THE FEASIBILITY OF THROUGH-THE-CYCLE RATINGS

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It has been proposed that the potential procyclicality of Basel II could be alleviated by using through-the-cycle (TTC) ratings in IRBA models. A TTC rating would be based on the structural component of credit risk of a debtor; cyclical fluctuations would be ignored. This paper tests the existence of such fluctuations in corporate sector credit risk. Almost no evidence on their existence is found at the company level. It is not possible to assign debtors satisfactory TTC ratings if there are no cyclical variations to be filtered out.

KEYWORDS
Through-the-cycle rating
Credit risk
Procyclicality

JEL G21, G33, L16

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1 INTRODUCTION

In recent years the Basel II capital adequacy framework has been introduced in many parts of the world. A central feature of the new system is the use of internal ratings; many banks are allowed to determine the credit risk of each debtor by using their own internal ratings based approach (IRBA) models. It has been suggested that the system might amplify business cycles. During any recession credit risk tends to worsen, leading to higher capital requirements per exposure, which may diminish the supply of loans and possibly lead to a credit crunch, which would worsen the recession. This literature has been reviewed by Gordy and Howells (2006) and Drumond (2009).

A number of potential solutions to the procyclicality problem have been presented, ranging from countercyclical capital buffers to dynamic loan loss provisioning. Unfortunately there seems to be very little in-depth analysis on the feasibility and usefulness of the various proposed remedies. If the problem and its potential solutions are to be taken seriously, detailed analysis on these approaches is needed.

This paper intends to contribute to assessing one of the proposed solutions, namely Through-The-Cycle (TTC) rating methods and their feasibility. This paper tests the existence of the cyclical component of credit risk. There seems to be no consensus on the precise definition of TTC ratings, but Löffler (2004) has phrased and explicitly used a good conceptual framework. Using its analogue, changes in credit risk are hypothesised to consist of permanent structural changes and transitory cycles.   TTC ratings are based on the structural component and ignore the cyclical component. If the mean-reverting cyclical component exists, and if it can be measured with acceptable accuracy almost on real time, TTC ratings can be calculated by eliminating the cyclical component from the perceived point-in-time credit risk.

Rating agencies' assessments are public, and they have been used in numerous contributions. These agencies often claim they present TTC ratings. Empirical evidence indicates that these ratings are slow to react to new information. (Altman and Rijken 2005, Löffler 2004) Otherwise, there seem to be relatively little literature on the time series properties of credit risk indicators at the debtor level, and there seems to be little or no evidence on the existence of transitory cycles in credit risk.

This paper uses a Merton (1974) type credit risk measure. The data have been provided by Moody's KMV. [2] The data are interpreted as point in time (PIT) estimates of corporate credit risk. It is analysed whether these estimates are subject to temporary cyclical variations that could be filtered out in order to get TTC estimates of credit risk. The results indicate that companies typically have got no persistent structural levels of credit risk. In some cases the behaviour of corporate credit risk during one phase of the cycle predicts its change during a following phase, but cross-company differences in cyclicality seem highly unstable over time; companies that suffered most from the previous recession may or may not improve their creditworthiness more than others during the following benign period. Cyclicalities may even be systematically reversed. Credit risk in small-cap firms has an observable tendency to revert to its past level, but no evidence on such regularity is found among large and medium size companies. Even among small-cap companies the tendency to reversion is not due to the hypothesised propensity of some companies to react particularly strongly to every upturn and downturn. Thus, TTC rating philosophies based on the idea of eliminating transitory cycles from the rating may not be fully feasible.

The long-term properties of aggregate credit risk cannot be directly derived from the credit risk of individual debtors. If the average credit risk in the economy were a unit root process, it could gradually migrate to any absurd extreme. However, simulations demonstrate that the average credit risk in the corporate sector may be stationary even though the credit risk of each individual company is a unit root process. This is possible because the population of companies is subject to continuous entry and exit. Exits through bankruptcy eliminate financially weak companies and prevents the average distance to default (DD) from declining indefinitely. Simultaneously, the entry of new companies prevents the average DD from increasing with no limits because entrants normally have a rather weak creditworthiness. If average credit risk is stationary, any deviation from the long term average is temporary, and can be regarded a "cycle".

The second section describes the data. Econometric results, including unit root tests and various regression analyses, are presented in section three. The fourth section presents simulation results. The fifth section concludes and discusses some of the findings.

[2] These data have been relatively seldom used for research purposes, but a suitable data set on Finnish publicly listed companies was readily available for this project, and the data provider granted the authorisation to use it for research purposes.

2 DATA

The raw data for the following analyses was provided by Moody's KMV. These data are based on option pricing theory and the Merton (1974) model for corporate credit risk. The inputs consist of market capitalization of corporate equity, its historical volatility and corporate debt on the balance sheet. With these inputs it is possible to calculate the so-called distance-to-default (DD), which is simply the number of standard deviations between the value of assets and a critical threshold value related to corporate debt. In KMV data, the probability a company would end up in 12 months in a situation where its assets would fall below this threshold value is calculated by using an empirically fitted distribution. (Crosbie and Bohn 2003) The DD is a point-in-time (PIT) measure of credit risk; no changes in DD are ignored as transitory and cyclical. In principle, the DD can be even negative in a working company; if assets appreciate in value, the company does not fail when the debt matures.

The predictive power of the method has been analysed in academic literature. Bharath and Shumway (2008) calculated their own data by using this methodology. To the extent it was possible to compare with available KMV data, differences were within reasonable limits. The authors concluded that the Merton model alone is not a perfect measure of credit risk, but its predictive power was clear. Rather similar results have been reported by Reisz and Perlich (2007); even though other models sometimes outperform the KMV method (or a close substitute for it, to be precise) in bankruptcy prediction, KMV type data have got strong predictive power. Li and Miu (2010) concluded that the Merton model is particularly good at predicting bankruptcies among financially weak companies. These previous analyses are now taken as sufficient evidence on the relevance of the data.

