TESTING THE HYPOTHESIS OF THE ADEQUACY OF THE DISTANCE-TO-DEFAULT AS AN INDICATOR OF CHANGES IN BANKS' RISK EXPOSURES

BOŽO JAŠOVIČ[1]

Received: June 6, 2016
Accepted: December 1, 2016

ABSTRACT: *A distance to default indicates the distance measured in standard deviations of the market value of assets from the default point. The hypothesis that distance to default is indicative of changes in the levels of risk of the banking system since it precedes accounting data that indicate similar changes was tested on the basis of selected financial ratios. We have applied a modification developed by Toda and Yamamoto of the standard Granger causality test to see whether there is causality between distance to default and the selected financial ratios. Contrary to expectations, we could only prove Granger causality from lagged values of distance to default (6–12 months) to a leverage ratio, whereas we were not able to obtain similar relationship with other ratios.*

Keywords: *financial stability, market discipline, distance to default, default risk, augmented Granger causality*

JEL Classification: G21, G28

DOI: 10.15458/85451.43

Introduction

In this paper, we aim to determine whether the *distance-to-default (dd)* indicator based on market data reflects better the changes in banks' risk profile in comparison with standard financial ratios calculated solely by using accounting information. We have chosen the Black-Scholes option pricing theory adapted to calculate the implied value of assets and their volatility as the theoretical basis for assessing the selected indicator. In the case of the Slovenian banks, the distance-to-default indicator could not be used as an "off-the-shelf" tool for a number of reasons. According to traditional B-S model distance-to-default indicator is calculated by using series of individual bank market share prices. We have followed this approach and derived the aggregate indicator as a weighted average of individual indicators. In the observed period only shares of three banks were traded on a stock exchange (NKBM, Abanka Vipa and Probanka) and in addition, in an earlier part of this period only shares of Probanka were listed. Due to this and low liquidity of Slovenian capital market we consider the sample as not representative and therefore present the calculation for an illustrative purposes only. Therefore, the traditional approach has been adjusted to take into account the specific features of the local environment and has been

1 Gorenjska banka d.d, Kranj, Slovenia, e-mail: bjasovic@siol.net

calculated by making use of indirect market data. Indirect market data (e.g. daily changes in interest rates, selected stock-exchange indices, specialised indices or individual prices of company shares, which may be representative for certain sectors of the economy) complement static accounting information and bring in market dynamics (volatility), which has a considerable influence on the value of bank portfolios and, in turn, also on their financial results. We have empirically tested on an aggregate level the fundamental hypothesis that the estimates of numerous market participants, which are reflected in prevailing market prices, may indicate in advance (precede) changes in a bank's risk profile in comparison with static financial ratios made available at intervals and referring to the past periods.

The results of empirical testing are not fully in line with the expectations based on the proposed hypothesis given the fact that the results obtained confirm it only up to a point. With the Toda-Yamamoto version of the Granger causality test, however, we have been able to prove that the adjusted distance-to-default measure indicates (precedes) 6 to 12 months in advance changes in the leverage ratio (capital to total assets ratio). A few other empirical studies also underline the significance of the leverage ratio, since it better reflects a bank's insolvency risk in comparison with other indicators. One of the explanations for the absence of Granger causality between the distance-to-default and other financial indicators is derived from the finding that the regulatory framework leaves quite some room for discretion at measurement of bank assets at fair value or at amortised cost at a considerable time lag.

The sections in the paper are arranged as follows: we start by presenting the empirical studies carried out to date that examined the application of the distance-to-default concept. Then we present the theoretical basis for the valuation of a company's equity by using the option pricing model. We proceed by describing the proposed changes to the calculation of the indicator by using indirect market data; we then present in the next section the empirical testing to demonstrate that changes in the computed distance-to-default indicator precede changes in the standard ratios (indicators) of bank performance. In the last section we wrap up by drawing some conclusions.

1. OVERVIEW OF EMPIRICAL STUDIES USING THE MODEL FOR THE VALUATION OF EQUITY AND LIABILITIES

Empirical studies of the distance-to-default have gained popularity both in the research sphere and in practical sense. The key guiding principle for the use of that approach is that the *dd* combines market data of numerous independent market participants in a single indicator. In addition, the fact that the indicator is used so often is attributable to the recognition that market participants' estimates, unlike periodical, static reports for supervisors, are prospective, i.e. turned into the future and are continuously available.

Gropp et al. (2002, 2004) empirically demonstrated that *dd*, calculated on the basis of the movements in market pricing of bank shares, indicates deterioration in the bank's credit rating with the lead time of 6 to 18 months. They proved by means of partial derivatives with regard to the value of assets, debt (financial leverage) and assets volatility completeness and unbiasedness of *dd* indicator (Gropp et. al., 2002, p. 10).

The distance to default as a bank risk indicator has been also used by Takami and Tabak (2007). They find the distance-to-default indicator to be significantly sensitive to the interest rate: the higher the interest rate, the lower the value of the distance to default and the higher the default risk. Having analysed the indicator on a sample of banks whose shares were listed on a stock exchange, they demonstrated that the indicator reflected fairly well the relative risk of each bank (the deviation of *dd* for individual banks from reference value).

Gray and Walsh (2008) have shown different possible uses of distance-to-distress measure calculated by using the Black-Scholes-Merton model: from the indicator that reflects risk exposure of individual institutions, to aggregate–sector-based indicator and its correlation with macroeconomic variables. Despite their affirmative position regarding the use of the aforementioned approach to analyse risk exposure of individual banks and the banking sector, they point out the limitations for the use of option pricing model, which arise from the lack of market-based information. In an aggregated sectoral analysis, imbalances pile up for a longer period and market participants begin to incorporate them consistently in their price estimates. The authors of the paper have merely indicated in their research study that there is a significant correlation between distance-to-default indicator and traditional risk measures with different time leads or lags.

Chan-Lau and Sy (2006) favour the indicators derived from market-based risk measures over balance-sheet indicators, which reflect changes in riskiness of the observed institutions with considerable time lags. The two authors have empirically calculated and compared the distance-to-default indicator for individual banks and concluded that it has proved useful for predicting bank rating downgrades. However, the indicator should be treated with a dose of scepticism, since the indicator disregards the probability that a bank will be subject to remedial regulatory actions. What they had in mind was maintaining a capital adequacy threshold set for banks and monitored by supervisors. Chan-Lau and Sy adjusted the *dd* indicator by raising the insolvency threshold using the quotient λ[2], which reflects the expected bank's capital adequacy ratio and named it distance-to-capital. It is worth noting that the two authors tested the empirical calculation of the indicator on individual banks; however, in the conclusions they point out that the *dd* approach could apply to analyse the entire banking sector, i.e. stability of the financial system.

The analysts from the ECB also analysed the banking system fragility by using the *dd* indicator. They emphasised that it is a measure based on market prices of shares that generates information regarding market asset value and asset volatility. By using a pre-defined point of insolvency the indicator shows how vulnerable the banking sector is

2 The authors increased liabilities in equation (1) by factor $\lambda = 1/(1\text{-PCAR})$. PCAR in the quotient stands for expected capital adequacy (Chan-Lau & Sy, 2006, p. 10).

(how many standard deviations away from the point of insolvency). Given the rising popularity market discipline has for supervisory purposes, the ECB analysts warn that the aforementioned approach should not be taken "at face value"–as a substitute for the conventional analysis based on balance-sheet data (ECB, 2005, p. 91).

