Monitoring of Credit Risk through the Cycle: Risk Indicators

Yashkir, Olga and Yashkir, Yuriy

Yashkir Consulting

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Olga Yashkir [*], Yuri Yashkir [†]
Yashkir Consulting Ltd.

Abstract

The new Credit Risk Indicator (CRI) based on credit rating migration matrices is introduced. We demonstrate strong correlation between CRI and a number of defaults (ND) through several business cycles. The new model for the simulation of the annual number of defaults, based on the 1st quarter CRI data, is proposed.

Monitoring of the business cycle dynamics is usually based on a set of microeconomic indicators, such as GDP, consumer confidence index, inflation rate, etc. (see, for example, (ECDG, 2012), (Carstensen et al., 2010), (Ziegler, 2009), (Altman et al., 2003), and (Ormerod, 2004)); indicators are updated quarterly in (ECDG, 2012); the procyclicity effect was analyzed in (Altman et al., 2003). Authors of (Okashima and Frison, 2000) investigated forecast of default rates by Moody's downgrade/upgrade ratio for high-yield corporate bonds. Each of indicators reflects a certain aspect of the business cycle, but a full picture requires taking into account several indicators simultaneously. One of ways of the integral approach to the business cycle is to consider the dynamics of defaults which reflects directly the worsening of the business cycle conditions. This approach, unfortunately, describes only past events, and can be used mostly for analysis of the historical data. In this paper we would like to bring attention to the dynamics of credit

[*] olga.yashkir@gmail.com
[†] yuri.yashkir@gmail.com

rating transition matrices. Transition matrices reflect movements of credit ratings and, potentially, give insights into possible future defaults.

Credit transition matrices reflect credit rating migrations, including defaults, during certain periods (for example, annual and quarterly matrices are provided by rating agencies). The matrix structure is very sensitive to the business cycle dynamics, therefore, the temporal behaviour of the transition matrix has predictive power with respect to recession periods in business cycles. Recession periods are typically characterized by an elevated number of defaults, therefore, the increase of rating downgrades and decrease of ratings upgrades could indicate a potential increase of the number of defaults.

It is important to note that the number of defaults and the amount of financial losses (total debt outstanding) have the same dynamics pattern (Figure 1). Therefore, we use the number of defaults as a measure of positioning in the business cycle.

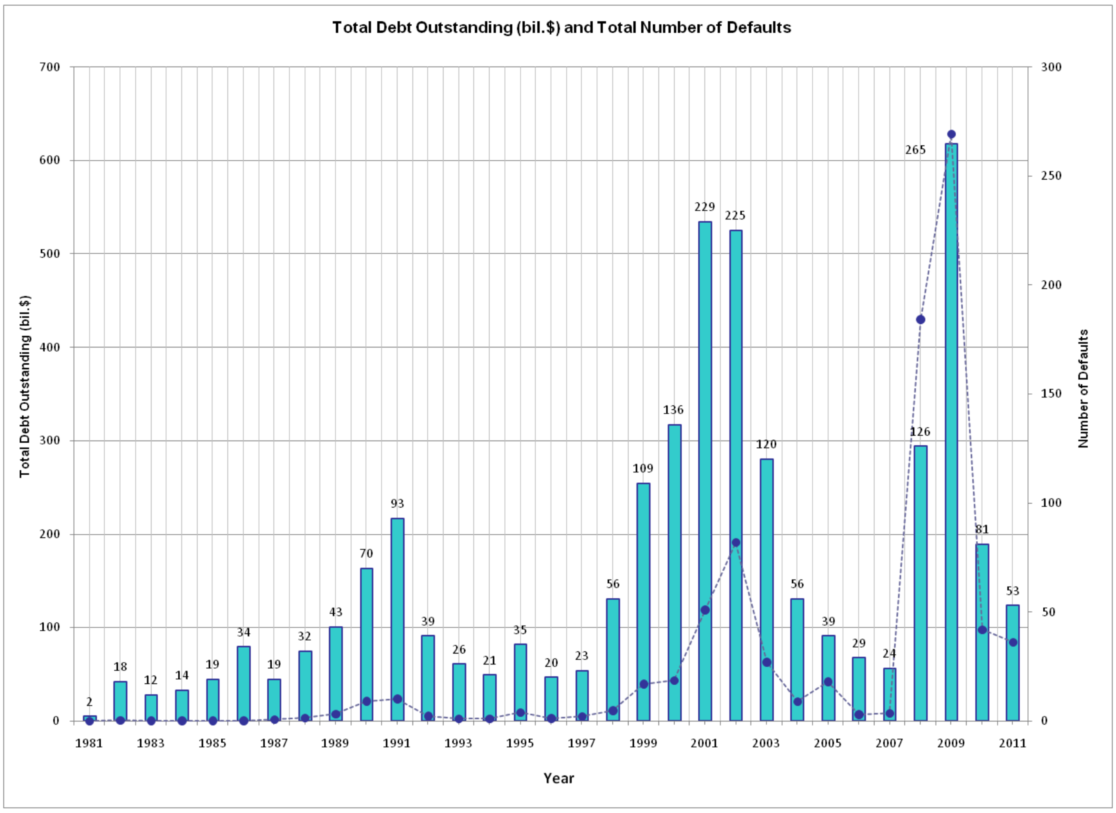

Figure 1: Total number of defaults (dots) and total debt outstanding (columns) from 1981 to 2011 (S&P, 2012)