The following analyses are carried out with monthly data on annual default probabilities of non-financial companies quoted on the Helsinki Stock Exchange. With the exception of banks and insurance companies, all the 119 firms with at least five years of data between August 1999 and December 2009 were included. Companies with shorter histories would hardly be of any use in the following analyses. Each observation corresponds to the last business day of the month. It might be interesting to extend the analysis to other countries or longer periods of time, but such data were not readily available to the author.

Unfortunately, the sample is still relatively short for analysis on cyclical phenomena, but fortunately it describes a highly cyclical economy. During the sample period the annual growth rate of the real GDP in Finland ranged from -7.7 percent in 2009 to +5.3 in 2000; few advanced countries have experienced macroeconomic fluctuations of this magnitude. No other country in the euro area experienced a similar collapse of economic activity during the deep recession of 2009.

Since 2006 companies listed on the Helsinki Stock Exchange have been divided into large, mid-cap and small-cap companies. Because stock prices are the most important short-term driver of estimated default probabilities in the data, and because pricing inefficiencies can be particularly severe in the case of small-cap stocks (See Avramov 2002 or Hung et al 2009), some of the analyses are carried out either without small-cap companies or specifically for small-cap companies only. In the following, each company was classified according to its size category in early 2010. Companies that were not quoted in 2010 were classified by their 2002 market capitalization. If the market cap was less than EUR 150 million, the company was classified as small; this threshold is the same as the one introduced by the Helsinki Stock Exchange in 2006. There are 60 companies in the small-cap category of the sample.

In the following analyses, a transformation is made for each observation. The DD that would under the normal distribution assumption imply the actual default probability reported by KMV is calculated.

$$EDF_{it} = \Phi(-D_{it}) \Rightarrow D_{it} = \sqrt{2}\,\Psi(2\ EDF_{it}) \qquad \{1\}$$

Where Φ is the cumulative standard normal distribution, Ψ is the inverse complementary error function of the standard normal distribution and EDF_{it} is the expected default frequency of company i month t reported by Moody's KMV. The resulting D_{it} may not equal the underlying DD, but this proxy suits the purposes of this paper.

There seems to be almost no seasonal variation in DDs . When the first difference of Ds in the monthly panel data is explained with panel OLS with no other explanatory factors than month specific dummy variables, the overall fit of the regression is almost zero (R^2 =0.01).

The most important short-term driver of credit risk in this model is the change in stock quotations. There is an ongoing debate on whether equity prices follow a pure unit root process, and whether temporary fluctuations can be identified in stock market data. (See e.g. Narayan and Narayan 2007; Bali et al. 2008; Choe et al. 2007). Whatever the best answer to the question on the time series properties of stock quotations is, the result cannot be directly applied to credit risk implied by the KMV model because stock prices are not the sole driver of DDs. The Merton model is based on the assumption that firm assets follow a random walk until the predefined future date. Asset values are assumed to contain no transitory cycles, and no other factor is assumed to vary before the predefined date when the debt is assumed to mature. This does not necessarily imply the DD must follow a unit root process in any data that can be meaningfully analysed with the Merton method. In the real world numerous factors not related to changes in asset prices affect the default probability. Managers and shareholders would typically react to different difficulties and opportunities by, for instance, expanding the undertaking, disposing of business units, issuing more equity capital to strengthen the solvency, adapting the dividend policy etc. For instance, it has been found that firms near credit rating upgrades or downgrades issue less debt relative to equity than firms not near a change in rating (Kisgen 2006) and recently downgraded firms typically reduce leverage (Kisgen 2009). Some typical patterns in the development of company credit risk may be due to managers' reactions to exogenous shocks, some phenomena can be caused by something else. The combination of different drivers of credit risk creates a very complicated process. This highly complex system is now regarded as a black box; the focus of the following analyses is on the typical time series properties of credit risk, not on causal mechanisms behind it.

3 EMPIRICS

The following analysis is based on the analogue of Löffler (2004). The distance to default is hypothesised to be determined by the following process.

$$D_{it} = S_{it} + C_{it} \tag{2}$$

where D_{it} is the point-in-time (PIT) DD of company i on the last day of the month t. S_{it} is the relatively stable structural through-the-cycle (TTC) component of the DD of the company i at the moment of time t. S_{it} follows a unit root process, is subject to infrequent abrupt shifts or remains constant, but does not undergo transitory cycles that would correlate with the macroeconomy. C_{it} is the cyclical component of credit risk. The cyclical component C_{it} is assumed to be stationary with mean zero, and to be highly correlated across firms.

$$C_{it} = \alpha\, C_{it-1} + \beta_i\ \Delta\, C_{macro,t} + \varepsilon_{it} \qquad \{3\}$$

where $0<\alpha<1$, the company specific cyclicality parameter β_i is positive for most firms and ε_{it} is the idiosyncratic shock of the company i in period t. The macro level cyclical shock $C_{macro,t}$ has got mean zero and it is common to all firms, and it causes correlation in firms' credit risks. The shock parameters may be autocorrelated.

A PIT rating would be based on D_{it}. A TTC rating would ignore the value of C_{it} by dropping off the whole component and focusing exclusively on S_{it}. Alternatively one might assign the cyclical component a firm specific constant negative value to yield default probabilities under adverse conditions. The choice between these approaches would affect the level of TTC default risk, not its variation over time.

The empirical predictions of this simple model can be briefly summarised as follows.