Vassalou and Xing (2004) investigated the probability of default of companies. The authors examined a vast number of companies (more than 4,000 in the last part of the observed period) between 1971 and 1999. They calculated the indicator of a company's default probabilities where default occurs when value of the indicator *dd* in a cumulative probability function of normal distribution (*N(-dd)*) is negative. Based on such comprehensive empirical research, they concluded that insolvency risk (default) is closely linked to the size of a company and the ratio between the book to market value of a company. The empirical research confirms that the probability of default in the observed corporate sector decreases monotonically as the company size increases and as the ratio of book to market value of equity decreases. The authors argue that asset volatility implicitly calculated from the daily fluctuations in market share prices is the key information for the estimates of default probabilities (Vassalou & Xing, 2004, p. 833).

Chan-Lau, Jobert and Kong (2004) have empirically tested the use of the distance-to-default indicator for banks that operate in emerging markets and have arrived at a conclusion that the *dd* measure could be used as a forecasting tool for distress looming on the banking system. They concluded that the early warning indicator predicts difficulties in banking systems with up to 9-month lead time (Chan-Lau et al., 2004, p. 13). Furthermore, the research study highlights that the risk-free rate of return is not a proper parameter in a risky world. In addition, it also points at the unsuitability of constant debt assumption which should be revisited. Despite the previously mentioned weaknesses, their conclusion is that the *dd* indicator could be useful tool in supervising banks. The research also uses the probit and logit regression models to assess the ability to predict the occurrence of a negative credit event (default or rating downgrade) and the conclusion drawn is that the *dd* can be useful for forecasting bank distress/vulnerability.

Gapen, Gray, Lim and Xiao (2004) have examined in their research study the corporate sector vulnerability by applying the option pricing model. Their key conclusion is that the approach combines balance-sheet data with market-based data where asset volatility is the key determinant of default probability. By taking into account asset volatility in the model, we are able to account for the fact that companies with a similar financing structure of (debt to equity ratio) have different values of indicator *dd*, i.e. probability of default. Asset volatility is largely related to the economic activity (industry) (Crosbie & Bohn, 2003, p. 9), i.e. its technological characteristics, while a company's financial leverage only increases its underlying asset volatility, which is then reflected on higher equity volatility. The research study underlines non-linear links in the Black-Scholes model, which enables a more reliable estimate of basic function driven by changes in underlying parameters.

Gapen et al. (2004) have warned that the model has its shortcomings since it uses normal distribution probability when calculating the distance-to-default indicator. Also Crosbie and Bohn (2003, p. 18) underline that using normal distribution for the calculation of *dd* is a bad choice. All authors underscore that in order to obtain more reliable estimates for the indicators, empirical distribution should be used.

In an analogy with the use of the model to value assets and liabilities of individual companies or banks based on market data, a similar approach could be followed at the sector-based level. Persson and Blavarg (2003) have shored up the thesis that the credit portfolio risk in banks largely reflects the corporate sector risk to which they are exposed by comparing time series of default probabilities for seven economic sectors (industries). Their conclusion is that increased credit risk in individual banks estimated with *dd* could be a consequence of increased risk in the corporate sector (Persson & Blavarg, 2003, p. 24). To explain the reasons that influence the indicator movement in banks, we should analyse the indicator for the corporate sector that account for the bulk of a bank's credit portfolio and has direct impact on its riskiness. Moreover, as regards the corporates, the two authors draw attention to the fact that only the shares issued by larger companies are traded on a stock exchange. They assess that expectations of market participants regarding the financial instruments issued by larger companies should also reflect up to a point the expectations of a sector (industry) as a whole and eventually influence the development of smaller, non-listed companies in a particular industry.

Willem van den End and Tabbae (2005) have focused their research on the sector-based approach. They assume that a sector-based analysis has an advantage over a traditional analysis based on macroeconomic aggregates, since with the latter, some risks might be hidden. Furthermore, at the sector-based level, it becomes possible to identify foreign exchange and balance-sheet structural imbalances, as well as the shortage of capital. The most significant advantages of the sector-based approach include interdependence and the possibility of a spill-over effect (contagion) between sectors. The authors distinguish in the research study two indicators, i.e. measures of risk: probability-of-default measure and loss measure. The latter presents, in accordance with the option pricing model, the value of put option, i.e. loss incurred by the excess of liabilities over the value of assets. The value of a put option for the banking sector is the assessment of the necessary capital that sector needs in order to absorb losses, i.e. the value of an implied government-backed guarantee to ensure macrofinancial stability. The authors have calculated both measures of risk for five sectors: banking, pension, insurance, corporate sector, and household sector. Given the fact that market asset value and asset volatility could not be calculated for all sectors by using direct market data, they have used alternative approaches: company-specific balance-sheet data provided that they are marked-to-market, discounted future cash flows or implied market values derived from option market prices (Willem van den End & Tabbae 2005, p. 9). We highlight the described approach since it indicates how to overcome the lack of direct market data (prices) when applying the Black-Scholes model.

Based on the above overview, we could summarise our observations in the following conclusions:

- Numerous studies point out the usefulness of information content inherent in market-based data, their forward-looking nature, the large number of participants that generate market data and, consequently, make them objective and available on on-going basis (see for instance Flannery, 2001; Flannery 1998).

- The authors explicitly stress that accounting data cannot be completely replaced by market information, it should be rather viewed as complementary source to accounting data.
- The authors are aware of the limitations or deficiencies resulting from the direct application of the structural model introduced by Black-Scholes hence they try to correct it with methodological adaptations, i.e. by testing the plausibility of the assumptions on which the model is founded.
- The studies recommend complementary use of the discussed approach both for the analysis of risk sensitivity of individual credit institutions and at the aggregate level for the analysis of macrofinancial stability.
- Some studies explicitly conclude that asset variability (volatility) determined on the basis of market data is indeed the key component that contributes to the explanatory power of the *dd* indicator (see, for instance, Gapen et al., 2004; Vassalou & Xing, 2004; Crosbie & Bohn, 2003).

2. THEORETICAL BASIS FOR APPLYING THE OPTION PRICING MODEL IN THE VALUATION OF COMPANY EQUITY AND LIABILITIES

The methodology for the calculation of the distance-to-default is derived from the Black-Scholes-Merton option pricing model (Black & Scholes, 1973) that can also be used to determine a firm's equity value and corporate liabilities (see also Merton, 1974). The assumption for the use of the model for equity valuation is that owners of companies have an option (call option)–the right to purchase all assets of the company by paying off all its liabilities. Having paid off all outstanding liabilities, only the equity holders have claim to the company's assets, and the price for exercising such an option (exercise price) is equal to the value of total liabilities.

Shareholders' equity has positive value only in the case that the value of the company's assets exceeds the value of its liabilities. Should that not be the case, owners would never exercise their call option to buy assets, since they would have to pay for the assets more than their value. If that is the case, the company's creditors could exercise the option they have (put option) and sell their claims on the company in exchange for taking over all its assets in order to minimise their loss.

Let us assume that a bank (or a company) is insolvent and unable to honour its obligations, meaning that the value of its assets is lower that the value of its liabilities. Under these circumstances, creditworthiness of banks (or any other company) can be measured with the difference between the value of its assets and the value of its liabilities (the distance to the default point). The smaller the difference is, the greater the probability of insolvency and vice versa. The *distance-to-default* (*dd*) as shown by the equation below measures how many standard deviations a bank is away from insolvency, i.e. the default point (Gapen et al., 2004, p. 34; Crosbie & Bohn, 2003, p. 18; Gropp et al., 2002, page 10):

$$dd = \frac{ln\frac{S_a^T}{O^t} + \left(\mu - \frac{\sigma_a^2}{2}\right)}{\sigma_a\sqrt{T}} \qquad (1)$$

where:

S_a = asset value,
O = amount of liabilities,
μ, σ_a = expected rate of return on assets and the volatility of returns,
T = time to maturity.