Two transition matrices for 2009 (recession, peak, period) and for 2006 (quiet period) are presented in the Table 1 (both matrices are based on the S&P data).

Table 1: Transition matrices for 2009 and 2006

2009 Annual transition matrix								
	AAA	AA	A	BBB	BB	B	CCC/C	D
AAA	0.91	**0.090**	0	0	0	0	0	0
AA	0	0.82	**0.170**	0.007	0.002	0	0	0
A	0	0.004	0.90	**0.083**	0.005	0.003	0	0.002
BBB	0	0	0.020	0.90	**0.060**	0.009	0.002	0.006
BB	0	0	0	0.030	0.82	**0.130**	0.007	0.008
B	0	0	0.002	0	0.030	0.77	**0.090**	0.112
CCC/C	0	0	0	0	0	0.080	0.33	0.590
2006 Annual transition matrix								
	AAA	AA	A	BBB	BB	B	CCC/C	D
AAA	0.98	0.020	0	0	0	0	0	0
AA	0.010	0.98	**0.020**	0	0	0	0	0
A	0	**0.040**	0.92	0.040	0.003	0	0	0
BBB	0	0.002	**0.050**	0.92	0.030	0.004	0	0
BB	0	0.001	0	0.050	0.89	**0.060**	0.001	0.003
B	0	0	0.001	0.001	**0.100**	0.86	0.030	0.009
CCC/C	0	0	0	0	0	**0.180**	0.67	0.154

The default probabilities (D, last column) for the peak period are significantly higher than the default probabilities for quiet periods starting from the investment grade A-rating. It is important to note that pre-diagonal elements (probabilities of one-notch migrations) are also sensitive to the business cycle period. In the matrix for recession period (2009) the pre-diagonal downgrade probabilities (shaded cells) are significantly higher than corresponding one-notch upgrade probabilities for all ratings starting from AA to CCC/C. The opposite picture is seen for the quiet periods where some of upgrade probabilities are higher than the downgrade probabilities (for example: CCC/C $\rightarrow$ B, B $\rightarrow$ BBB, and BBB $\rightarrow$ A). Also, for the quiet period, there were defaults only for BB to CCC/C with probability of default for CCC/C being smaller (0.154) than the probability to be upgraded to B (0.18).

As a quantitative measure of the business cycle conditions, we introduce the Credit Risk Indicator (CRI) as a ratio between sums of lower and upper pre-diagonal credit rating matrix elements $m_{k,k+1}$ and $m_{k,k-1}$ as follows:

$$CRI = \frac{\sum_{k=2}^{n-1} m_{k,k+1}}{\sum_{k=2}^{n-1} m_{k,k-1}} \tag{1}$$

where k is a credit rating ($k = 1$ is the highest credit rating AAA, and $k = n$ is the lowest non-default rating CCC/C), $m_{k,p}$ is the credit rating transition matrix element. The sum in (1) does not contain ratings AAA (no upgrade possible) and CCC/C (downgrade is to the default state).

The definition of CRI is based on the assumption that the one-notch rating migration $m_{k,k\pm1}$ would be most sensitive to business cycle conditions: deteriorated market conditions would increase downgrade probabilities $m_{k,k+1}$ and decrease upgrade probabilities $m_{k,k-1}$.

Our further investigation of CRI is focused on quarterly transition matrices from Q1 2000 to Q4 2011 (S&P CreditPro data). The following chart (Figure 2) shows quarterly calculated CRI values (open circles) plotted together with the annual number of defaults (filled squares). The CRI values and the number of defaults (ND) are visibly highly correlated. The actual correlation value is equal to 85% for quarterly CRIs. Similar effect was found in (Okashima and Frison, 2000) (the correlation between default rate and downgrade/upgrade ratio lagged by 3 quarters was 0.81).