1. If structural changes of credit risk are not particularly commonplace, many companies have got stationary DDs because variations are entirely due to fluctuations of C.
2. Companies' DDs should tend to revert to their past values; if the DD has increased in the past, it will probably decline in the future because some of the changes in DD are due to transitory fluctuations of C.
3. Companies' reactions to cycles remain relatively constant. If the DD of a company deteriorates more than average during a recession, it will improve remarkably strongly during the following benign period because the company has got a persistently large value of β_i.

These empirical predictions will be tested in the following subsections.

3.1 UNIT ROOT TESTS

Panel unit root tests typically have got higher power than unit root tests on individual series (See Maddala and Wu 1999 and references therein). However, serial correlation, especially negative one, may seriously bias many unit root test results. (See Schwert 1989, Hlouskova and Wagner 2006) The ADF test can be applied, even though the presence of negative serial correlation accentuates the importance of lag length selection in unit root tests; the use of standard Akaike and Schwarz criteria would often lead to excessively short lag structures. (Ng and Perron 1995; Lopez 1997). The modified Akaike criterion is used in the following analyses. It takes into account the consequences of the potentially biased sum of autoregressive coefficients. Using the modified criterion significantly improves the reliability of unit root test results (Ng and Perron 2001).

Many panel unit root tests simply evaluate the joint significance of p-values obtained by testing each series separately. The null hypothesis is unit roots in the whole data, the alternative hypothesis being that at least some of the series are stationary. If most of the variation in credit risk is cyclical and if structural changes are not particularly frequent, it would be natural to expect that some subgroup of companies has not undergone any structural changes and the null hypothesis would be rejected. The common denominator of members of the stationary subgroup could be related to company size, industry or some non-observable characteristics. However, as can be seen in table 1, these tests do not provide much evidence against the null hypothesis of unit roots in the whole data. Three different test statistics are reported. The Fisher ADF-approach applies the chi squared distribution to a function of logarithmic p-values of ADF tests on individual series. Choi (2001) proposed a Z-statistic of the significance of unit root tests. A test statistic based on averaging individual ADF test statistics has been presented by Im et al (2003).

TABLE 1: PANEL UNIT ROOT TESTS

Panel unit root tests (levels) for 119 companies, modified Akaike criterion in lag length selection

Method	Test statistic	p-value
ADF Fisher Chi-squared, intercept, no trend	208.87	0.914
ADF Choi Z stat, intercept, no trend	0.2086	0.583
Im, Pesaran Shin W-stat, intercept, no trend	-0.0837	0.467

Some interesting methods cannot be applied to panel data because there is no straightforward way to evaluate the joint significance of tests on individual series. Ng and Perron (2001) recommended a GLS detrending combined with the modified Akaike criterion in lag length selection when residuals are characterised by negative serial correlation. This method was applied to each company separately. It was found that in 16 cases out of 119 the unit root hypothesis would be rejected at the 10 % level. The number is relatively high, and close to the upper boundary of what could still be considered a random outcome. On the other hand, there were only two companies for which the null hypothesis would be rejected at the 5 % level, and in only one case it would be rejected at the 1 % level. Hence, there is not much evidence against the hypothesis of unit roots in the underlying data generating process. (See table 2) The results corroborate the findings of panel unit root tests reported in table 1.

The results discussed so far prove that the C parameter alone has not been the sole driver of credit risk in equation 2. Instead, a significant part of variation in credit risk must be due to changes in the structural component S. Even if there were only one major change in S, the methods applied so far would typically accept the null hypothesis of unit roots. Unit root tests that allow for the presence of a structural break were applied to the data. Following Lanne et al (2003), the analysis was begun by optimising the number of lags by running separate ADF analyses with individual intercepts and trends. The number of lags suggested for each company by the modified Akaike criterion was used at the following stages; these preliminary analyses were not used for any other purpose. As a second step, the date of the structural break was determined endogenously. A deterministic component, consisting of constants and the shift caused by a structural break, was deducted from the original series by using a GLS procedure. The structural breaks were identified in two different ways, first by assuming an abrupt shift dummy in level and then by assuming a somewhat smoother exponential shift. Finally, the unit root test was run on residuals after deducting the deterministic component. (See Saikkonen and Lütkepohl 2002). Lanne et al (2002) tabulated critical values for the t-value of the lagged non-deterministic component of the original series. Again, each company was tested separately because there is no straightforward way to apply the method to panel data. As can be seen in the table 3, in most cases the number of rejections is fairly low at each significance level, and roughly equal to what one would expect as a random outcome, with the exception of the relatively high number of rejections at the 5 % level with the smooth exponential shift. Hence, the number of structural shifts of credit risk seems much higher than one in the vast majority of companies.

TABLE 2: UNIT ROOT TESTING OF COMPANY LEVEL DISTANCE TO DEFAULT

Separate unit root tests for 119 companies

Method	Test statistic	Nr of rejections at the 10 % level	Nr of rejections at the 5 % level	Nr of rejections at the 1 % level
Ng-Perron - Elliot-Rothenberg-Stock (1996) test stat, Modified Akaike criterion, GLS detrending	Elliot-Rothenberg-Stock (1996)	16*	2	1
Shift in level, abrupt shift dummy	Lanne & al (2002)	13	5	0
Shift in level, smooth exponential shift	Lanne & al (2002)	15	9*	1

A star denotes that the probability of obtaining at least the reported number of rejections at the given significance level is less than 10 %.
In level shift tests the number of lags has been obtained for each company separately by running a separate ADF test with company specific trends and fixed effects.
The number of lags proposed by the modified Akaike criterion was used in level shift tests reported above, in both determining the break date and unit root testing itself.