According to some authors (e.g. Chan-Lau et al., 2004, p. 5; Gropp et al., 2004, p. 55), the distance-to-default is a complete and unbiased indicator of bank fragility, i.e. changes in its risk profile. The foundation for such a conclusion is the finding that the indicator captures the most significant determinants of insolvency risk: expectations regarding earnings i.e. return on assets, financial leverage (indebtedness) and risk associated with the volatility of assets. The expectations regarding rising returns decrease insolvency risk and, therefore, increase the value of the indicator *dd*. The value of the indicator *dd* also increases, if financial leverage (bank indebtedness) decreases and if asset volatility declines. Inverse processes have an impact on lowering the value of the indicator and consequently lead a bank (company) closer to the point of insolvency (Gropp et al., 2002, p. 10).

For the calculation of the indicator *dd,* the data on the market value of a bank's assets and asset volatility are necessary. Since such data are not directly available, a direct calculation by using equation (1) is less appropriate for practical reasons. It is why most research studies have used the indirect approach to calculate implied asset value and their volatility by using the model developed by Black and Scholes (Black & Scholes, 1973). For the calculation it is necessary to have as input a series of market share prices and their volatility (standard deviation), market capitalisation, the size of debt and risk-free rate of return.[3]

By following the Black-Scholes model (B-S model), we are in a position to estimate the value of capital as the value of the call option of the company where the exercise price is equal to the nominal value of its debt, by applying the following formula (Hull, 2005, p. 295):[4]

$$K = S_a N(d_1) - Oe^{-rT} N(d_2) \qquad (2)$$

where:

N(d..) = cumulative density function of the standard normal distribution,

3 See for instance in Bukatarević, Jašovič, Košak and Šuler, 2008.

4 The derivation of the Black-Scholes-Merton model was carried out under the assumption that fluctuations in share prices follow the general Wiener process (stochastic share price movement process). (For more details see Hull (2005, p. 291– 295).

$$d_1 = \frac{ln\left(\frac{S_a}{O}\right) + \left(r + \frac{\sigma_a^2}{2}\right)T}{\sigma_a\sqrt{T}} \tag{3}$$

$$d_2 = d_1 - \sigma_a\sqrt{T} \tag{4}$$

r = risk-free rate.

A relationship between share price volatility and asset volatility is given with the following equality:

$$\sigma_k = \frac{S_a}{K}\sigma_a N(d_1) \tag{5}$$

where:

K = capital,
σ_k = volatility of share prices or returns.

Given that market prices for listed bank shares traded on regulated markets are continuously available, and given that standard deviation of returns can be computed on the basis of those prices, it is possible to solve with the iterative method the system of simultaneous equations (3) and (5) so that we obtain the implied assets value S_a and their standard deviation σ_a. We then use both variables for the calculation of the indicator *dd* following the equation (1).

3. METHODOLOGICAL ADJUSTMENT USING INDIRECT MARKET DATA TO CALCULATE THE DISTANCE-TO-DEFAULT INDICATOR

Since bank shares traded on a regulated securities market are "in short supply" and also due to poor liquidity of the equity market in Slovenia in general, we have undertaken the calculation of the distance-to-default indicator with the use of "indirect" market data. Market expectations in the corporate sector are best reflected by share prices of companies listed on a stock exchange. As a rule, these are shares issued by larger companies whose pricing mostly reflects market sentiment in a particular sector as a whole (as, for instance, Persson & Blavarg, 2003, p. 24). Market expectations of investors who invested in shares of such companies have implied effects on the bank portfolio risk dynamics. That impact is direct and given that bank balance sheets tend to be non-transparent (investors are not informed of all bank's investments), the described approach is more appropriate than the approach using market prices of bank shares used to calculate the implied value of assets and their volatility (by applying B-S model), which in such light actually is »indirect«. Moreover, we must not forget to emphasise that using indirect market data is more relevant for the sector-based distance-to-default indicator (for the entire banking sector) since it indicates changes in risk exposure at the sectoral level. For a single bank risk analysis it is more appropriate to calculate *dd* indicator in line with traditional methodology (based on market share prices of a concrete bank) where we also capture specific expectations of market participants, which relate to that particular bank only.

Willem van den End and Tabbae (2005, p. 9) have also pointed out that in the absence of market prices of financial instruments, other sources of market data can be used in order to apply the Black-Scholes model. It is the latter approach seen as a key guide to the adjustments on which this paper elaborates below.

We use the alternative, indirect approach to calculate the time series for the distance-to-default indicator. By tapping different sources of market data we introduced market variability in the model. We assume that a bank portfolio is composed of the following segments:

1. w_1 – cash and cash equivalents;
2. w_2 – loans to banking and non-banking sector (retail and corporate, other than items 4, 5 and 6) largely influenced by movement in variable EURIBOR;
3. w_3 – debt securities portfolio;
4. w_4 – loans to companies from the manufacturing sector;
5. w_5 – loans to companies from trading sector;
6. w_6 – loans to companies from 'other services' sector;
7. w_7 – equity securities, capital investments and derivatives;
8. w_8 – other (fixed assets, accounting categories).

In the equation (6), the shares of above portfolio segments are used as risk weights (w_{it}) for the calculation of σ_{at} of bank assets (investments) at the end of every month during the observed period beginning January 1996 and ending June 2009. We present for an illustrative purposes time series of risk weights per each segment at year ends and at the end of observed period.

Table 1: Time series of shares of bank portfolio segments (in %)[5]

Date	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8
31.12.1996	3,45%	1,96%	27,87%	35,81%	10,52%	5,07%	9,61%	5,70%
31.12.1997	3,72%	2,08%	34,26%	28,83%	9,34%	5,17%	10,89%	5,72%
31.12.1998	3,68%	3,30%	29,83%	30,27%	9,94%	6,23%	11,60%	5,14%
31.12.1999	3,38%	3,69%	25,56%	31,34%	10,15%	7,73%	13,22%	4,94%
31.12.2000	3,16%	3,61%	23,94%	32,33%	9,98%	8,03%	13,68%	5,27%
31.12.2001	5,32%	28,57%	27,09%	10,07%	7,87%	13,10%	3,34%	4,65%
31.12.2002	3,15%	26,67%	32,32%	9,85%	7,70%	12,05%	3,20%	5,07%
31.12.2003	2,80%	25,85%	32,59%	11,24%	7,88%	12,05%	3,05%	4,54%
31.12.2004	2,48%	29,83%	27,47%	12,04%	8,60%	12,53%	3,01%	4,02%
31.12.2005	2,05%	32,35%	26,15%	11,82%	8,69%	12,09%	3,66%	3,18%
31.12.2006	3,12%	36,57%	20,73%	11,53%	7,72%	13,51%	3,85%	2,97%
31.12.2007	1,43%	40,49%	15,50%	11,42%	8,13%	16,43%	4,19%	2,43%
31.12.2008	2,61%	41,95%	13,13%	11,75%	8,39%	16,77%	3,47%	1,93%
30.6.2009	2,35%	42,46%	13,83%	11,11%	7,84%	16,32%	3,88%	3,09%

Source: Bank of Slovenia

For each of the described eight segments, we have assigned a source of "indirect" market data, which has most significant impact on the value of movements in that segment (in the same order as description of the segments above):

1. w_{1-}movement in one-month LIBOR in EUR until the end of 1999, then the interbank interest rate EONIA for overnight deposits;
2. w_{2-}movement in in six-month LIBOR in EUR until the end of 1999, then the interbank interest rates EURIBOR for 6-month period;
3. w_{3-}movement in average return on bond indices composed of 5 European sovereign bond indices (GDBR5 Index, GECU10YR Index, GECU2YR Index, GECU30YR Index and GECU5YR Index), 4 U.S. sovereign bond indices (USGG10YR Index, USGG2YR Index, USGG30YR Index and USGG5YR Index) and BIO, Slovenian bond index;
4. w_{4-}movement in average return on shares of the companies Gorenje, Krka, Pivovarna Laško and Žito (representatives of manufacturing sector);
5. w_{5-}movement in average return on shares of the companies Mercator, Merkur and Petrol (representatives of trading sector);
6. w_{6-}movement in average return on shares of the companies Helios, Intereuropa, Luka Koper, Sava and Terme Čatež (representatives of "other services" sector);
7. w_{7-}movement in average return on equity indices composed of 9 European indices (AEX Index, ATX Index, BEL 20 Index, CAC Index, DAX Index, ISEQ Index, MIBTEL Index, UKX Index and SMI Index), 3 U.S. indices (CCMP Index, INDU Index and SPX Index) and SBI, Slovenian stock exchange index;
8. w_{8-}movement in consumer price index.

