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Liquidity analysis and prediction in the processing industry by applying VG process: The case of the Czech Republic

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Abstract

This paper is devoted to liquidity analysis and prediction possibilities in the processing industry in the Czech Republic. The objective of this paper is to propose and apply pyramidal decomposition of the current liquidity ratio time series of the processing industry in the Czech Republic. Further, we analysed the primary factors affecting liquidity ratio evolution and predicted a two-year probability distribution of the current liquidity ratio by applying the variance gamma process. In the paper, we identified four main factors, which influence liquidity in the processing industry in Czech Republic. Based on these findings, we modelled probability distribution of the liquidity for the period 2016 and 2017 with respect to the empirical distribution. It was shown that when Gaussian distribution is used, the risk is undervalued especially for heavy tails (extreme values) of the probability distribution.

Keywords

Liquidity, processing industry, pyramidal decomposition, variance gamma process.

JEL Classification: G17, G30

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1. Introduction

Liquidity of a company, i.e. the ability to meet short-term obligations, is a crucial short-term goal of financial management and decision-making. Liquid asset shortages (primarily cash and cash equivalents) may cause financial distress and can lead to bankruptcy in extreme cases. Generally, there are many reasons why a normally successful company may be illiquid, but the most important reason is secondary insolvency. In this situation, the company's customers are not able to meet their obligations on or before the maturity of their debt. When there are no other ways to obtain short-term funds for operational activities' financing, the company may face the problem of secondary insolvency.

In day-to-day operations, the liquidity of a company is achieved mostly by the efficient use of assets. In the medium term, liquidity in the non-financial sector is addressed by managing the structure of short-term liabilities.

The level of liquidity needed for a company differs from one industry to another. Judging whether a company has adequate liquidity requires analysis of historical short-term funding requirements, its current liquidity position and expected future short-term funding needs. Moreover, large companies are usually better able to control the level and composition of their liabilities than small companies. Therefore, they may have more potential funding sources, including public capital and money markets. Greater discretionary access to money markets also reduces the requirement of the size of the liquidity relative to companies without such access.

One of the commonly used tools for analysis of a company's liquidity is the usage of financial ratio analysis together with pyramidal decomposition. Liquidity financial ratios (current liquidity, quick liquidity, and cash liquidity) reflect a company's position (ability to pay current liability) at a point in time. Decomposition analysis helps to deeply analyse the factors affecting selected key measures and quantify the strength of their impact on the key measures.

The processing industry in the Czech Republic is one of the main sources contributing to the growth of the country's gross domestic product (GDP). The GDP fell between 2012 and 2013 by 0.9%. This was caused primarily by the evolution of economic activities during the first quarter of 2013 when the total output of the economy dropped by 2.3%. In the next few quarters, the economy recovered slowly and by the end of the year the GDP grew by 1.2%.

Similar evolution during this period was recorded in the value-added measure which, compared to the GDP, does not include tax collection. The proportion of the industry showing GDP growth was 32%, out of which 25% was the processing industry.

According to the classification of economic activities (CZ-NACE), the processing industry includes 24 different sectors. In 2013, production increased in 14 sectors, whose share of the total revenues of the processing industry was approximately 63% (the most important sectors of the processing industry are traditionally the manufacturing sector, pharmacy, mining and quarrying, etc.). Next, the proportion of revenues of the processing industry out of the total national product revenues was approximately 91%, out of which 25% were revenues from the car production sector.

Modelling, prediction, optimal level of corporate liquidity and factors affecting liquidity are at the foreground of many authors' interest. The following papers examine some studies and results recently developed by scientists and academics worldwide. Anderson and Carverhill (2005) proposed a continuous time model of a levered firm generating cash flow which fluctuates with business conditions. These models predict liquidity holdings and some other financial ratios (e.g. leverage ratios, yield spread, and default probabilities) in line with market development. Baum et al. (2008) investigated the link between the optimal level of non-financial firms' liquid assets and uncertainty and developed a partial equilibrium model of precautionary demand for liquid assets showing that firms alter their liquidity ratio in response to changes in either macroeconomic or idiosyncratic uncertainty. Anjum and Malik (2013) analysed the main determinants affecting company cash holdings for the purposes of optimal liquidity prediction. Particularly, the size of the company, leverage, length of the cash conversion cycle and sales growth proved to be the most significant variables affecting liquidity. Next, Bhunia (2008) examined predictive ability with respect to liquidity and profitability positioning of a company through discriminant analysis. Liquidity and profitability performance were tested on the basis of D-score and cut-off score. Bolek and Grosicki (2013) explored the possibility of forecasting company liquidity based on testing the coefficient of variability. Moreover, they analysed static and dynamic liquidity measures to ascertain which were better at predictions in traditional and technology-based sectors. Chen and Liu (2007) employed an artificial neural network to predict corporate liquidity (cash holdings) based on the samples for 45 countries during the period of 1994 to 2004. Moreover, they identified five major determinants of corporate liquidity suggesting that future corporate liquidity models should focus on these major factors rather than including too many variables. Finally, Kim et al. (1998) predicted liquidity by modelling optimal investment in liquid assets as a function of selected factors (cost of external financing, variance of future cash flows and return of future investment opportunities).

The objective of this paper is to propose the pyramidal decomposition of the current liquidity ratio of companies operating in the processing industry, and on the basis of the analysis of results, to predict the annual liquidity with respect to the development of the non-Gaussian evolution of relevant variables affecting the liquidity.

The paper is structured as follows. First, pyramidal decomposition of a key liquidity ratio is proposed and applied on the time series of the current liquidity ratio of the processing industry. The aim is to detect the key variables (component ratios) most affecting the current liquidity. Next, on the basis of the results provided by the pyramidal decomposition, the liquidity of the processing industry is predicted by applying the variance gamma process. In the end, the results of the prediction are summarised and commented upon.