3.2 ARE THERE TRANSITORY CREDIT RISK FLUCTUATIONS?

The evidence presented in section 3.1 corroborates the hypothesis that credit risk at the firm level is a unit root process. These results do not necessarily prove the hypothesised cyclical component C of equation 2 is non-existent, or at least too weak to be detected. The structural component S may have undergone numerous irrevocable changes in most companies, but this does not imply the stationary C component cannot exist.

In order to shed some light on the possible tendency of DD figures to undergo transitory fluctuations, a few panel regressions were run with annual data. The company level DD for each year is the three months simple moving average ($\check{D}_{it}=\{D_{it}+D_{it-1}+D_{it-2}\}/3$) of December. The analyses were carried out with data on the 117 companies for which it was possible to find data on six consecutive fourth quarters. Because the data does not seem stationary, the regression was run in differences. The annual difference of the distance-to-default was regressed on its past values. No weighting was applied. The results are presented in table 3. The first equation was run with no period or company specific effects. The Hausman test indicated that the random period effects model is more suitable than the fixed period effects model (Chi sq = 0.21), and the 3rd

equation could be considered the main model for the whole data. The first, second and fourth lags are statistically significant. Thus, the DD is characterised by an observable tendency to return to its past level.

TABLE 3 ANNUAL CHANGE OF DISTANCE TO DEFAULT
Explained variable $\check{D}_{it}$-$\check{D}_{it-12}$; Decembers only

	1	2	3	4	5	6	7
	No year specific effects	Fixed period effects	Random period effects	Small-cap firms excluded; fixed period effects	Small-cap firms excluded; random period effects	Small-cap firms only; fixed period effects	Small-cap firms only; random period effects
Constant	0.02	0.01	0.01	-0.02	-0.02	0.05	0.05
	(0.2)	(1.3)	(0.1)	(-2.2)**	(-0.2)	(4.5)***	(0.6)
$\check{D}_{it-12}$-$\check{D}_{it-24}$	-0.07	-0.09	-0.09	-0.13	-0.13	-0.10	-0.10
	(-0.7)	(-0.9)	(-2.1)**	(-1.0)	(-1.0)	(-1.2)	(-1.2)
$\check{D}_{it-24}$-$\check{D}_{it-36}$	-0.04	-0.09	-0.09	0.00	0.00	-0.17	-0.17
	(-0.6)	(-2.1)**	(-2.2)**	(0.0)	(0.0)	(-4.6)***	(-4.8)***
$\check{D}_{it-36}$-$\check{D}_{it-48}$	-0.16	-0.05	-0.05	-0.07	-0.07	-0.04	-0.04
	(-1.9)*	(-1.7)*	(-1.3)	(-1.2)	(-1.3)	(-0.7)	(-0.7)
$\check{D}_{it-48}$-$\check{D}_{it-60}$	-0.14	-0.10	-0.09	-0.06	-0.06	-0.14	-0.14
	(-3.9)***	(-2.6)***	(-2.7)***	(-1.3)	(-1.3)	(-3.2)***	(-3.2)***
R2	0.04	0.39	0.02	0.51	0.02	0.31	0.05
F	6.592***	44.01***	3.819***	36.81***	1.75	13.857***	3.643***
N	624	624	624	330	330	294	294

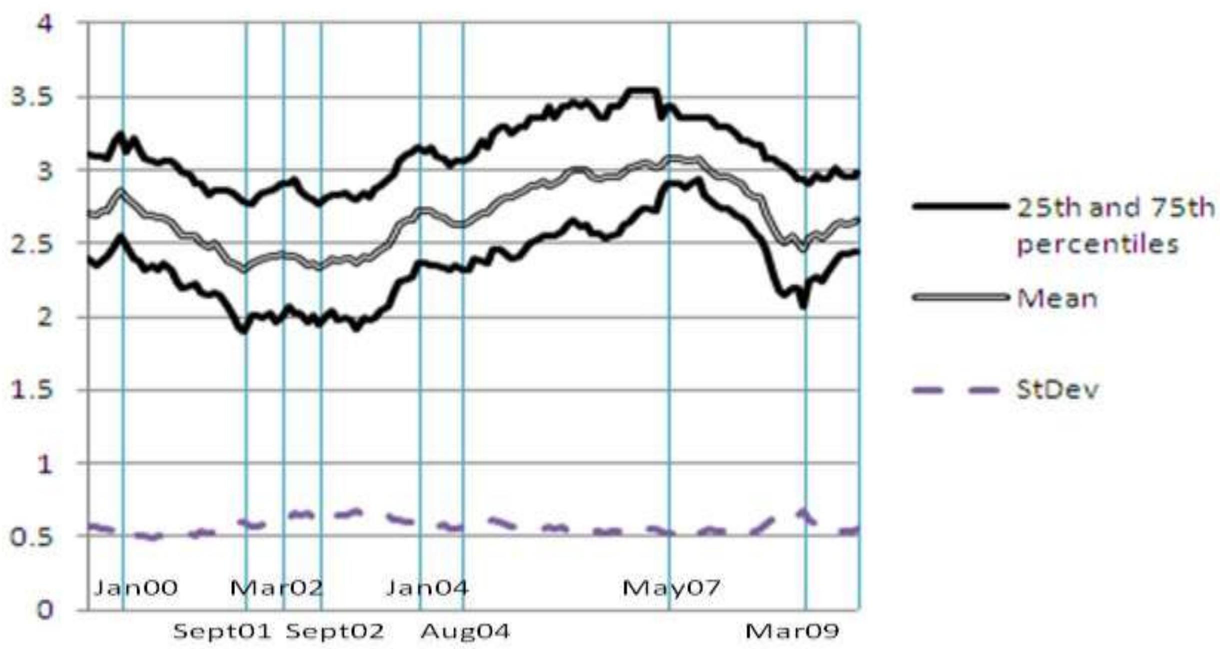
t-values corrected for heteroscedasticity and autocorrelation
* denotes 10 % significance, ** 5 % significance and *** 1 % significance

Interestingly, the existence of the tendency to return to past values is related to firm size. There seems to be almost no evidence on the existence of temporary fluctuations in the data if small-cap firms are excluded from the sample. (Equations 4-5 in table 3). If, instead, the focus is on small-cap firms, the DD clearly tends to return to its past values (Equations 6-7). It is difficult to say whether this is a genuine property of credit risk in small-cap firms or something related to potentially inefficient pricing of small-cap companies on the stock exchange. There is almost no difference in the standard deviation of the explained variable between the two size groups; in both groups it is slightly higher than 0.361.