5 Data series are available in Bank of Slovenia statistical publications. The segments on an aggregate level were grouped together with the help of Financial Stability Department. Data series are available from author upon a request.

We have calculated from the above market sources on a daily frequency for the moving one-year window the returns, variances and standard deviations at the annual level for the entire observed period from the beginning of 1997 until June 2009. Variances of returns of all variables were included in the calculation of variance-covariance matrix from equation (6):

$$\sigma_{at} = \sqrt{\sum_{i=1}^{n} w_{it}^2 \, var_{it} + \sum_{i=1}^{n} \sum_{j=1}^{n} w_{it} w_{jt} cov_{ijt}} \qquad (6)$$

where:
$w_{..t,}$ = shares of individual segments *(i = j = 1–8)* in the banking system portfolio at the end of the month *t*,
var_{it} = variance of selected returns,,
cov_{it} = covariance of returns.

The above calculated time series volatility σ_{at} on a daily basis was translated to a monthly series as the daily data average at the annual level in an individual month and then used for the calculation of the distance-to-default indicator at the aggregate level with monthly frequency. We have used the book values for assets, equity and liabilities at an aggregate level for the banking sector at the end of each month in the calculation of *dd* indicator.

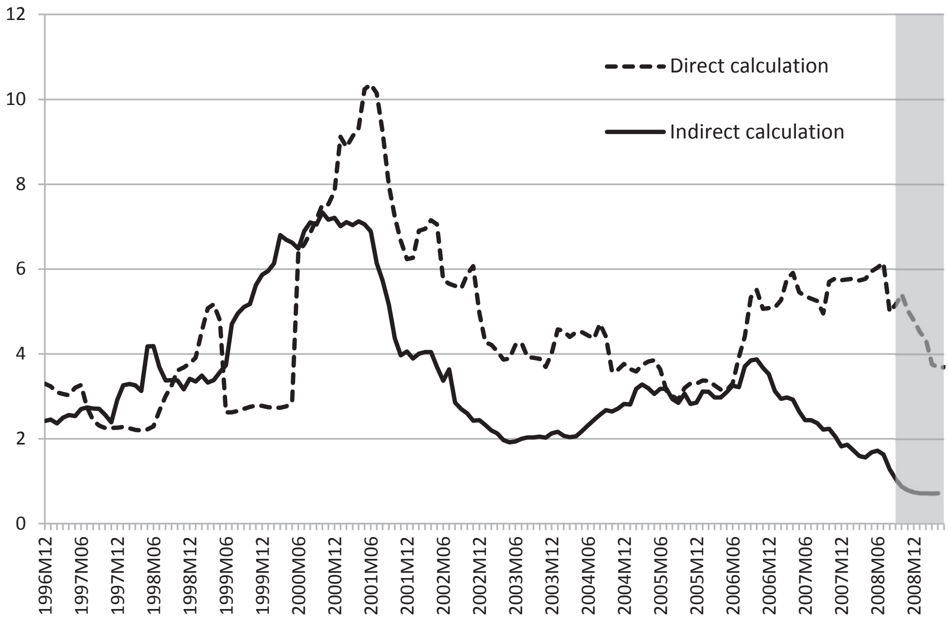
The essential point of using market data is that they reflect investors' expectations and uncertainty (volatility) in relation to the future price fluctuations. Asset volatility is the key parameter when calculating the indicator *dd* and without volatility (σ_a), the Black-Scholes model is useless, since in such a case we are dealing with a specific, deterministic situation typical of traditional, static analyses. In our modification to the methodology, we have ensured that by providing a large set of statistically processed market data, the volatility (uncertainty) has been introduced in the calculation, which impacts to a highest possible degree the fluctuation of the value of a selected bank's portfolio segments. Similar conclusions have been presented also in some of the aforementioned studies, which explicitly state that asset variability (volatility), determined on the basis of market data, is indeed the key component that contributes to the indicator's explanatory power (see, for instance, Gapen et al., 2004; Vassalou & Xing, 2004; Crosbie & Bohn, 2003).

Figure 1 shows a comparative movement of both calculated series of the distance-to-default indicator *dd*. Under the first approach–based on movement of bank share prices[6]–we have calculated implied asset value and asset volatility (by using the traditional B-S model) and then used the output in the calculation of the indicator *dd* for an individual bank; the aggregate indicator has been calculated based on risk-weighted average of individual indicators. In the second, adjusted approach, for the calculation of the indicator *dd* we

6 To calculate the time series of indicator dd, we have used the movement in the price of shares in Probanka, NKBM and Abanka Vipa. In the greater part of the period observed only the shares of Probanka were listed on a stock exchange. Due to this the sample is not representative and we present it only for an illustrative purpose.

have used the assets book value and calculated the asset volatility on the basis of a large set of the market data that have the highest impact on certain bank asset segments.

Figure 1: Movement in distance-to-default indicator computed directly from prices of bank shares and indirectly from market data based on adjusted methodology during the period 1997–June 2009 (number of standard deviations)



Legend: The shaded area shows the period in which the quarterly GDP growth was negative.
Source: Author's calculations.

The indicator calculated directly from the bank share prices moves consistently at the higher level than the indirectly computed indicator; hence, it reflects banks' lower risk profile. Based on the anecdotic evidence, we could argue that market optimism was reflected in high valuation of bank shares (we have to caution that for the greater part of the observed period, we dealt with one issuer only). The favourable market capitalisation of the banks was mirrored in a high implied asset value and, as a consequence, in the value of the *dd* indicator. Even in the first half of 2008 when the global financial crisis was already evident, the indicator was still moving at a relatively high level and it only started to decline in the second half of 2008. We may conclude that the series calculated on the basis of the bank share prices exhibits, contrary to expectations, a relatively delayed reaction to the crisis situation. One of plausible explanations for it is that bank shareholders, despite the turbulences on financial markets, valued the bank shares relatively high knowing that the Slovenian banks did not have toxic assets in their portfolios. Only later on, when the financial crisis spread to the real sector, the value of the indicator started to fall because of investors' negative perception.

The movement in the indirectly calculated indicator corresponds more to the expectations. If we focus on the pre-crisis period, the value of the indicator was increasing from mid-2004 onward all the time until the second half of 2006, and then the trend reversed and its value kept on decreasing. In mid-2009, the indicator value hit the rock-bottom. The indicator calculated in the indirect manner and by use of several different market data series reflects the perception of market instability in the eyes of different investor groups. The downward trend of the indicator's value started as early as in second half of 2006 when the sub-prime mortgage crisis started to unfold in the United States and with the full-blown crisis in 2007 and 2008 (the demise of the investment bank Lehman Brothers), that tendency only continued. Against that background, a movement in the indicator computed on the basis of "indirect" market information changes much more according to expectations and in line with anecdotal evidence on the evolution of the financial crisis. Market participants were recognising crisis impulses and valued their investments accordingly as reflected in the fluctuations of market categories we have used for the calculation of *dd* indicator.