2. Liquidity analysis description

The methodological part of the paper is divided into two subchapters. The first subchapter analyses the historical development of liquidity by applying pyramidal decomposition and influence quantification; the second subchapter is focused on the description of a special case of the Lévy process, i.e. the variance gamma process, which enables modelling higher moments of the probability distribution.

2.1 Description of pyramidal decomposition of current liquidity ratio and influence quantification

The decomposition of the current liquidity ratio is based on the indirect format of cash flows, where the net change in current assets (but not the change in cash and cash equivalents) will be determined. The determination of current assets is based on the following balance formulas:

$$A = E + D,$$
$$A^{LT}_{netto} + CA + OA = E + D^{LT} + CD + OD,$$
$$CA = E + D^{LT} + CD + OD - A^{LT}_{netto} - OA,$$
$$CA = EAT + E^{*} + D^{LT} + CD + OD - A^{LT}_{netto} - OA,$$

where A is assets, E is equity, D is debt, A^{LT}_{netto} is net long-term assets, CA is current (short-term) assets, OA is other assets, D^{LT} is long-term debt, CD is current (short-term) debt, OD is other debt, EAT is earnings after tax and $E^{*} = E - EAT$.

Net change in current assets can be determined as

$$\Delta CA = EAT + \Delta E^{*} + \Delta D^{LT} + \Delta CD + \Delta OD - \\ - \Delta A^{LT}_{netto} - \Delta OA. \tag{1}$$

Current liquidity ratio in a period t is defined as

$$\frac{CA_t}{CD_t} = \frac{CA_{t-1}}{CD_t} + \frac{\Delta CA_t}{CD_t} \tag{2}$$

which can be rewritten as

$$\frac{CA}{CD_t} = \frac{CA_{t-1}}{CD_t} + \frac{EAT}{CD_t} + \frac{\Delta E^{*}}{CD_t} + \frac{\Delta D^{LT}}{CD_t} + \\ + \frac{\Delta CD}{CD_t} + \frac{\Delta OD}{CD_t} - \frac{\Delta A^{LT}_{netto}}{CD_t} - \frac{\Delta OA}{CD_t}. \tag{3}$$

For the analysis of the current liquidity ratio we propose following a pyramidal decomposition, in which the current assets are determined by employing the above described indirect format, see Figure 1. The first level of the decomposition relies on the current assets in the period *t–1* relative to the current debt, which is subsequently adjusted by the changes in the assets' components relative to the current debt. Primary components of the pyramidal decomposition are highlighted.

In the lower levels of the decomposition, attention is devoted to the analysis of chosen financial ratios analysing the structure of the current assets, the net profit generation, the components of the long-term assets and the components of the long-term debt.

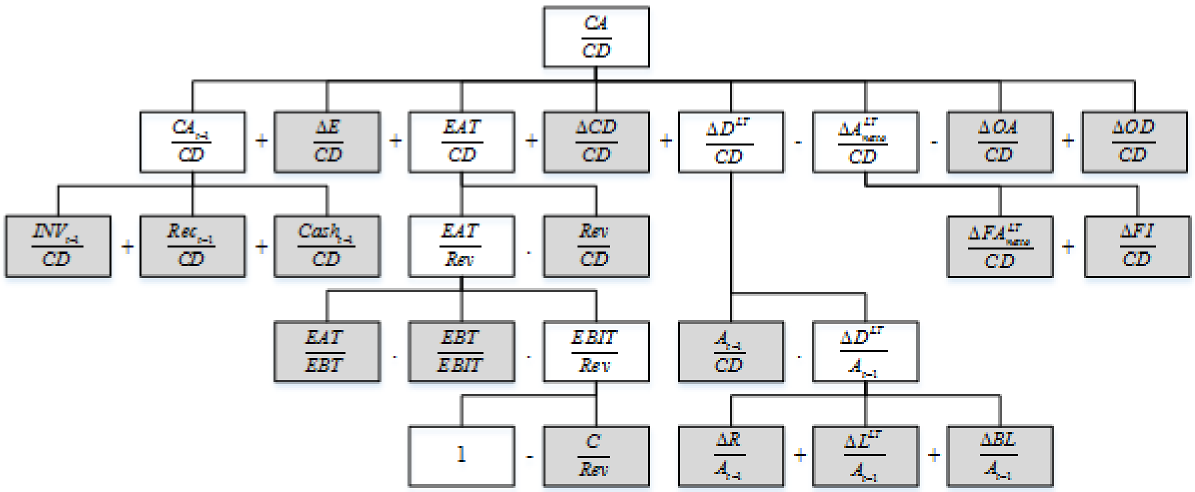

Figure 1 Pyramidal decomposition of current liquidity ratio
Notation used: *CA* – current assets, *CD* – current debt, *EAT* – earnings after tax, *EBT* – earnings before tax, *EBIT* – earnings before interest and tax, *E* – equity, D^{LT} – long-term debt, *A* – total assets, A^{LT} – long-term assets, *OA* – other assets, *OD* – other debt, *Inv* – inventory, *Rec* – receivables, *Cash* – (cash + cash equivalents), *Rev* – revenues, *FA* – fixed assets (without financial investments), *FI* – financial investments, *BL* – bank loans, *R* – reserves, L^{LT} – long-term non-bank liabilities, *C* – costs.

For in-depth analysis of the impact of component ratios on the base ratio, it is useful to apply the analysis of deviations, which enables one to quantify the impact of the changes in the component ratios on the base ratio. The pyramidal decomposition together with the analysis of deviation helps to identify not only the relationships between the financial ratios, but moreover, to quantify the impact of selected ratios on the base ratio.