3.3 FIRM SPECIFIC CREDIT RISK AND THE CREDIT CYCLE

In section 3.2 it was found that firm-specific DD has got, at least in small-cap firms, some tendency to return to its past level. This, however, does not prove the hypothetical cyclical component exists. By definition, cyclical fluctuations of DD in different companies should be highly correlated, and the existence of this correlation has not been tested. The macro level credit cycle is not directly observable but it affects the average credit risk in the economy. The chart 1 presents the development of the mean of the DD. Its cross-sectional 25th and 75th percentiles and standard deviation are also presented in the chart. If anything, cross-sectional variation across firms has widened when credit quality has deteriorated. Spectral analysis found no satisfactory evidence on the existence of genuine cycles in the average.

CHART 1; THE DEVELOPMENT OF AVERAGE DD AND CROSS-SECTIONAL VARIATION



Irregular "cycles" can be defined by identifying local minima and maxima in the sample. The period from one extreme of average credit risk to the next one is now called a phase. Using a simple version of the basic idea applied by e.g. Bry and Boschan (1971, p.16-29), peaks and troughs in the mean DD were defined by the following criterion. If an observation is greater or smaller than any of the following and preceding five observations, it is a turning point. If the original Bry-Boschan method were applied as such to this rather short sample, there would be hardly any turning points left because of numerous elimination criteria. In these analyses nothing but the extremes observed in April and June 2006 are eliminated because a two months phase is definitely too short to be a cycle. Local maxima can be identified in January 2000, March 2002, January 2004, and May 2007. Local minima are found in September 2001, September 2002, August 2004, and March 2009. These results pass one compliance test proposed by Bry and Broschan: peaks and troughs alternate. These turning points are marked in chart 1 by vertical lines. Moreover, December 2009 is rather arbitrarily classified a peak even though the data does not tell us how average credit quality developed thereafter. At least in quarterly data these fluctuations are closely correlated with the proxy for output gap[3]; the immediate correlation is +0.57.

If the business cycle sensitivity of each firm, the parameter β_i in equation 3, remains broadly constant for lengthy periods of time, the development of credit risk during the previous phases of the cycle should be relevant to changes of credit risk during any future upturn or downturn. To take an example, the drastic deterioration of credit risk between May 2007 and March 2009 should have been stronger among cyclical companies that experienced particularly strong improvements of creditworthiness during the preceding benign phase.

A number of cross-sectional OLS analyses were run. The change in the DD of each company was regressed on the change of DD of the same company during the two previous phases irrespective of the number of months the phases lasted. If the hypothesised persistent cyclicality exists, the change of DD during the previous phase should obtain a negative regression coefficient because each upturn is, by definition, always followed by a downturn, and vice versa. Analogically, the change lagged by two phases should obtain a positive coefficient. OLS results of cross-sectional analyses on the whole sample are

[3] The output gap was calculated as the Hodrick-Filter residual ($\lambda = 1600$) run on logarithmic real GDP data for the period Q1/1995 - Q4 /2013; the data after Q3 /2009 were those of the latest Bank of Finland macroeconomic forecast.

presented in table 4. In three cases out of seven the first lag has got a statistically significant negative coefficient, as hypothesised. Two coefficients of the second lag have got the expected positive sign that would be significant at the 5 % level, and two of them have got a statistically significant negative sign, which is inconsistent with the hypothesis to be tested. Out of the seven significant coefficients five have got the expected sign and two the "wrong" sign, which would not be particularly unlikely if the signs were assigned randomly. The average of both coefficients is low, about -0.15 for the first lag and -0.02 for the second. With the exception of the latest upturn, the R squared values are low.

TABLE 4; CROSS-SECTIONAL OLS ANALYSES ON IDENTIFIABLE CYCLES
CHANGE OF DD AS A FUNCTION OF ITS PAST CHANGES

Whole sample - all the phases			Explanatory variables				
Phase		Change in average D	C	Change of D during phase t-1	Change of D during phase t-2	R2	F
Mar09-Dec09	Upturn	0.189	0.009	-0.307	-0.047	0.36	28.41***
	9 months		(0.2)	(-6.3)***	(-0.8)		
May07-Mar09	Downturn	-0.648	-0.674	0.172	0.533	0.06	3.43**
	22 months		(-9.6)***	(1.6)	(2.7)***		
Aug04-May07	Upturn	0.446	0.533	-0.092	-0.237	0.04	2.22
	33 months		(9.6)***	(-0.6)	(-2.0)*		
Jan04-Aug04	Downturn	-0.099	-0.049	-0.155	-0.133	0.06	3.59**
	7 months		(-1.6)	(-3.0)***	(-2.0)**		
Sept02-Jan04	Upturn	0.404	0.405	-0.447	-0.323	0.16	10.21***
	16 months		(10.42)***	(-4.6)***	(-2.2)**		
March02-Sept02	Downturn	-0.099	-0.021	-0.183	0.100	0.08	3.92**
	6 months		(-0.5)	(-1.3)	(2.3)**		
Sept01-March02	Upturn	0.126	0.120	-0.011		0.00	0.14
	6 months		(4.9)***	(-0.4)			