4. EMPIRICAL TESTING OF ASSUMPTIONS OF THE ADEQUACY OF DISTANCE-TO-DEFAULT AS A PREDICTOR OF BANK RISK EXPOSURE

Our starting point is the basic assumption that market data (prices, indices, returns) are a valuable additional source of information for an analysis of financial stability. What is the grounding for making such an assumption? Market data have the following properties:

- they are a reflection of numerous market participants–less informed small investors, professional market analysts, institutional investors, credit rating agencies, investment advisors and others–and reflect their prevailing judgement;
- they are prospective, forward-looking, since they reflect prevailing expectations;
- they are continuously available without lengthy time lags, if not even in real time.

In comparison with official, accounting data and reports submitted by financial institutions to their supervisors, market-based data have several advantages. Official reports are published with a delay; they refer to the past and tend to disclose a limited scope of data. If we add the tendency sometimes displayed by reporting institution that makes the reporting entity look better than it actually is, then the usefulness of information obtained on the basis of market data is even more valuable. We are not arguing that official information should not be treated as reliable or that it might not be required. On the contrary, in the absence of official, accounting information, any serious analysis of the financial condition of an individual institution or the system made solely on the basis of market data would be all but credible. That said, we want to demonstrate that a traditional, static analysis based merely on official accounting data should be complemented by market information drawn from numerous market transactions (see for instance Curry et al., 2003; Krainer & Lopez, 2003; Krainer & Lopez, 2002; Gunther et al., 2001; Berger et al., 2000).

In our case, we have calculated the indicator *dd* from the market data sets by applying two methodologically different approaches. Now we want to determine whether the fluctuations in the indicator by taking into account properties of market data communicates some information, even before it is disclosed in official reports. More specifically, we would like to establish whether a change in the *dd* indicator indicates in advance (precedes) a probable movement in certain variables (parameters) - before they appear also in accounting data after some time has passed. To this end we have selected such variables (parameters) of bank performance that to certain extent also indicate the changes in degree of riskiness in the banking system:

- C_DOB_SKM - profit before tax in the 12-month moving window;
- C_PLL_SKM - costs for net impairments and provisions in the 12-month moving window;
- K_DVP_SKM - share of debt securities in total assets;
- K_KAP_SKM - share of equity in total assets;
- P_KU_SKM - capital adequacy ratio in percentage;
- P_NPL_SKM - percentage of claims classified as D and E (approximation for non-performing assets) in classified assets;
- P_OSLAB_SKM - percentage of impairments and provisions in gross assets;
- P_ROA_SKM - return on assets in the 12-month moving window in percentage;
- S_TA_SKM - total assets.

The selection of the variables from static accounting records proves the necessity to use both types of information, since in the absence of historical data, it would also be difficult to verify the reliability of market data, i.e. indicators, calculated on their basis. Moreover, static indicators reflect changes in institutions' risk profiles and the question we can ask is how long a lag is between the realisation of risk to its identification and disclosure in reports.

If we go back to the above variables, each of them reflects in its own right the changed performance influenced by changed risk. Pre-tax profit starts to decline with the narrowing net interest margin and/or banks have to book increased impairments for credit risk due to deteriorating portfolio quality and vice versa. Credit risk costs (net impairments) grow, if the quality of credit portfolio deteriorates and, by contrast, banks form impairments at a slower pace and even decide to release accumulated impairments, if portfolio quality starts to improve in favourable economic conditions. The need for additional impairments arises, however, during the period of economic contraction and bank de-leveraging that follows the period of unsustainable credit growth. The share of debt securities in total assets is a specific indicator that directly reflects a change in the level of secondary liquidity reserves in banks: a fall in that share is a signal for sound economic conditions and vice versa–its rise indicates stressed financial conditions in which risk aversion rises and the aspiration to maintain stable liquidity is high.

The leverage ratio (capital to total assets) and the capital adequacy ratio may seem rather similar at first glance, but they differ both in their approach to on- and off-balance sheet items inclusion in terms of risk and the approach to the calculation of capital. The concept of credit risk weights attributed to asset classes in accordance with Basel recommendations is often subject to a critical scrutiny for allegedly failing to reflect risk appropriately (see for instance Haldane, 2012). The conceptual differences in the calculation of both indicators, is precisely the reason for including both indicators in our analysis.

The share of assets classified as D and E categories can be used as an approximation for non-performing loans (bad assets). Otherwise, the number of days past due (more than 90 days) is commonly used as a criterion for non-performing loans but given the fact that it was not consistently used in the past, we have chosen as its substitute the share of banks' claims classified as D and E, which as a rule by their substance are non-performing, i.e. bad assets. It was our assumption that when the economic conditions deteriorate, the portion of non-performing exposures on banks' balance sheets surges. At this point we should add that banks are usually rather late and start to apply a conservative assessment approach to their claims and form loan loss impairments with a delay. This practice is also attributable to the provisions of International Financial Reporting Standards that did not allow forming *ex ante* impairments for expected losses, which means that unless there was objective evidence of a customer's financial difficulties meaning that such a customer would not be able to make the full repayment of the debt, no provisioning was allowed.

The return on assets is a combined ratio which may reflect deterioration in bank business/operations: reduced profitability that impacts the numerator, and unsustainable bank assets growth, that impacts the denominator of that parameter. It is expected that the value of that indicator will start to decline when the economic conditions get tighter: profits that are in the numerator start to plunge, while total assets in the denominator after high unsustainable growth do not decrease at the same dynamics, but only after a breakout of a crisis when a deleveraging process starts. The latter parameter, total assets, was included in the denominator of the previous indicator: however, we also examine it independently as it exhibits a different correlation with other variables than return on assets. We assume that during the period before economic conditions tighten, banks' total assets swelled driven by fast credit activities in a boom cycle. A surge in total assets growth is followed by a period of crisis and depressed economic conditions. As it is to be expected, total assets start to decline only in the post-crisis period with a contraction of credit activity, the diminished reliance on wholesale financing and when banks begin to adjust their business models to the changed situation (divestiture of non-core assets).

Table 2: Descriptive statistics for selected variables for the period February 1997–June 2009[7]

	C_DOB_SKM	C_PLL_SKM	K_DVP_SKM	K_KAP_SKM	P_KU_SKM	P_NPL_SKM	P_OSLAB_SKM	P_ROA_SKM	S_TA_SKM
	EUR 000	EUR 000	ratio	ratio	percentage	percentage	perentage	percentage	EUR millions
Median	185.173,0	137.614,0	0,2295	0,0858	11,66%	3,71%	3,35%	0,98%	19.283,0
Average	213.682,4	132.682,4	0,2147	0,0935	13,08%	3,39%	3,22%	0,95%	22.420,4
Minimum	59.375,0	29.881,0	0,1058	0,0763	10,46%	1,56%	2,26%	0,35%	7.183,0
Maksimum	538.368,0	420.663,0	0,3051	0,1200	20,07%	4,88%	3,78%	1,35%	49.682,3
Standard deviation	136.373,5	64.111,0	0,0654	0,0135	2,82%	0,95%	0,40%	0,20%	12.600,6
Number of observations	149	149	86	149	149	149	149	149	149

Source: Bank of Slovenia and author's calculations.

Table 3: Correlation coefficients between the selected variables for the period February 1997–June 2009

	C_DOB_SKM	C_PLL_SKM	K_DVP_SKM	K_KAP_SKM	P_KU_SKM	P_NPL_SKM	P_OSLAB_SKM	P_ROA_SKM	S_TA_SKM
C_DOB_SKM	1,000	0,262	-0,790	-0,682	-0,624	-0,879	-0,791	0,479	0,868
C_PLL_SKM		1,000	-0,228	-0,625	-0,607	-0,543	-0,250	-0,536	0,627
K_DVP_SKM			1,000	0,217	0,418	0,960	0,965	-0,131	-0,969
K_KAP_SKM				1,000	0,925	0,757	0,377	0,038	-0,771
P_KU_SKM					1,000	0,740	0,329	0,060	-0,697
P_NPL_SKM						1,000	0,846	-0,133	-0,955
P_OSLAB_SKM							1,000	-0,220	-0,830
P_ROA_SKM								1,000	0,039
S_TA_SKM									1,000

Source: Bank of Slovenia and author's calculations.