Generally, any base ratio x can be expressed as a function of component ratios a_i, i.e. $x = f(a_1, a_2 ... a_n)$. The change in the base ratio can be determined as a sum of influences of component ratios,

$$\Delta y_x = \sum_i \Delta x_{a_i}, \tag{4}$$

where x is the base ratio, Δy_x is the change in the base ratio, a_i is the i-th component ratio, Δx_{a_i} is the impact of i-th component ratio on the change in the base ratio.

Basically, the function $x = f(a_1, a_2 ... a_n)$ in pyramidal decomposition can be expressed using two basic operations:

- additive relationship:
  $x = \sum_i a_i = a_1 + a_2 + ... + a_n$,
- multiplicative relationship:
  $x = \prod_i a_1 = a_1 \cdot a_2 \cdot ... \cdot a_n$.

Quantification of the impact under the additive relationship is generally applicable. The total impact is divided in proportion to the changes in the component ratios:

$$\Delta x_{a_i} = \frac{\Delta a_i}{\sum_i \Delta a_i} \cdot \Delta y_x, \tag{5}$$

where $\Delta a_i = a_{i,1} - a_{i,0}$, $a_{i,0}$ is the value of the i-th component ratio at the beginning of the analysed period and $a_{i,1}$ is the value of the i-th component ratio at the end of the analysed period.

Regarding the way in which the multiplicative relationship is handled, we can distinguish five basic methods: a method of gradual changes, a decomposition method with surplus, a logarithmic method, a functional method and the integral method. Their description including derivation can be found in Dluhošová (2004).

In this paper, the integral method is applied; for detailed derivation see Dluhošová and Zmeškal (2014). Quantification of the influences according to the integral method is similar to the logarithmic method; the only difference is that only the linear component of the Taylor series approximation is applied, with the resulting influence quantification for any component ratio being expressed as:

$$\Delta x_{a_i} = \frac{R_{a_i}}{R_{x'}} \cdot \Delta y_x, \tag{6}$$

where $R_{a_i} = \dfrac{\Delta a_i}{a_{i,0}}$ and $R_{x'} = \sum_{i=1}^{N} R_{a_i}$.

2.2 Description of the methodological tools for prediction of the stochastic processes via variance gamma process

Because future evolution of particular indicators is not deterministic, stochastic processes must be used for estimation of the future evolution. The suitable processes can be either discrete or continuous. Continuous processes are used especially for analytic solutions; discrete processes can be applied for simulation solutions. Considering the high complexity in the analytic solution of Lévy processes, we use the simulation approach in this paper. The history and basic principles of financial modelling via Lévy processes are studied in particular detail by Cont and Tankov (2010), or Schoutens (2003). More rigorous and detailed treatment is provided by Bertoin (1996) and Applebaum (2009).

The results of empirical studies show that the probability distribution of the returns of most financial variables are usually skewed and have higher kurtosis. Many models, which are able to model also the third and fourth moment of the probability distribution, have recently been introduced. In general, they can be classified into the family of Lévy processes. This family consists of processes whose increments are independent and stationary, while building blocks of complex Lévy models are the Wiener process and the Poisson process. Similar to geometric Brownian motion (GBM), an exponent is usually used to restrict the processes to positive values only. It follows that we have to transform a simple Lévy model, X_t, into exponential Lévy models with the price dynamic of the asset, S_t, and deterministic increment μ as follows:

$$S_t = S_0 \exp(\mu t + X_t).$$

In this paper, we will use the variance gamma (VG) process for the modelling of the future evolution of particular indicators. The VG process is one of the most frequently used within the non-Gaussian processes. We will define the VG process on the basis of a subordinated exponential Lévy process in this paper, i.e. Lévy process $\{X(t)\}_{t\geq 0}$ is an exponent and follows the definition of the Brownian motion driven by gamma process. In this case, classical time is replaced by a gamma process with gamma distribution $g \in G\left[\frac{t}{\nu};\nu\right]$.

The most important feature of the VG process is that it allows us to also model higher moments of the underlying distribution; in particular, parameter of the gamma distribution ν is primary used to fit the kurtosis, while θ is used to control the skewness. We can then define the VG process, $VG(g(t;\nu);\theta;\sigma)$, as

$$VG(t) = \theta \cdot g(t) + \sigma Z(g(t)) = \theta \cdot g(t) + \sigma \cdot \sqrt{g(t)} \cdot z. \quad (7)$$

where σ is the volatility of the process.

The resulting formula for expression of the dynamic of the financial asset value is:

$$\begin{aligned} S_t &= S_0 \cdot \exp(\mu \cdot dt + VG(t) - \omega t) = \\ &= S_0 \cdot \exp\left(\mu \cdot dt + \theta \cdot g(t) + \sigma \cdot \sqrt{g(t)} \cdot z - \omega t\right), \end{aligned} \quad (8)$$

where ω, $\omega = -\frac{1}{\nu} \cdot \ln(1 - \theta \cdot \nu - \frac{1}{2} \cdot \sigma^2 \cdot \nu)$, means the correction parameter for expected values.[1]

In this paper, the parameters of the VG process are estimated using the generalised method of moments (GMM), and formulas for the first four moments for the VG and GBM process are depicted in Table 1.

Table 1 Comparison of basic moments for VG and GBM model

Moments	VG (θ,σ,ν)	GBM (μ,σ^2)
Mean	θ	μ
Variance	$\sigma^2 + \nu\theta^2$	σ^2
Skew	$\theta\nu(3\sigma^2 + 2\nu\theta^2)(\sigma^2 + \nu\theta^2)^{-3/2}$	0
Kurt	$3\left(1 + 2\nu - \frac{\nu\sigma^4}{(\sigma^2 + \nu\theta^2)^2}\right)$	3

3. Application

The application part of this paper is divided into two parts. First, development and analysis of the current liquidity ratio by pyramidal decomposition application in the processing industry of the Czech Republic during 2007–2015 is performed. Moreover, the impact of the chosen component ratios on the change in current liquidity during this period is explained by applying the integral method. Component ratios with the highest impact on the first level of decomposition (i.e. the riskiest factors) will be considered in a model in simulation of random variables and liquidity prediction.