Heteroscedasticity consistent (White) t-values in parentheses
* denotes 10 % significance, ** 5 % significance and *** 1 % significance

Some of the explanatory variables may lack statistical significance because they describe the development of credit risk during a very stable phase, when the DD in different companies has been driven almost exclusively by something else than non-existent cyclical forces. Analogically, if the explained variable corresponds to a very stable period, changes in DD of most companies are mainly due to factors that have little to do with cyclicality. In the cross-sectional OLS analyses presented in table 6, it is tested whether firm specific changes in DDs during the strongest cyclical swings are related to changes during previous accentuated phases. Phases where the absolute value of the average of DDs has changed less than by 0.3 are excluded as both explanatory and explained variables. As can be seen in table 5, there is little evidence on the existence of persistent differences in companies' cyclicalities. As hypothesised, the upturns in September 2002 - January 2004 and August 2004 - May 2007 were stronger in companies that were affected particularly severely by the downturn in January 2000 - September 2001. Instead, the statistical relationship between the upturn in September 2002 - January 2004 and the upturn in August 2004 - May 2007 is inconsistent with the permanent cyclicality hypothesis. Companies that benefited particularly strongly from the first upturn benefited less than others from the second one, which is inconsistent with the hypothesis that persistent differences in cyclicalities exist. Interestingly, this reverted relationship has the largest coefficient of the whole table. The most dramatic phase of the sample, namely the collapse in 2007-2009, is not related to previous strong phases.

TABLE 5: CROSS SECTIONAL OLS, STRONG PHASES ONLY

Explained variable			Average value	Explanatory variables					
					Change of	Change of	Change of		
$D_{i\ end\text{-}of\text{-}phase} - D_{i\ end\ of\ previous\ phase}$			Average value of explained variable	C	D in Aug04-May07	D in Sept02-Jan04	D in Jan00-Sept01	R2	F
May07-Mar09	Downturn	22 months	-0.687	-0.76 (-5.8)***	0.06 (0.4)	-0.02 (-0.9)	-0.09 (-0.9)	0.01	0.37
Aug04-May07	Upturn	33 months	0.428	0.50 (9.2)***		-0.42 (-3.8)***	-0.17 (-2.0)**	0.14	7.36***
Sept02-Jan04	Upturn	16 months	0.394	0.28 (8.0)***			-0.22 (-4.0)***	0.15	17.42***

t-values corrected for heteroscedasticity (White)

Averages of the explained variable may differ from table 4 because samples may differ.

* = 10 % significance, ** = 5 % significance, *** = 1 % significance

One possible explanation to these phenomena may be the existence of several underlying drivers of credit risk. For instance, if the deterioration of credit quality is due to rising interest rates but the subsequent recovery is due to strong export demand, the latter effect may mainly benefit companies that did not suffer much from the preceding negative shock. The upturn in 2002 - 2004 may be due to the reversion of the factor that caused the downturn in 2000 - 2001. The upturn in 2004-2007 may have been caused by some other forces but counteracted by the reversion of factors that contributed to improving credit quality in 2002-2004. Even though the Basel II framework is based on the Asymptotic Single Risk Factor approach (See Basel Committee 2005), Koopman et al (2009) found evidence on the workings of multiple drivers of rating transitions after controlling for observable macroeconomic factors. This finding has been corroborated by Jiménez and Mencía (2009) with data on actual defaults in different sectors. The hypothesis of multiple drivers of credit risk in KMV data was tested with factor analysis. Four principal components were extracted from the monthly differences of Ds in the period September 1999 - May 2007. The estimated loadings to these four factors were used as explanatory variables in a cross-sectional OLS analysis. The explained variable was the deterioration of distances to default in the May 2007 - March 2009 period. Only one set of factor loadings was a statistically significant explanatory variable at the 5 % level. Thus, the multiple factor hypothesis found no support in this rather simple test. Detailed results are available from the author upon request.

Cycles of different companies might be imperfectly synchronised; each company may react to the same macroeconomic factors but some of them may react faster than others. The most extreme phase of the whole data, i.e. the financial crisis of 2007-2009, and the preceding lengthy benign period were analyzed in order to test this hypothesis. Each extreme value is the highest or lowest monthly value observed during a certain period of time. The extremes of DD for each company i are defined as follows.

- $D_{i\ crisis} = \mathrm{Min}[D_{i\ Nov\ 2008} \ldots D_{i\ Sept\ 2009}]$
- $D_{i\ peak} = \mathrm{Max}[D_{i\ Jan2007} \ldots D_{i\ Nov\ 2007}]$
- $D_{i\ pre\text{-}peak} = \mathrm{Min}[D_{i\ Jan\ 2004} \ldots D_{i\ Dec\ 2006}]$

These data were used to calculate differences $D_{i\ crisis}$-$D_{i\ peak}$, and $D_{i\ peak}$ -$D_{i\ pre\text{-}peak}$. One would expect that there must be a highly negative correlation between these differences because cyclical companies experienced the strongest improvement before the crisis and the worst collapse during it. Interestingly, the correlation between these variables is non-significant and, against expectations, positive (+0.12, N=108).

3.4 CYCLICALITY OR IDIOSYNCRATIC VARIATION IN SMALL-CAP COMPANIES?

In section 3.2 it was found that the DD of a typical small-cap firm is characterised by a certain tendency to return to its past level. This property might be related to cyclicality. Hence, table 4 regressions were run for the sub-sample of small-cap firms. As can be seen in table 6, the results are largely similar to those observed in the whole sample. In some cases the first lag is statistically significant and obtains the expected sign. However, the second lag has got the "wrong" negative sign more often than the "correct" positive sign irrespective of whether insignificant coefficients are ignored or not, which is clearly inconsistent with the hypothesis of persistent differences of companies' cyclicalities.