We have gathered monthly series for the period from February 1997 to June 2009 and Tables 2 and 3 show some descriptive statistics and correlation coefficients for all the described variables of the bank operations. We find the observed period to be relevant for our research since it is sufficiently long and encompasses at least two peaks (cycles) in the fluctuation of the indicator *dd*. Furthermore, it is adequate from the view point of the evolution of the latest financial and economic crisis: the first signs emerged with the sub-prime mortgage lending crisis in July 2007 in the United States to be followed by a full-blown distrust in the financial markets and the collapse of the interbank market in autumn 2008 when the investment bank Lehman Brothers failed (for more details of the unfolding of the financial crisis see De Larosiere et al., 2009, p. 11). Economic recession unfolded in the aftermath of those events and in 2009 all EU Member States with the exception of Poland had negative economic growth. In terms of the economic cycle, the second part of the period under review was the most dynamic one: a strong cyclical upswing coupled with unsustainable credit growth which ultimately tilted to a contraction period marked by credit crunch. The observed period ends in mid-2009 when Slovenia was already in the third quarter in a row of negative quarterly GDP growth (the shaded area in Figure 1). From that time on, the strained situation in the financial markets and its consequences began to manifest in standard financial ratios for bank performance (banks posted losses

7 Data series of selected variables are available from author upon a request.

from operations, there was pressure to increase impairments for credit risk, credit activity contracted, etc.). Testing distance-to-default indicator under such circumstances would hardly be productive. The question we should ask is whether the information extracted from a large market data set, preceded the described dynamics of the economic cycle, even before it appeared in banks' accounting data and business reports or standard bank performance ratios. Therefore, we continue by testing the hypothesis that the distance-to-default indicator, points to stressed conditions and increasing risk associated with a bank's operations even before it is reflected in the standard, static indicators of bank financial performance.

We have carried out our empirical test by applying the Granger causality test. The assumption underlying the test is that the future cannot predict the past, but it is the other way round. If changes in a particular variable predict changes in the other variable, then we are talking about Granger causality (Gujarati, 1995, p. 620; Asteriou & Hall, 2007, p. 281). Granger has developed a relatively simple test that defines causality by saying that the variable y_t Granger-causes x_t, if x_t can be predicted more accurately by using past values of the y_t variable rather than not using such past values, while all other terms remain unchanged. Therefore, we are not to interpret causality in statistics as we would have done in everyday use, since it relates to a cause and effect relationship. By using the Granger causality test, we are able to prove that changes in one variable predict changes in the other variable.

The direct Granger causality test can be carried out only with the stationary time series. It is a commonplace in the time series that describe economic phenomena to be non-stationary, since their mean value and/or variance change over time given the fact that they comprise trends or breakpoints. To that end, we have carried out the ADF test (ADF, Augmented Dickey-Fuller Test, see in Asteriou & Hall, 2007, p. 297) of stationarity for all-time series of bank performance indicators and both time series of the distance-to-default. The results of the ADF unit root test are presented in Table 4.

Table 4: Results of the Augmented Dickey-Fuller Unit Root Test

	t - test	**Probability**		**t - test**	**Probability**
Variable	***t***	***p***	**Variable**	***t***	***p***
Δ_1 C_DOB_SKM	-10,4136	0,00***	Δ_1 P_OSLAB_SKM	-15,2170	0,00***
Δ_1 C_PLL_SKM	-11,4574	0,00***	Δ_1 P_ROA_SKM	-11,3207	0,00***
Δ_1 K_DVP_SKM	-8,3084	0,00***	Δ_1 S_TA_SKM	-1,8189	0,37010
Δ_1 K_KAP_SKM	-15,1904	0,00***	Δ_2 S_TA_SKM	-9,2725	0,00***
Δ_1 P_KU_SKM	-11,0158	0,00***	Δ_1 DTOD_PON_1L	-9,5310	0,00***
Δ_1 P_NPL_SKM	-12,3422	0,00***	Δ_1 DTOD_VAR_COV_1I	-8,9714	0,00***

Legend:
- Δ_1 or Δ_2 designate the first or the second difference of the baseline time series;
- *** designates the rejection of null hypothesis at the 1% level of significance.

Source: Author's calculations.

By testing for stationarity, we have determined that all tested time series (both distance-to-default indicator time series and all bank performance variables time series) are non-stationary in levels of data (it was not possible to reject the null hypothesis). We have tested the first difference time series and rejected the null hypothesis at low level of significance and confirmed stationarity of the series of differences save for the variable total assets (S_TA_SKM) where we have been able to determine the stationarity only at the level of second differences.

The finding that all baseline time series in value levels are non-stationary has significant consequences when conducting the Granger casualty test. In such a case, it is not possible to use the Granger test directly, but the augmented Granger causality test should be performed (see for instance Toda & Yamamoto, 1995; Giles, 2011; Binh, 2010). Toda and Yamamoto have shown that the VAR model can be evaluated by applying a time series at the value levels and then tested for introduced restrictions in the model regardless of the different levels of integration or cointegration of time series (Toda & Yamamoto, 1995, p. 225). They have developed an alternative causality test where the VAR model has to be evaluated with the number of lags $n + d$, or $m + d$, where d presents the additional number of lags, which equals the highest level of integration of the used variables. When testing for linear restrictions, we do not take into account the coefficients of the additional d lags, since they are introduced in the model in order to ensure the validity of the standard asymptotic theory. Therefore, additional lags appear in the model specification as exogenous variable (Giles, 2011, p. 5). The expanded Granger causality test requires the assessment of the VAR model specified with the following equations:

$$y_t = a_1 + \sum_{i=1}^{n+\boldsymbol{d}} \beta_i x_{t-1} + \sum_{j=1}^{m+\boldsymbol{d}} \gamma_j y_{t-j} + \varepsilon_{yt} \tag{7}$$

$$x_t = a_2 + \sum_{i=1}^{n+\boldsymbol{d}} \theta_i x_{t-1} + \sum_{j=1}^{m+\boldsymbol{d}} \delta_j y_{t-j} + \varepsilon_{xt} \tag{8}$$

We have carried out the augmented Granger causality test between the distance-to-default indicator series and the selected banking performance ratios[8]. For each test we have chosen different monthly lagged variables, since the test is sensitive to the selected lag-length. It should be highlighted that the literature suggests using rather a higher number of lags than just a few, since thus the problem of autocorrelation is eliminated. We set in the test the null hypothesis that the coefficients of lag variable as a group are not different from zero. We test the assumption by applying the X^2 (*Chi Square*) test and if the calculated value exceeds the critical value for the selected level of significance, then we can reject the fundamental assumption (null hypothesis) and conclude that the changes in the lagged variable (in our case: distance-to-default) precede (Granger cause) changes in the dependent variable (selected banking performance ratio). An overview of the test results is presented in Table 5.

8 We have performed the Granger causality test also with a series *dd* calculated on the basis of bank share prices. Since the sample is not representative, we do not present the calculation.