3.1 Input data

Historical data of the current liquidity ratio and its evolution in the processing industry is available through web pages of the Ministry of Industry and Trade of the Czech Republic.[2] On these pages, one can find the comprehensive financial analysis and statistics

[1] Parameter ω assures that $E[S_t] = S_0 \cdot \exp(\mu \cdot dt)$, while θ and σ are estimated from the real statistical values. A different situation exists within risk-neutral pricing. See, e.g., Tichý (2011) for more detail.

[2] www.mpo.cz

of selected industrial sectors of the Czech Republic including comments and additional sources of information. Figure 2 shows average current liquidity ratio development of the processing industry in the Czech Republic over the period of 2003–2015. The positive trend in current liquidity ratio development during this period is obvious. The bottom was reached in 2003, followed by a relatively stable period from 2005 to 2008 and an improvement in evolution from 2009. Current liquidity in 2015 was on the level of 1.78. The factors behind this development are analysed in the subchapter 3.2.

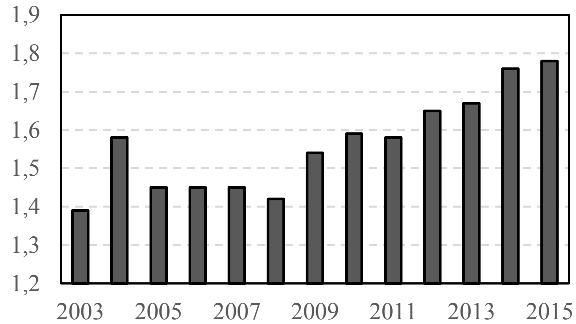

Figure 2 Current liquidity ratio (processing industry, average values 2003–2015)

3.2 Influences quantification of component ratios on current liquidity ratio

For deeper analysis of the factors affecting the current liquidity ratio evolution, we use the pyramidal decomposition depicted in Figure 1 and apply the integral method for influence quantification. The decomposition and influence quantification of current liquidity ratio is performed for the period 2007–2015. Results of the component ratio influences at the first level of pyramidal decomposition are depicted in Figure 5 in the appendix. From the results, it is apparent that the ranking of influences of component ratios changed significantly during the analysed period which is shown in detail in Table 2. The most significant (from the perspective of the influence on the current liquidity ratio) are in last column of the table. It follows that the largest risks are the following component ratios: $\frac{CA_{t-1}}{CD_t}$, $\frac{\Delta E^*}{CD_t}$, $\frac{\Delta A^{LT}_{netto}}{CD_t}$ and $\frac{\Delta CD}{CD_t}$. Conclusions of this analysis will be used next in the current liquidity ratio prediction in Chapter 3.3.

Table 8 in the appendix summarises the results of the influence quantification analysis of all considered component ratios in pyramidal decomposition. The results stated in Table 8 in the appendix confirm the fact that the influence of component ratios and final ranking changes significantly over time. The sharpest fall (by 0.0242) in the current liquidity ratio is recorded between 2007–2008. Based on the analysis results, the drop was caused primarily by the significant decrease in equity. In contrast, the most significant annual improvement in this ratio was observed between 2008–2009 (increased by 0.1201) caused again by the change (increase) in equity and between 2013–2014.

In spite of the fact that the ranking of the significance of component ratio was fluctuating, it has been determined that the most significant factors affecting a processing industry company’s liquidity are the current assets and their components (inventory, accounts receivable and short-term marketable securities). Changes in these factors most affected the

Table 2 Ranking of component ratios according to their influence (1st level of decomposition)

Ratio	07_08	08_09	09_10	10_11	11_12	12_13	13_14	14_15	Average[3]	Rank
CA_{t-1}/CD	0.439	–0.073	–0.186	0.032	0.205	–0.098	0.059	0.165	0.241	1
EAT/CD	–0.059	–0.067	0.085	–0.026	0.037	–0.026	0.087	0.025	0.079	6
$\Delta\ ALT/CD$	0.438	–0.075	–0.205	0.041	–0.041	–0.020	–0.025	0.125	0.186	3
$\Delta\ E/CD$	–0.449	0.212	0.082	–0.033	0.067	–0.040	0.037	–0.179	0.210	2
$\Delta\ DLT/CD$	–0.103	0.094	0.069	–0.040	–0.047	0.043	0.041	–0.106	0.104	5
$\Delta\ CD/CD$	–0.305	0.032	0.208	0.008	–0.137	0.104	–0.049	–0.018	0.165	4
$\Delta\ OA/CD$	–0.001	0.003	–0.002	0.004	–0.010	0.007	–0.002	0.002	0.006	8
$\Delta\ OD/OD$	0.016	–0.005	–0.002	0.002	–0.003	0.009	–0.013	0.004	0.010	7

[3] Calculated like $\frac{\sqrt{\sum_t \Delta x^2_{a_i,t}}}{\sum_i \sqrt{\sum_t \Delta x^2_{a_i,t}}}$.

current liquidity over the horizon analysed. Current assets are financed primarily from short-term liabilities and that is why the changes in this balance sheet's component are significant from the liquidity evolution perspective. During 2007–2010, the current liquidity was mainly influenced by the changes in the long-term assets' structure, particularly by changes in financial investments. Furthermore, it follows from the analysis performed that the proportion of long-term sources of equity and liabilities falls, which results in a decrease in the long-term leverage of companies operating in the processing industry during this period. Long-term capital sources are represented particularly by long-term debt, the proportion of which rose, in contrast with the falling proportion of long-term bank loans. This structure of assets' funding is given by the fact that the companies operating in the processing industry represent mostly large companies and most of these companies in the Czech Republic are in the ownership of foreign shareholders. These companies use not only equity for the financing of their activities, but long-term capital from parent companies as well. Companies use more intercompany debts representing the current and long-term debt of companies.