TABLE 6: CROSS-SECTIONAL OLS ANALYSES ON IDENTIFIABLE CYCLES
CHANGE OF DD AS A FUNCTION OF ITS PAST CHANGES

Small cap firms - all the phases			Explanatory variables				
Phase		Change in average D (this sample)	C	Change of D during phase t-1	Change of D during phase t-2	R2	F
Mar09-Dec09	Upturn 9 months	0.160	0.07 (1.4)***	-0.20 (-3.2)***	-0.03 (-0.4)	0.13	3.46***
May07-Mar09	Downturn 22 months	-0.494	-0.42 (-4.9)	0.00 (0.0)	0.58 (2.0)**	0.06	1.49
Aug04-May07	Upturn 33 months	0.465	0.61 (6.8)	0.02 (0.0)	-0.33 (-2.3)**	0.08	2.33
Jan04-Aug04	Downturn 7 months	-0.115	-0.05 (-1.4)	-0.18 (-3.2)***	-0.20 (-2.7)***	0.18	6.0***
Sept02-Jan04	Upturn 16 months	0.429	0.44 (8.2)***	-0.47 (-3.1)***	-0.37 (-1.6)	0.15	4.6**
March02-Sept02	Downturn 6 months	-0.099	-0.04 (-0.8)	-0.11 (-0.7)	0.08 (1.4)	0.05	1.12
Sept01-March02	Upturn 6 months	0.085	0.08 (2.5)	-0.01 (-0.4)		0.00	0.14

Heteroscedasticity consistent (White) t-values in parentheses; * = 10 % significance, ** = 5 % significance, *** = 1 % significance

The analysis on strong phases was repeated with the sub-sample of small cap companies. As can be seen in table 7, the results are largely similar to those of table 5; two of the three strong fluctuations are partly explained by previous ones, but the coefficients do not always obtain the "correct" signs. The strongest phase of the sample, namely the downturn in 2007 - 2009, is not correlated with previous strong phases.

TABLE 7: CROSS-SECTIONAL OLS ANALYSES

Small Cap companies - strong phases only

Explained variable			Explanatory variables					
				Change of	Change of	Change of		
$D_{i\ end\text{-}of\text{-}phase} - D_{i\ end\ of\ previous\ phase}$		Average value of explained variable	C	D in Aug04-May07	D in Sept02-Jan04	D in Jan00-Sept01	R2	F
May07-Mar09	Downturn 22 months	-0.519	-0.47 (-3.2)***	0.02 (0.1)	0.15 (0.6)	0.19 (1.6)	0.07	0.82
Aug04-May07	Upturn 33 months	0.420	0.56 (6.3)***		-0.58 (-3.6)***	-0.17 (-1.9)*	0.25	6.47***
Sept02-Jan04	Upturn 16 months	0.419	0.26 (3.5***			-0.25 (-3.2)***	0.20	10.40***

t-values corrected for heteroscedasticity (White)

Averages of the explained variable may differ from table 6 because samples may differ.

4 STATIONARITY AT THE AGGREGATE LEVEL - SIMULATIONS

The section 3 demonstrated that instead of being stationary, firm-specific credit risk has probably got a unit root. If the distance-to-default of every company is a unit root process, we might draw the conclusion that the average credit risk in the economy should also be a unit root process. Companies' average default probability might gradually migrate to 99,9 percent, or the economy might end up in a situation where corporate bankruptcies are unheard of. These extreme alternatives do not seem realistic.

In principle, the average of a large number of unit root processes could be stationary in the presence of a suitable cointegration. This possibility is not realistic in this case; the long-term correlation between firms should be negative. It is difficult to see which forces would cause a negative relationship between the default probabilities of two companies in entirely different industries. A more plausible explanation is related to continuous entry and exit. Only those companies that exist at a given moment of time are included in the average.

In order to draw some conclusions on the implications of this way of thinking, a number of simulations were run. The oldest company of the sample in section 3 was 360 years old in 2009. Taking this as the starting point in model calibration, simulations were run for 360 consecutive "years". During each period t a number of new companies were established. The number of start-ups (N_t) grows in a growing economy. The number of new start-ups in period t is determined by a very simple function.

$$N_t = 5\,\mathrm{Round}(1.025^{t-1}) \qquad \{4\}$$

In total, 1 450 645 companies were established in each simulation, about 91,5 % of them during the last 100 "years". The distance-to-default develops as a unit root process, unless the firm fails.

$$D_{it} = D_{it-1} + \varepsilon_{it} \qquad \{5\}$$

where ε_{it} is an iid normally distributed random variable with mean zero and standard deviation 0.198. This standard deviation was calibrated to produce the cross-sectional standard deviation of the ten year difference (December 1999, December 2009) in section 3 data. In order to save computing capacity, it was assumed that firms of the same cohort can be divided into 5 groups of equal size. Companies in the same group are always identical and they are assigned the same distance-to-default. Each group i of start-ups is assigned the distance-to-default $1.33+\varepsilon_{it}$. Firms' DDs change already before the first possible moment of bankruptcy at the end of the entry period. The parameter value 1.33 was calibrated to produce the observed five-year survival rate of newly established Finnish firms, which is reported by Nurmi (2004, p.40) to be slightly less than 60 %.

Firms do not exit in any other way than through bankruptcy. Each year t the firms of the group i exit iff

$$\Phi(D_{it})<R_{it} \qquad \{6\}$$

Where Φ is the cumulative standard normal distribution and R_{it} is an evenly iid distributed random variable between 0 and 1. A firm may exit even during the same year it is established.