Table 5: The results of the Granger test–values X^2 and corresponding probabilities (p) (dd, calculated by using adapted methodology, February 1997–June 2009, monthly series)

		Number of monthly lags				
Variable		**2**	**4**	**6**	**8**	**12**
C_DOB_SKM	X^2	1,5150	2,0021	2,9495	3,1576	7,4933
	p	0,4688	0,7354	0,8152	0,9241	0,8234
C_PLL_SKM	X^2	1,7982	3,2649	5,5101	5,6259	4,7317
	p	0,4069	0,5145	0,4802	0,6891	0,9663
K_DVP_SKM	X^2	1,3347	10,3139	10,9263	3,7109	10,6023
	p	0,5131	**0,0355****	**0,0907***	0,8822	0,5633
K_KAP_SKM	X^2	4,7983	6,6886	14,8312	15,6122	20,6755
	p	**0,0908***	0,1533	**0,0216****	**0,0483****	**0,0553***
P_KU_SKM	X^2	0,5162	4,1889	5,1531	7,5471	11,8765
	p	0,7725	0,3810	0,5243	0,4789	0,4556
P_NPL_SKM	X^2	1,3958	3,0893	3,2725	4,6516	8,4581
	p	0,4976	0,5430	0,7739	0,7941	0,7484
P_OSLAB_SKM	X^2	0,9807	2,3316	6,8204	7,7198	14,1308
	p	0,6124	0,6750	0,3378	0,4613	0,2924
P_ROA_SKM	X^2	6,1574	5,2266	6,8483	7,1213	11,5871
	p	**0,0460****	0,2648	0,3351	0,5236	0,4794
S_TA_SKM	X^2	1,5763	2,2342	4,9274	5,1222	8,3780
	p	0,4547	0,6928	0,5532	0,7444	0,7549

Legend:
*** designates the rejection of null hypothesis at the 1% level of significance;
** designates the rejection of null hypothesis at the 5% level of significance;
* designates the rejection of null hypothesis at the 10% level of significance.
Source: Author's calculations.

The results in Table 5 show the value of X^2 statistics and the corresponding probabilities, i.e. significance levels for the rejection of the null hypothesis on the non-existence of Granger causality. The results contradict the expectations that changes in the *dd* indicator precede changes in most indicators (ratios) of bank performance. The variables for which the null hypothesis may be rejected with a higher degree of probability (5% or 10% level of significance), are the share of debt securities and the share of capital in total assets. For these two variables we may assert that the indicator *dd* precedes their changes with the lead time of 4 months up to one year; the result for the share of debt securities in total assets should be interpreted with a caution given the fact that at a higher number of lags, it is not possible to prove the existence of Granger causality. A similar argument holds true also for the return on total assets ratio, where the null hypothesis is rejected only at the lowest number of lags.

Evidence for existence of Granger causality for the capital in total assets ratio (leverage ratio) does not come as a surprise. The market sentiment is also reflected in a number of market prices we have used for the calculation of the variability of bank assets. Some of the selected market parameters even have direct impact on movement in value of bank assets and, as a consequence, influence also the selected banking performance ratios. In this regard, we draw attention to the adjusted methodology we have used for the calculation of the indicator *dd*. The values of assets are entered in the calculation at their book value since the domestic equity market does not provide pricing information on bank shares for the calculation of the implied asset value. We have calculated the volatility that reflects market sentiment, i.e. prospective view of market participants on the developments in financial markets by using a large data set of market prices (indices) and use of variance-covariance matrix and thus included the synthesised market data in the calculation of *dd*. With a certain time lag and in a limited scope, market changes are also reflected on the book value of bank assets that influence the modified *dd* value. In this process, the equity is a residual claim, which at a high financial leverage typical for credit institutions, becomes highly sensitive to the fluctuations in asset value, which are the consequences of the changed market situation. Consequently, the existence of Granger causality between *dd* and the leverage ratio does not come as a surprise, even though it was not possible to prove Granger causal relation between *dd* and total assets. Nevertheless, what does come as a surprise is the existence of causality also at shorter time lag, where the null hypothesis is rejected at a relatively low level of significance (10%). With longer time lags (6–12 months), the results are more reliable (at a 5% level of significance).

Adrian and Shin (2010) warned of the changes in leverage where leverage is the inverse value of the share of capital in total assets. They claim that the net value of financial institutions (shareholders' equity value), given high leverage, is particularly sensitive to changes in market pricing, i.e. asset valuation. Based on empirical evidence, they report that movement in leverage is procyclical, since it swells during boom cycles and plunges during busts (Adrian & Shin, 2010, p. 1). In an analogy with the capital in total assets (leverage ratio), it would mean that leverage ratio falls during booms and then starts to increase again during downturns. In the case that financial institutions would refrain from additional borrowing on the market during booms, they would have excess capital which the authors call »surplus capacity« in an analogy with non-financial companies (ibid, p. 29). Financial institutions (banks) borrow additional funds (and reduce the capital in total assets or leverage) and, consequently, »deploy« surplus capital. Should there be no additional borrowing, the leverage would drop, i.e. the equity in total assets (leverage ratio) would rise. In the conditions of an economic upswing, there are expectations regarding rising asset values and a fear that capital would end up idle; hence when looking for additional placements, credit standards decline and losses start to pile up. However, these losses will not surface until recession hits. The authors have concluded that such behaviour played a role in the development of sub-prime mortgage market in the United States where the financial crisis erupted (ibid, p. 30).

However, there are also other elements that drive changes in bank financial leverage. Baumann and Nier (2003) have explored the impact of market discipline, risk-related elements and other impact on the share of capital in total assets (the leverage ratio we have used in our analysis). They found that the banks, which are subject to stronger market discipline, have on average higher shares of capital in total assets (Baumann & Nier, 2003, p. 137). That finding means that it is not possible to understand the mechanism of rising leverage in boom cycles in a mechanical sense, but we have to take into account other aspects as well. The authors represented market discipline in their model by means of different variables (government support, disclosure index, listing on a regulated securities market, deposit guarantee scheme, etc.).

The question that arises at this point is: why Granger causality between distance to default and capital adequacy ratio has not been demonstrated given the fact that in its substance it is similar to the leverage ratio. The key substantive reason is linked to the differences in the calculations of both indicators. The calculation of capital adequacy is based on risk-weighted assets where bank's assets are given a weighting that should reflect exposure to risk associated with a particular investment. The allocation of investments based on risk exposure can be, up to a point, also the result of judgement or national regulatory discretions. On the other hand, regulatory capital determined on the basis of special rules and regulations represents a broader concept than the book value of equity. With the new Basel standards, the regulatory framework for the calculation of risk-weighted assets and regulatory capital should have converged; nonetheless, there are still considerable differences in computations from one country to another and also among banks. In addition, the Basel standards give free hands to banks to choose different methodological approaches to the calculation of capital adequacy (standardised or advanced approach); hence there are differences in designating risk-weighted assets among banks that operate in the same country. These differences and, on top of that, the doubts as whether the given risk weights correctly reflect risk faced by banks, are the reason for making the concept for the capital adequacy calculation a popular target for criticism. And there are more reasons for concern: ever-increasingly complex rules for the calculation of risk-weighted assets and regulatory capital that are often changed. So it should not come as a surprise that criticism also comes from the ranks of regulators proposing more straightforward and clear regulation. They even produced empirical evidence that "...a straightforward metric of solvency, such as a leverage ratio, might do better at predicting failure than one, like a risk-weighted capital ratio, that banks could more easily game" (Haldane, 2012, p. 11).

5. CONCLUDING REMARKS

Based on the presented empirical testing by using the augmented Granger causality test, we may conclude the following:

- The adapted methodology for the calculation of the distance-to-default indicator *dd* is a proper tool to identify changes in exposure to risk of the entire banking system, since it uses as an input a large set of market data , which impact equally all banks; hence we talk about *dd* as a possible indicator of financial stability.
- The changes in the distance-to-default indicator whose value also depends on market sentiment and synthesised market data should, in accordance with our expectations,

precede changes in those variables of the banking performance, which are most sensitive to the changed market conditions.