3.3 Estimation of the current liquidity ratio probability distribution in the processing industry for 2016 and 2017

When the liquidity analysis of the processing industry is performed and key risky variables are detected, prediction of the probability distribution of the current liquidity ratio can be performed. For prediction purposes, the variance gamma process and methodology described in Chapter 2.2 is applied. For comparison purposes, the simulation is performed by applying the GBM process as well. As a basis for the financial plan proposal, a simulation of revenues in the processing industry is used. Moreover, all moments of the probability distribution are considered and maintained. Other variables necessary for the liquidity determination are estimated as a fixed proportion of the simulated revenues. Relevant key variables come from the first level of the pyramidal decomposition proposed in Chapter 2.1, see (3). For the crucial risky variables (i.e., $\frac{CA_{t-1}}{CD_t}$, $\frac{\Delta E^*}{CD_t}$, $\frac{\Delta A^{LT}_{netto}}{CD_t}$, $\frac{\Delta CD}{CD_t}$), the random evolution of the variable with respect to revenues is simulated. Prediction of the probability distribution of the liquidity can be summarised into the following steps:

i. revenue simulation on the basis of the historical statistics by applying the variance gamma process,
ii. simulation of relevant variables (CD, E^*, A^{LT}_{netto}) relative to revenues on the basis of the historical statistics and calculation of their values for the subsequent period (CD_t, E^*_t, $A^{LT}_{netto,t}$),
iii. calculation of the remaining variables (here it is assumed that their proportion relative to revenues is fixed as in the past),
iv. liquidity determination for each scenario and probability distribution estimation for the period I.Q.2016–IV.Q.2017.

For the prediction of particular financial variables, $n = 50{,}000$ simulations are performed. For the purpose of variance minimisation of the simulated random variables and keeping of the modelled statistics as close as possible to those required, the stratified sampling (SS) method for the GBM process and the Latin hypercube sampling (LHS) method for the VG process is applied. See Tichý (2008) or Avramidis et. al. (2004) for more details.

i. Modelling revenues via VG and GBM process based on the empirical characteristics

Input empirical data for revenue modelling are composed of quarterly historical time series of revenues in the processing industry in period I.Q.2007–IV.Q.2015. Data were gathered from analytical reports from the Ministry of Industry and Trade in the Czech Republic (MPO). The historical evolution of revenues is shown in Figure 3.

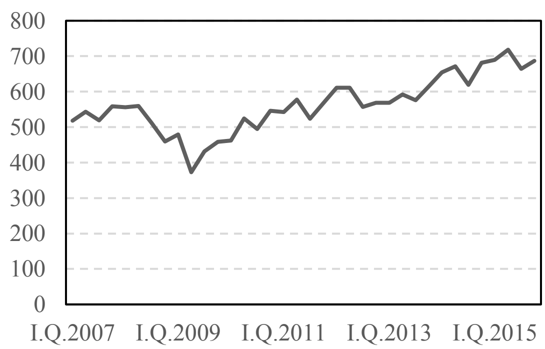

Figure 3 Historical evolution of revenues (quarterly)

Absolute values of the revenues were transferred onto the continuous returns with the following characteristics: $mean = 0.008$, $stdev = 0.079$, $skew = -1.009$ and $kurt = 4.825$. Using GMM and formulas from Table 1, the parameters for the VG process were estimated: $\theta = -0.0839$, $\sigma = 0.0602$, $\nu = 0.3667$ and correction parameter $\omega = -0.0809$. According to (7) 50,000 scenarios were simulated for the VG process in period I.Q.2016–IV.Q.2017. For comparison, the GBM model was also used for revenue prediction. Modelled and empirical characteristics are depicted in Table 3.

Table 3 Characteristics of empirical and modelled quarterly returns of revenues

	mean	var	stdev	skew	kurt
empirical	0.008	0.006	0.079	–1.001	4.825
model(VG)	0.008	0.006	0.079	–1.006	4.866
model(GBM)	0.008	0.006	0.079	–0.003	3.005

It is obvious from Table 3 that the VG process is able to plausibly capture not only the first two moments of the probability distribution but also skewness and kurtosis. Using (8), the future evolution of the revenues in the annual data for period I.Q.2016–IV.Q.2017 was modelled for both the VG and GBM process. The resulting probability distributions are shown in Figure 6 in the appendix.

ii. Modelling of the key relevant variables

For the determination of the variables (CD_t, E_t^*, $A_{netto,t}^{LT}$) analysed in the pyramidal decomposition, first, it is necessary to analyse and describe the historical evolution of these variables with respect to revenues and, for the purpose of prediction, to maintain these relationships and their empirical characteristics in the future. This enables the maintaining of the random evolution of these variables. For modelling of these relationships, both the VG and GBM processes are used; the procedure is analogous to the revenues prediction. First, log-returns of these variables relative to revenues were calculated, their characteristics were determined and on the basis of the results, and the parameters of the VG and GBM process were estimated. Table 4 shows the estimated parameters for returns of particular relationships.

Table 4 Estimated parameters of continuous returns of key relationships for VG processes

	Θ	σ	ν	ω
CD/Rev	0.043	0.071	0.231	0.045
A^{LT}*/Rev*	0.115	0.066	0.162	0.119
E^**/Rev*	0.045	0.088	0.334	0.049

According to (7), 50,000 scenarios were subsequently simulated for the VG and GBM processes. Modelled and empirical characteristics are depicted in Tables 9–11 in the appendix. We can again observe the obvious advantage from utilisation of the VG process for modelling of the variables, which leads to the apparent capture of all the moments of the probability distribution. Using (8) 50,000 scenarios were then calculated for the possible development of particular relations and the development of relevant items for the next period were subsequently calculated.

iii. Calculation of the remaining variables

The remaining variables needed to calculate liquidity according to (3), which were not identified as key variables, were further determined for each scenario via a fixed portion of the revenues, which was estimated to be similar to the average value of the ratio between particular variables and revenues. See Table 5 for the resulting ratios.

