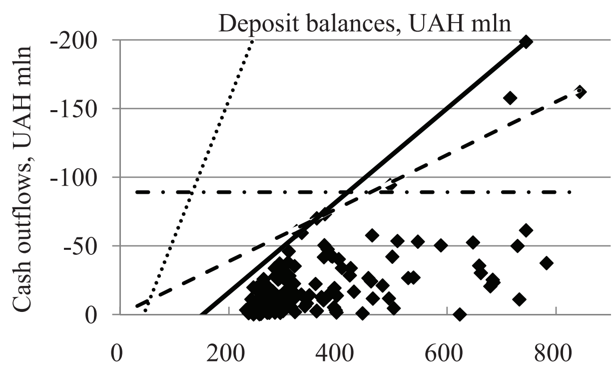

Fig. 3. Dependence of cash flows on deposit balances under crisis conditions for confidence level τ = 0.01 (recommended by Basel): «dotted line» — formula (3), «dashed line» — formula (4), «dashdotted line» — formula (5), «solid line» — formula (7)

Source: developed by author.

As can be seen in *Fig. 2* and *3*, the distributions of empirical points on the «cash flow and balance» plane are similar for both normal and crisis conditions.

Empirical data attests to the existence of a core irreducible level of deposits. The deposit balances do not fall down below a given core level. The more deposit balance, the greater the cash outflow, and vice versa. So far, empirical data testifies that there is such a level of deposits at which a further outflow is stopped.

Table 4 presents the parameters of the above-mentioned models (3—7).

It should be noted that the interception values of different models for normal and crisis conditions cannot be compared, as, in these periods, the bank had different deposit levels.

Table 4

The parameters of the models under normal and crisis conditions

#	Model	Formula	Condition	Intercept	Slope
1	Core level	(3)	normal	0.796	-1.000
			crisis	43.699	-1.000
2	GBM	(4)	normal	0.000	-0.463
			crisis	0.000	-0.194
3	BIS	(6)	normal	0.000	-0.400
			crisis	0.000	-0.400
4	LQR	(7)	normal	4.544	-0.831
			crisis	50.934	-0.335

Source: developed by author.

Fitting and testing a quintile regression. To fit the model (7), we used rq function from *R-package* quantreg (Koenker, 2000).

Table 5 presents the results of the model (7) fitting for normal and crisis conditions at confidence level τ = 0.01.

Table 5

The parameters of the model (7) under normal and crisis condition for confidence level τ = 0.01

#	Conditions	Coefficients:	Value	Std. Error	t value	Pr(>|t|)
1	normal	Intercept, a(τ)	4.54419	0.82941	5.47885	0.00000
		Slope, b(τ)	-0.83118	0.06196	-13.41526	0.00000
2	crisis	Intercept, a(τ)	50.93380	21.29745	2.39154	0.01812
		Slope, b(τ)	-0.33491	0.05893	-5.68302	0.00000

Source: developed by author.

In the outputs above, we can see that the intercept and slope are significant because both their p-values are less than 0.05. Further, we used goftest function from R-package qtools to test the goodness of fit of obtained quantile regressions (Geraci, 2016). This function is based on the cusum process of the gradient vector, developed by He and Zhu (He & Zhu, 2013).

The outputs reported in Table 6 indicate that the goodness of fit of the quantile linear regression (7) is appropriate since the p-value is no less than 0.05. «A large test statistic (small p-value) is evidence of lack of fit» (Geraci, 2016). Thus, a hypothesis about a linear relationship between cash flows and deposit balances is confirmed.

Table 6

The results of the goodness of fit of the quantile linear model (7) for τ = 0.01

#	Conditions	Test statistic	p-value
1	normal	0.0052	0.05
2	crisis	0.0033	0.15

Source: developed by author.

We see in *Fig. 2* and *3* that the formula (3) (the core level model) always overestimates liquidity risk under both normal and crisis conditions. The formulas (4) and (5) (the GBM and CFaR models) overestimate liquidity risk in a zone of low values of deposit balances and underestimate the one in a zone of its high values. In this time, the LQR model (7) more accurately covers the actual data than the considered models (3—5). It has no areas where the observed outflows exceed the estimated ones. As a result, there are no areas of undervalued liquidity risk.

Conclusions. Plots of cash outflows versus deposit balances are a useful and visual instrument to analyze the cash outflows of non-maturity deposits. Such plots demonstrate similar dependencies both for normal and crisis conditions. Empirical data confirms the existence of a core level of deposit balances. The data for cash outflows and deposit balances are sufficient input data to construct quantile regression for the worst cash outflows of non-maturities deposits.

Linear quantile regression summarizes the core deposit level and GBM models. As a result, the worst level of deposits depends on current its balance. This corresponds to the fact that the slope of linear quantile regression is less than one. It has also a constant, non-irreducible component, namely, intercept. It means that deposit outflows stop, beginning at given current level of deposits. Note that the GBM model assumes that deposit outflows can occur at any value of the current deposit balance, whatever low it might be.

The feature of quantile regression is in the fact that it allows us to directly find the worst cash outflow. The constructed model has satisfactory goodness-of-fit with empiric data.