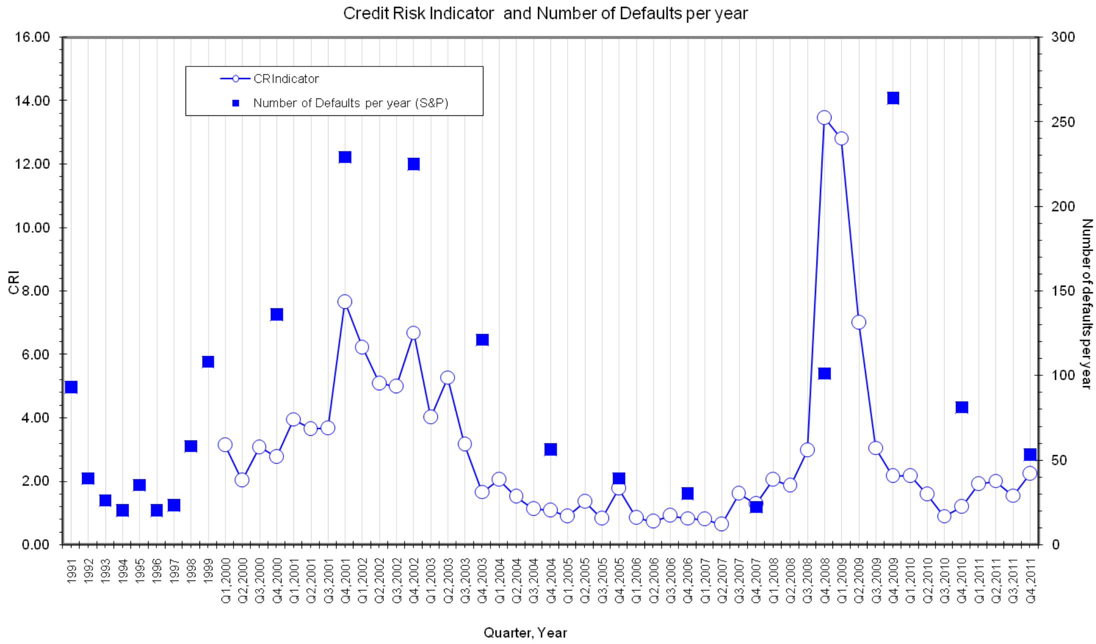

Figure 2: Credit Risk Indicator and Number of Defaults per year

There are two distinct areas of CRI behavior: stable periods (CRI values do not deviate far from 1) and unstable periods (CRI systematically increases or decreases). For example, during a stable period (Q3 2004 to Q1 2008) the CRI values based on one notch migration probabilities $m_{k,k\pm1}$ do not differ too much, therefore values of CRI fluctuate around 1 (0.64 to 1.61). During this period the annual number of defaults is either declining or is at its low. Peak periods of the business cycle (2001 - 2002, and 2008 - 2009) are very well emphasized by Credit Risk Indicator curve.

The quarterly transition matrices were available from year 2000, therefore, the 1991 - 1992 peak is not included. The following reasonable assumptions can be made: the CRI values calculated using the 1-st quarter transition matrix data may have a predictive power with respect to the total number of defaults at the end of the year.

The plot of annual number of defaults versus the CRI values for 1st quarter matrices shown in the graph (Figure 3) demonstrates that this is the case (time period 2000 - 2006 includes both peak and quiet periods).

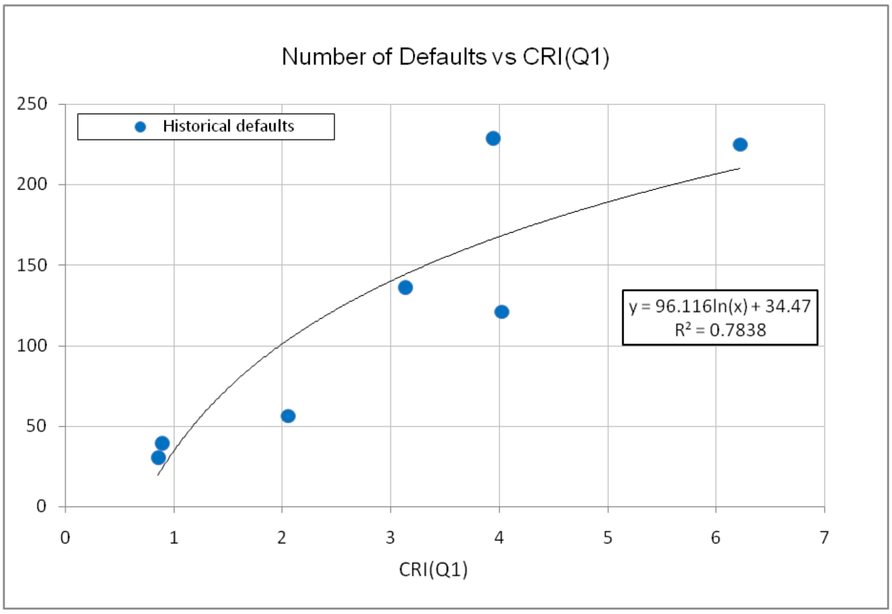

Figure 3: Total annual number of defaults versus Q1 Credit Risk Indicator for 2000 - 2006 period