Table 5 Relationships among selected variables and revenues

indicator	*EAT/Rev*	D^{LT}*/Rev*	*OA/Rev*	*OD/Rev*
mean	0.049	0.132	0.007	0.007

Predicted values for the particular items were calculated according to the equation $X_t^{(n)} = \text{Rev}_t^{(n)} \cdot \phi\left(\dfrac{X}{\text{Rev}}\right)$, where t is the forecast period, $X^{(n)}$ is the value of the particular variable for the n-th scenario, $\text{R}ev^{(n)}$ are the estimated revenues for the n-th scenario and $\phi\left(\dfrac{X}{\text{Rev}}\right)$ is average value of the historical ratio between particular variables and revenues.

iv. Estimation of the liquidity probability distribution for 2016 and 2017

Based on the estimated variables and their substitution into the first level of decomposition of liquidity (3), the liquidity in the processing industry for 2016 and 2017 was modelled. The probability distribution of this estimation for both processes used is shown in Figure 4, and the basic characteristics are depicted in Table 6.

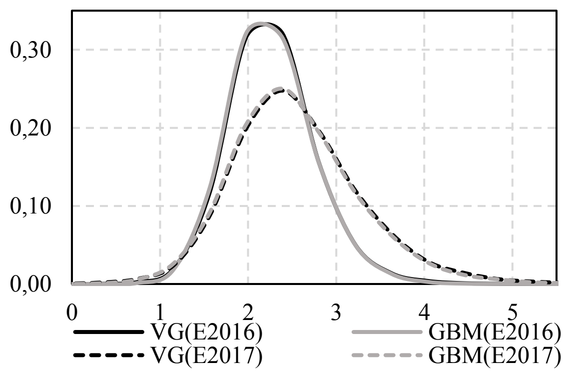

Figure 4 Probability distributions for liquidity prediction in the processing industry for 2016 and 2017

Table 6 Characteristics of probability distributions for modelled liquidity

	mean	stdev	skew	kurt
VG_2016	2.034	0.493	0.515	4.173
GBM_2016	2.025	0.487	0.426	3.658
VG_2017	2.287	0.755	0.686	4.864
GBM_2017	2.265	0.730	0.664	4.546

The mean of the current liquidity ratio probability distribution for 2016 is 2.03 for the VG process and 2.02 for the GBM process (and 2.28 and 2.26 for 2017, respectively), which represents a slight increase compared to the 2015 values. This increase may be caused in particular by the improving economic situation, which was reflected in parameters estimated on the basis of empirical characteristics. Final probability distributions are slightly positively skewed and kurtosis is higher than normal. By analysing the extreme values of the cumulative probability distribution functions (CDF), the quantiles of the distributions can be determined. See Table 7.

Table 7 Chosen modelled liquidity percentiles

percentile	0.05%	0.1%	0.5%	1%	5%
VG_2016	0.161	0.292	0.694	0.842	1.161
GBM_2016	0.474	0.585	0.751	0.887	1.181
VG_2017	0.021	0.032	0.586	0.772	1.281
GBM_2017	0.073	0.265	0.655	0.831	1.279

Results depicted in Table 7 provide the following: by applying the GMB process, compared to the VG process, the risk is undervalued, especially for heavy tails (extreme values) of the probability distribution. This may play a key role in the prediction of the economy's growth in the Czech Republic, especially because of the importance of this industry in relation to its proportion of the GDP. The results can be used in the comparison of the financial analysis of companies in a particular sector, financial planning or estimation of the cost of capital, stress-testing of an economy, etc. Predictions are summarised and discussed.

4. Conclusion

In this paper, the current liquidity ratio development in the processing industry of the Czech Republic over the period of 2007 to 2015 was analysed. Furthermore, pyramidal decomposition of this ratio was proposed and key variables having a significant impact on the current ratio were identified. As follows from the analysis, the most significant components during this period were the following: $\frac{CA_{t-1}}{CD_t}$, $\frac{\Delta E^*}{CD_t}$, $\frac{\Delta A^{LT}_{netto}}{CD_t}$ and $\frac{\Delta CD}{CD_t}$. Subsequently, the current liquidity ratio was predicted. Prediction relies on the risk factors which are considered to be the ratios with the highest impact on the current ratio. For prediction purposes, stochastic processes were employed, which enabled modelling of higher moments of probability distribution. Specifically, the variance gamma process was applied, which is a model from the group of Lévy processes. All results were compared with results obtained using GBM. The probability distribution of the current liquidity ratio for 2016 and 2017 was estimated and the probability function was constructed. Next, basic statistics of the distribution were computed including quantiles. Disadvantages of using GBM when projected liquidity, mainly underestimation of risk, have been demonstrated graphically and numerically.

The above applied approach and results that are applicable to the solutions to many different issues of financial management and financial decision-making, such as financial analysis, financial planning, risk management, and stress-testing, have been summarised and discussed.

References

ANDERSON, R.W., CARVERHILL, A. (2005). A model of corporate liquidity. *Working paper*. London: London School of Economics and Political Science. http://dx.doi.org/10.2139/ssrn.567648

ANJUM, S., MALIK, Q. (2013). Determinants of corporate liquidity – an analysis of cash holdings. *Journal of Business and Management* 7(2): 94–100. http://dx.doi.org/10.9790/487X-07294100

APPLEBAUM, D. (2009). *Lévy Processes and Stochastic Calculus*. Cambridge: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511809781

AVRAMIDIS, A. N., L'ECUYER, P., TREMBLAY, P.A. (2003). Efficient simulation of gamma and variance gamma processes. In: Chick, S. et al. (eds). *Proceedings of the 2003 Winter Simulation Conference*. New Orleans: IEEE, 319–326. http://dx.doi.org/10.1109/WSC.2003.1261439

BAUM, C.F., CAGLAYAN, M., STEPHAN, A., TALAVERA, O. (2008). Uncertainty determinants of corporate liquidity. *Economic Modelling* 25(5): 833–849. http://dx.doi.org/10.1016/j.econmod.2007.11.006

BERTOIN, J. (1996). *Lévy Processes*. Cambridge: Cambridge University Press.