- In the case of our study, we can only confirm the existence of Granger causality from *dd* to the capital in total assets or leverage ratio.
- Furthermore, as reported in some other empirical studies, the capital in total assets ratio is a significant objective of market discipline and it better mirrors risk of bank insolvency than, for instance, capital adequacy ratio (see Haldane, 2012; Adrian & Shin, 2010 or Nier & Baumann, 2003).
- The existence of Granger causality was also confirmed for the debt securities in total assets ratio; nevertheless, caution is advised for the interpretation of the result due to specific conditions related to the functioning of foreign exchange market in Slovenia before euro adoption.
- In the case where bank performance variables are calculated on the basis of specific regulations and methodologies or are the result of management discretion, the existence of Granger causality between the indicator *dd* and the selected variable was not proved.
- The ultimate objective of further research would be to determine more precise (functional) links between *dd* and performance variables where Granger causality was identified, or compare the values of *dd* with particular critical values of performance variables given the fact that they are used to identify risk to financial stability.

Empirical research done so far still falls short of coming up with a methodologically finished analytical tool for a financial stability analysis, but merely corroborates the need for further research effort with the aim to work out an indicator that could be deployed for the identification of risk when the financial stability of the banking system is analysed. The described methodology adjustment would be more appropriate for a sectoral, systematic analysis of financial stability in the circumstances when no longer-term series of market prices of bank shares are available. The official supervision of financial institutions shall be complemented by market discipline or surveillance (see Flannery, 1998; Tarullo, 2008). Market surveillance means that informative content of market messages (prices) will influence decision-making processes in banks and companies and, at the same time, these messages must be grasped also by bank supervisors in the analyses of banks' risk exposures.

REFERENCES

Adrian, T., & Shin, H. S. (2008). Liquidity and Leverage. *Staff Report no. 328.* New York: Federal Reserve Bank of New York.

Asteriou, D. & Hall, G. S. (2007). *Applied Econometrics. A Modern Approach using EViews and Microfit*. Revised Edition. New York: Palgrave Macmillan.

Baumann, U. & Nier, E. (2003). Market discipline and financial stability: some empirical evidence. *Financial Stability Review*, June 2003, 134–141. London: Bank of England.

Berger, A., Davies, S. & Flannery, M. (2000). Comparing Market and Supervisory Assessments of Bank Performance: Who Knows What When? *Journal of Money, Credit, and Banking*, *vol. 32* (3), 641–667.

Binh, P. T. (2010). Toda–Yamamoto Version of Granger Causality. (Augmented Granger Causality).*Time Series Analysis*. http://www.slideshare.net/QuangHoang1/7-toda-yamamotogranger-causality (accessed October 20, 2013).

Black, F. & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, *81*(3), 637–654.

Bukatarević, V., Jašovič, B., Košak, T. & Šuler, T. (2008). The Use of Market Information in the Analysis of the Financial Stability of Banks. *Financial Stabilty Review–Expert Papers on Financial Stability, May 2008,* 1–12. https://www.bsi.si/iskalniki/reports.asp?MapaId=1698 (accessed April 17, 2010).

Chan-Lau, J. & Sy, A. (2006) Distance-to-Default in Banking: A Bridge Too Far? *IMF Working Paper*, WP/06/215. Washington, D.C.: Intenational Monetary Fund.

Chan-Lau, J., Jobert, A. & Kong, J. (2004). An Option-Based Approach to Bank Vulnerabilities in Emerging Markets. *IMF Working Paper*, WP/04/33. Washington, D.C.: Intenational Monetary Fund.

Crosbie, P. & Bohn, J. (2003). Modeling Deafult Risk. *White Papers*, 18. december 2003. Moody's KMV Research. http://www.moodysanalytics.com/~/media/Insight/Quantitative-Research/Default-and-Recovery/03-18-12-Modeling-Default-Risk.ashx (accessed October 8, 2008).

Curry, T., Elmer, P. & Fissel, G. (2003). Using Market Information to Help Identify Distressed Institutions. A Regulatory Perspective. *FDIC Banking Review*, *Vol. 15*(3), Washington, D.C.: Federal Deposit Insurance Corporation.

De Larosiere, J., Balcerowicz, L., Issing, O., Masera, R., Mc Carthy, C., Nyberg, L., Perez, J. & Ruding, O. (2009). *Report of the High Level Group on Financial Supervision in the EU*. Brussels: European Commission.

European Central Bank. (2005). *Financial Stability Review*, June 2005. Frankfurt: European Central Bank.

Flannery, M. (2001). The Faces of »Market Discipline«. *Journal of Financial Services Research*, *20*(2/3), 107–119.

Flannery, M. (1998). Using Market Information in Prudential Bank Supervision: A Review of the U.S. Empirical Evidence. *Journal of Money, Credit and Banking, 30*(3), 273–305.

Gapen, T. M., Dale, F. G., Lim, C. H., & Xiao, Y. (2004). The Contingent Claims Approach to Corporate Vulnerability Analysis: Estimating Default Risk and Economy-Wide Risk Transfer. *IMF Working Paper*, WP/04/121. Washington, D.C.: Intenational Monetary Fund.

Giles, D. (2011). Testing for Granger Causality. *Econometrics Beat: Dave Gile's Blog*. http://davegiles.blogspot.ca/2011/04/testing-for-granger-causality.html (accessed November 14, 2013).

Gray, D. & Walsh, P. J. (2008). Factor Model for Stress-testing with a Contingent Claims Model of the Chilean Banking System. *IMF Working Paper*, WP/08/89. Washington, D.C.: Intenational Monetary Fund.

Gropp, R., Vesala, J. & Vulpes, G. (2004). Market Indicators, Bank Fragility, and Indirect Market Discipline. *FRBNY Economic Policy Review*, September 2004, 53–62. New York: Federal Reserve Bank of New York.

Gropp, R., Vesala, J. & Vulpes, G. (2002). Equity and Bond Market Signals as Leading Indicators of Bank Fragility. *Working Paper Series* No. 150. Frankfurt: European Central Bank.

Gujarati, N. D. (1995). *Basic Econometrics*. Third Edition. New York: McGraw Hill.

Gunther, J., Levonian, M. & Moore, R. (2001). Can the Stock Market Tell Bank Supervisors Anything They Don't Already Know? *Economic and Financial Review,* Second Quarter 2001, 2- 9. Dallas: Federal Reserve Bank of Dallas.

Haldane, A. G. (2012). The dog and the frisbee. In *Jacksone Hole Economic Policy Symposium. The Changing Policy Landscape* (pp. 109–159). Kansas City: Federal Reserve Bank of Kansas City.

Hull, J. (2005). *Options, Futures, and Other Derivatives*. Sixth Edition. New Jersey: Prentice Hall.

Krainer, J. & Lopez, J. (2003a). How Might Financial Market Information Be Used for Supervisory Purposes? *FRBSF Economic Review*, 29–45. San Francisco: Federal Reserve Bank of San Francisco.

Krainer, J. & Lopez, J. (2002). Incorporating Equity Market Information into Supervisory Monitoring Models. *Federal Reserve Bank of San Francisco*. http://www.frbsf.org/publications/economics/papers/2001/wp01-14bk.pdf (accessed June 10, 2008).

Merton, C. R. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance, 29*(4), 449–470.

Persson, M. & Blavarg, M. (2003). The use of market indicators in financial stability analysis. *Economic review,* 2/2003. Stockholm: Sveriges Riksbank.

Tarullo, D. (2008). *Banking on Basel. The Future of International Financial Regulation.* Washington D. C.: Peterson Institute for International Economics.

Todda, Y. H., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics, 66*(1/2), 225–250.

Vassalou, M. & Xing, Y. (2004). Default Risk and Equity Returns. *The Journal of Finance, 59*(2), 831–868.

Willem van den End, J. & Tabbae, M. (2005). Measuring financial stability: applying the MfRisk model to the Netherlands. *DNB Working Paper*, No. 30/March 2005. Amsterdam: Dutch National Bank.