The best fit of the total annual Number of Defaults (ND) vs. Q1 CRI dependency can be represented by a logarithmic curve

$$F(C_{Q1}) = \alpha \cdot \ln(C_{Q1}) + \beta, \tag{2}$$

where $\alpha = 96.12$, $\beta = 34.47$, and C_{Q1} is the CRI based on the first quarter data of the year for which a number of defaults is calculated. Therefore, we can introduce the following simple stochastic model for a total number of defaults for i^{th} year:

$$ND^{(i)} = F(C_{Q1}^{(i)}) + F(C_{Q1}^{(i)}) \cdot \sigma \cdot \varepsilon^{(i)}, \tag{3}$$

where σ is a standard deviation of relative differences between the historical and modelled number of defaults (σ =0.45) and ε is a standard Gaussian random driver. The value of R^2 equal to 0.7838 shows a very good fit of the model to the historical data (in (Okashima and Frison, 2000) the best linear regression fit with 3 quarters lag produced R^2=0.65). This model provides the expected number of defaults with a required confidence level. The model (3) was applied to the time period from 2000 to 2011. This time period includes "in-sample" period 2000 - 2006, based on which model was calibrated, and "out-of-sample" period 2007 - 2011 which illustrates the validity of the model. In Figure 4 the predicted number of defaults for the 15% to 85% confidence level corridor is plotted (curves). The historical numbers of defaults (filled circles) and expected (model) numbers of defaults (squares) per year are also plotted.

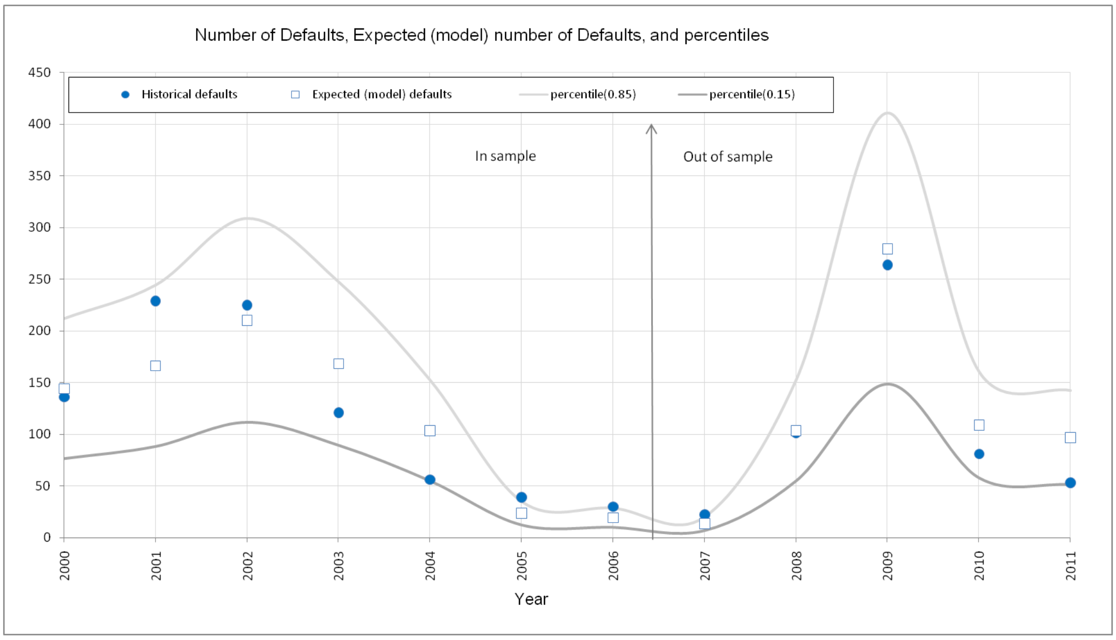

Figure 4: Comparison of the expected number of defaults (model) with the historical number of defaults; curves represent the 15th and 85th percentile of the modelled number of defaults

The historically observed numbers of defaults registered at the end of the year fit very well within chosen confidence level interval of the model, which uses CRI calculated at the end of the first quarter of the year. We can conclude, therefore, that Credit Risk Indicator has evident predictive power.

Summary

- We propose new Credit Risk Indicator (CRI) as the ratio of the average one-notch downgrade probability to the average one-notch upgrade probability in the migration matrix as a dynamic indicator of the business cycle state.

- The CRI values are highly correlated (85%) with the annual number of defaults in the global portfolio.
- Increase (decrease) of the CRI value calculated using the 1st quarter data provides estimation of increase (decrease) of the annual number of defaults. Increase of the estimated number of defaults indicates a possible deterioration of credit conditions of the business cycle, and vice versa.
- The monitoring of the CRI changes can be used for the qualitative estimation of the business cycle direction.

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