BHUNIA, A. (2008). A discriminant analysis and prediction of liquidity profitability. *Vidyasagar University Journal of Commerce* 13: 100–106.

BOLEK, M., GROSICKI, B. (2013). Forecasting liquidity in traditional and technology-based sectors – the case of Poland. *Financial Internet Quarterly 'e-Finance'* 9(4): 25–38.

CHEN, N., LIU, Y. (2007). Application of artificial neural network to corporate liquidity determination. *Intelligent Information Hiding and Multimedia Signal Processing* 2: 557–560. http://dx.doi.org/10.1109/IIHMSP.2007.4457771

CONT, R., TANKOV, P. (2010). *Financial Modelling with Jump Processes*. Chapman & Hall/CRC press. http://dx.doi.org/10.1201/9780203485217

DLUHOŠOVÁ, D. (2004). An analysis of financial performance using the EVA method. *Czech Journal of Economics and Finance* 54(11–12): 541–559.

DLUHOŠOVÁ, D., ZMEŠKAL, Z. (2014). Generalised approach to deviation analysis of non-linear company discounted value measure. In: *METAL 2014. 23. ročník mezinárodní konference metalurgie a materiálů*. Brno: Tanger.

KIM, C., MAUER, D. C., SHERMAN, A. E. (1998). The determinants of corporate liquidity: Theory and evidence. *Journal of Financial and Quantitative Analysis* 33(3): 335–359. http://dx.doi.org/10.2307/2331099

SCHOUTENS, W. (2003). *Lévy Processes in Finance: Pricing Financial Derivates*. Chichester: Wiley. http://dx.doi.org/10.1002/0470870230

TICHÝ, T. (2011). *Lévy Processes in Finance: Selected Applications with Theoretical Background*. Ostrava: VSB-TUO.

TICHÝ, T. (2008). Examination of selected improvement approaches to Monte Carlo simulation in option pricing. *Politická ekonomie* 56(6): 772–794. https://doi.org/10.18267/j.polek.663

Additional sources

Analytical materials, statistics – FA of the Corporate Sector of Industry and Construction 2003–2015. *MPO.* Available from: <http://www.mpo.cz/en/minister-and-ministry/analytical-materials/default.html>.

Analytical materials, statistics – Survey of Czech Economy 2003–2015. MPO. Available from: <http://www.mpo.cz/en/minister-and-ministry/analytical-materials/default.html>.

Appendix

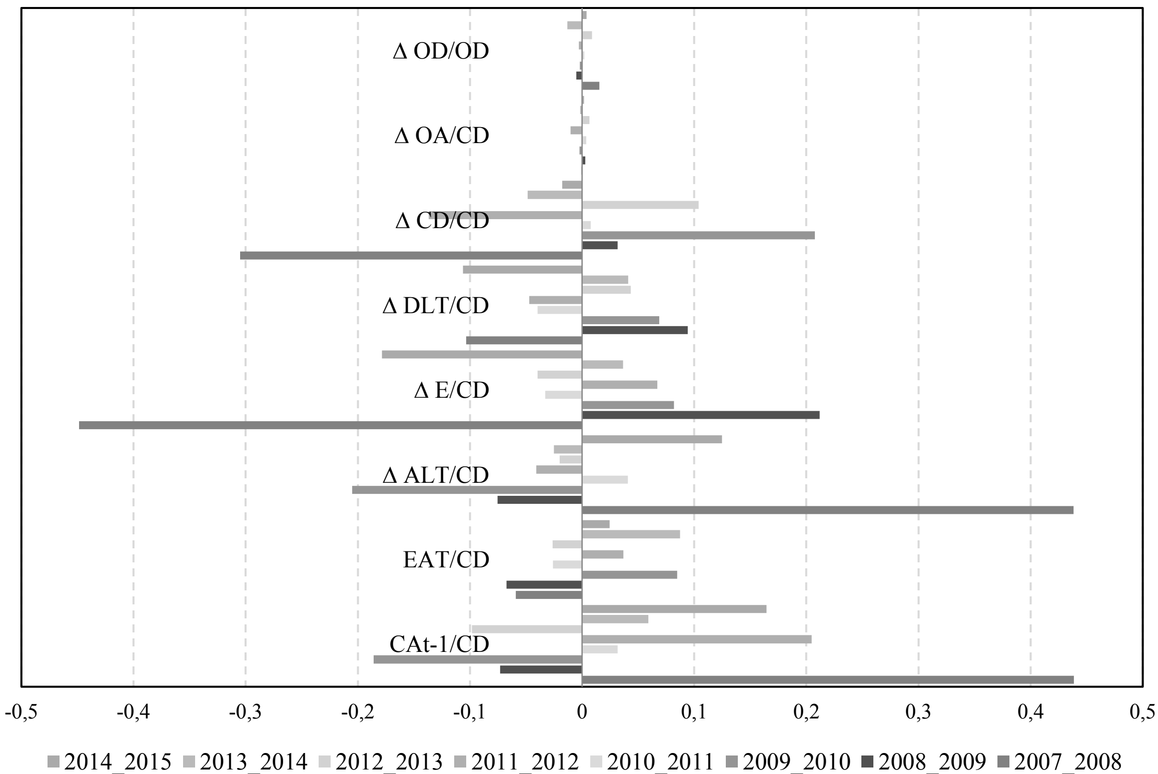

Figure 5 Impact of component ratios on the current liquidity ratio (2007–2015; first level of decomposition)