It is shown that the model of core balance overestimates the liquidity risk especially in times of crisis. The GBM and CFaR models overestimate liquidity risk in a zone of low values of deposit balances and undervalue it in a zone of its high values. At the same time, the quantile regression has no areas where the observed outflows exceed the estimated ones. It accurately covers the actual data. As a result, there are no areas of undervalued liquidity risk.

The developed methodology for quantile assessment of deposit outflows will be useful for risk management both in banking supervision and banks. With its assistance, it is possible to determine regulatory requirements for banks' liquidity risk and internal requirements for successful liquidity risk management. The quantile regression measures will be valuable for monitoring liquidity risk and limiting the liquidity risk appetite for banks. As a result, utilizing quantile regression will help the regulator and banks to make informed decisions about liquidity risk.

Subsequent studies should be aimed at constructing quantile regressions that take into account the impact of clients' characteristics on their willingness to take out their deposits from bank's accounts.

References

1. Bank for International Settlements (BIS). (2008). Principles for Sound Liquidity. Risk Management and Supervision. Retrieved from https://www.bis.org/publ/bcbs144.pdf.
2. Bank for International Settlements (BIS). (2013). Basel III: The Liquidity Coverage Ratio and Liquidity Risk Monitoring Tools. Retrieved from https://www.bis.org/publ/bcbs238.pdf.
3. Bank of Japan. (2014). Survey on Core Deposit Modeling in Japan: Toward Enhancing Asset Liability Management. Financial System and Bank Examination Department. BOJ Reports & Research Papers, 1—32. Retrieved from https://www.boj.or.jp/en/research/brp/ron_2014/data/ron140331a.pdf.
4. EBA. (2014). Guidelines on Common Procedures and Methodologies for the Supervisory Review and Evaluation Process (SREP). EBA/GL/2014/13. Retrieved from https://www.eba.europa.eu/documents/10180/935249/EBA-GL-2014-13+(Guidelines+on+SREP+methodologies+and+processes).pdf.
5. Geraci, M. (2016). Qtools: A Useful Package for Quantiles. Retrieved from https://mran.microsoft.com/snapshot/2017-02-04/web/packages/Qtools/vignettes/Qtools.pdf.
6. He, X. M., & Zhu, L. X. (2003). A Lack-of-Fit Test for Quantile Regression. Journal of the American Statistical Association, 98, 1013—1022.
7. Koenker, R. (2000). Quantile Regression in R: A Vignette. Retrieved from https://cran.r-project.org/web/packages/quantreg/vignettes/rq.pdf.
8. Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica, 46* (1), 33—50.
9. Kördel, A. (2017). Modeling Deposit Rates of Non-Maturity Deposits. Degree Project IN. KTH Royal Institute of Technology. School of Engineering Sciences. Sweden: Stockholm. Retrieved from https://www.math.kth.se/matstat/seminarier/reports/M-exjobb17/170529.pdf.
10. Onorato, M. (2012). Liquidity risk management. IBM Corporation Software Group. Business Analytics: Finance. Retrieved from https://www.risk.net/media/download/945331/download.
11. Risk Metrics Group. (1999). Corporate Metrics. Technical Document. The Benchmark for Corporate Risk Management. Retrieved from https://www.msci.com/documents/10199/8af520af-3e63-44b2-8aab-fd55a989e312.
12. Rodriguez, R. N., & Yao, Y. (2017). Five Things You Should Know about Quantile Regression. Paper SAS, 525. Retrieved from https://support.sas.com/resources/papers/proceedings17/SAS0525-2017.pdf.
13. Vento, G. A., & La Ganga, P. (2009). Bank Liquidity Risk Management and Supervision: Which Lessons from Recent Market Turmoil? *Journal of Money, Investment and Banking, 10*, 78—125. Retrieved from https://www.academia.edu/7596453/Bank_Liquidity_Risk_Management_and_Supervision_Which_Lessons_from_Recent_Market_Turmoil.pdf.
14. Voloshyn, I. V. (2004). Estimation of Banking Risks: New Approaches. Kyiv: Nicka-Center. Retrieved from https://www.researchgate.net/publication/282671374_Estimation_of_banking_risks_new_approaches.
15. Vozhzhov, A., & Lunjakova, N. (2009). Account of Influencing of Deposit Risks in Processes of Transformation of Bank Resources. *Formation of Market Economy in Ukraine, 19*, 16—26.
16. Xiao, Z., Guo, H., & Lam, M. S. (2015). Quantile Regression and Value at Risk. in Lee, C.-F. & Lee, J. (Eds.). Handbook of Financial Econometrics and Statistics, 1143—1167. New York: Springer Science+Business Media.
17. Yan, M., Hall, M. J. B., & Turner, P. (2011). Estimating Liquidity Risk Using the Exposure-Based Cash-Flow-at-Risk Approach: An Application to the UK Banking Sector. *Discussion Paper Series, 06.* Retrieved from http://www.lboro.ac.uk/departments/sbe/RePEc/lbo/lbowps/Yan_Hall_TurnerWP6.pdf.