Table 8 Impact of component ratios on the current liquidity ratio (2007–2015; overall decomposition)

	Ratio	07_08	08_09	09_10	10_11	11_12	12_13	13_14	14_15
	Current liquidity	–0.0242	0.1201	0.0483	–0.0125	0.0705	–0.0214	0.1359	0.0174
component ratio	Inv_{t-1}/CD	0.1274	0.0001	–0.1314	0.0069	0.0639	–0.0107	–0.0072	0.0325
	Rec_{t-1}/CD	0.2245	–0.0425	–0.1322	0.0861	0.0523	–0.0869	0.0487	0.0308
	$Cash_{t-1}/CD$	0.0867	–0.0306	0.0777	–0.0612	0.0885	–0.0007	0.0175	0.1013
	EAT/EBT	–0.0029	–0.0309	0.0475	–0.0109	–0.0020	–0.0134	–0.0050	0.0263
	$EBT/EBIT$	–0.0041	0.0385	–0.0123	0.0068	0.0020	0.0062	0.0468	–0.0327
	C/Rev	–0.0527	–0.0661	0.0451	–0.0264	0.0228	–0.0063	0.0239	0.0240
	Rev/CD	0.0007	–0.0089	0.0046	0.0044	0.0143	–0.0128	0.0216	0.0071
	$\Delta FA^{LT}/CD$	0.2799	–0.0696	–0.1093	0.0140	–0.0353	0.0094	0.0038	0.0474
	$\Delta FI/CD$	0.1583	–0.0056	–0.0957	0.0270	–0.0056	–0.0293	–0.0289	0.0773
	$\Delta E/CD$	–0.4487	0.2119	0.0820	–0.0328	0.0672	–0.0398	0.0366	–0.1784
	A_{t-1}/CD	–0.0061	0.0008	–0.0077	–0.0010	0.0022	–0.0007	0.0018	0.0082
	$\Delta R/A_{t-1}$	–0.0171	–0.0006	0.0182	–0.0057	–0.0091	0.0169	0.0022	–0.0004
	$\Delta L^{LT}/A_{t-1}$	–0.0237	0.0693	0.0803	–0.0514	–0.0534	0.0313	0.0374	–0.1170
	$\Delta BL/A_{t-1}$	–0.0565	0.0248	–0.0217	0.0185	0.0131	–0.0041	–0.0002	0.0030
	$\Delta CD/CD$	–0.3050	0.0318	0.2075	0.0076	–0.1369	0.1040	–0.0485	–0.0176
	$\Delta OA/CD$	–0.0005	0.0029	–0.0023	0.0036	–0.0104	0.0067	–0.0016	0.0017
	$\Delta OD/CD$	0.0155	–0.0052	–0.0019	0.0020	–0.0030	0.0088	–0.0131	0.0040

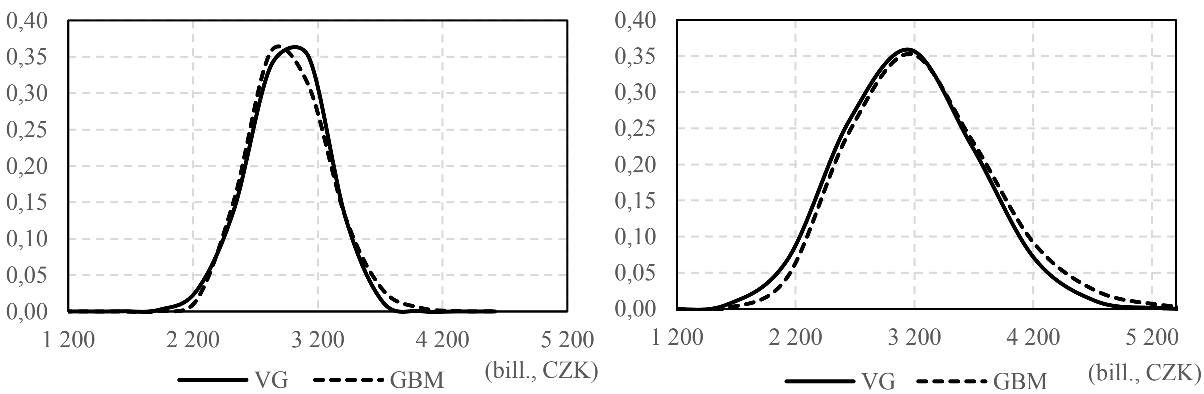

Figure 6 Probability distributions for revenue prediction for 2016 (left figure) and 2017 (right figure)

Table 9 Characteristics of empirical and modelled quarterly returns of *CD/Rev*

	mean	var	stdev	skew	kurt
empirical	–0.0019	0.0055	0.0741	0.3896	3.7955
modelled (VG)	–0.0016	0.0055	0.0742	0.3918	3.8214
modelled (GBM)	–0.0013	0.0055	0.0742	–0.0035	3.0054

Table 10 Characteristics of empirical and modelled quarterly returns of *ALT/Rev*

	mean	var	stdev	skew	kurt
empirical	–0.0008	0.0065	0.0808	0.6184	3.7562
modelled (VG)	–0.0009	0.0065	0.0804	0.6095	3.7364
modelled (GBM)	–0.0009	0.0064	0.0803	–0.0041	3.0154

Table 11 Characteristics of empirical and modelled quarterly returns of E^{*}/Rev

	mean	var	stdev	skew	kurt
empirical	0.0031	0.0084	0.0914	0.4786	4.1569
modelled (VG)	0.0032	0.0082	0.0908	0.4813	4.2043
modelled (GBM)	0.0033	0.0080	0.0892	–0.0763	2.9966