The first 260 "years" were discarded and nothing but the last 100 moments of time were used in subsequent analysis. The average distance-to-default was calculated for each year taking into account nothing but firms that had been established but not failed by the end of the year. This simulation was repeated a hundred times, producing a panel of ten thousand observations on average DD in the artificial economy. These time series converge towards an equilibrium where the average DD seems constant. The mean DDs was 1,86 for the first observation (t=261) and 1,87 for the last observation (t=360).

The panel unit root test proposed by Levin et al (2002) suits the setting particularly well. The method assumes that series of the sample are identical with respect to the first-order partial autocorrelation, but other parameters can vary across units. The null hypothesis is that each time series of the panel has got a unit root, the alternative hypothesis being that none of them have. As pointed out by the original authors (p 18), the method is of limited use unless the time series are free from contemporaneous correlation and identical with respect to the presence of a unit root. Because of the nature of the data generating algorithm these criteria should be satisfied in the artificial sample. The model applied in the following is numbered 2 by Levin, Lin and Chu (LLC); each time series has got its own intercept, but no trends are allowed in the data. It can be essentially important to choose the right bandwidth, a parameter value used in correcting test statistics for serial correlation. Westerlund (2009) tested with Monte Carlo simulations different details concerning the use of the LLC test. He strongly recommended the use of the bandwidth selection criterion $K_i = 3.21T^{(1/3)}$. The lag length selection criterion proved to be of secondary importance. The Schwarz-Bayesian lag length selection criterion was one of the methods considered by Westerlund whereas the modified Akaike criterion was not; results based on both criteria are reported in table 8. Moreover, the results of panel ADF were calculated for comparison. These methods unanimously reject the unit root hypothesis.

TABLE 8; UNIT ROOT TESTS ON AVERAGE DD IN ARTIFICIAL PANEL DATA

	Stat	P-value	Lag selection criterion
Levin-Lin-Chu 2002 (LLC)	-15.09	0.000	Schwartz-Bayesian
Levin-Lin-Chu 2002 (LLC)	-7.56	0.000	Modified Akaike
Panel-ADF; Fisher chi squared	511.82	0.000	Modified Akaike
Panel-ADF; Choi Z-stat	-11.47	0.000	Modified Akaike

The LLC test was run with the Bartlett kernel, the bandwidth criterion

$K_i = 3.21T^{(1/3)}$; No trends are included

N=100; T=100

The relative stability of the average DD is due to the balance between two counteracting forces. The average distance-to-default among surviving firms of each cohort increases over time when disproportionate exit takes place among firms whose DD has deteriorated, or not improved enough to promise a long life. Simultaneously, the relative weight of each cohort steadily declines even if no exit takes place because increasing numbers of new firms enter. In reality exit may take place even without bankruptcy and default, for instance because of voluntary closures due to non-economic factors, such as retirement of the entrepreneur, or M&A. Hence, the long-term forces that would force the average DD upwards are counteracted by multiple factors.

This way of thinking offers a possible explanation to the observed propensity of newly established firms to fail at a higher probability than seemingly similar older firms. An old firm must have survived for many years to be observed, which is unlikely unless the firm has developed a low probability of default soon after entry. This reasoning is essentially the same as the one presented by Thompson (2005) who argues that high exit rates are commonplace among new firms because this group includes a lot of companies that were established with an inherently high failure probability, which is unlikely in the case of firms that have managed to survive several decades.

5 DISCUSSION

It has been proposed that the presumed procyclicality problem of Basel II could be alleviated by using through-the-cycle (TTC) ratings in banks' IRBA models. Many discussions on this possibility are not based on any explicit assumptions on the nature of business and credit cycles and their mutual interactions. However, the feasibility of TTC ratings depends on the time series properties of credit risk at the debtor level. There is relatively little literature on this topic, but this paper has presented some empirical evidence on this issue. The original KMV data provided by Moody's was used to calculate monthly proxies for distance-to-default (DD) of 119 Finnish publicly listed companies. The DD seems to follow a unit root process in most companies and few if any firms have got an equilibrium value of credit risk that would remain constant for lengthy periods of time. In the case of small-cap firms, some tendency to reversion to previous levels of credit risk can be observed. However, this serial correlation among small-cap firms is of little use in eliminating the cyclical component of credit risk in banks' capital adequacy calculations because these transitory fluctuations seem idiosyncratic rather than cyclical. Little evidence on the existence of regular transitory cyclical fluctuations of credit risk was found at the company level. The cyclicality of a typical company seems highly unstable and varies from cycle to cycle. Thus, TTC rating philosophies based on the idea that transitory cycles must be filtered out do not seem fully feasible.

Another often used definition of TTC ratings combines the current credit risk with its perceived sensitivity to the macroeconomic environment. If two debtors are characterised by equal probabilities of default at the moment, the company with a higher sensitivity to business cycles would be given a weaker credit rating. Emphasising this vulnerability in credit quality should be possible, provided it is possible to estimate the sensitivity of different debtors. Unfortunately, it was found in section 3.3 that the cyclicality of the creditworthiness of a typical company undergoes frequent and fundamental changes. Firms that were strongly affected by the previous stage of business cycles can suddenly become almost insensitive to the macroeconomic environment, and vice versa. This does not prove it must be impossible to distinguish cyclical companies from non-cyclical ones. Instead, it was simply found that historic correlations are of little use in assessing this vulnerability.

Some of the findings in section 3 could be consistent with the hypothesis of multiple credit risk drivers. Some earlier contributions (Koopman et al 2009; Jiménez & Mencía 2009) have found evidence in favour of this hypothesis but the simple analysis mentioned in section 3.3 found no evidence to support it. This analysis was by no means exhaustive. Applying sophisticated factor analysis techniques and different rotations to the same data set might be an interesting way to expand the analysis and a satisfactory explanation to the irregular changes of companies' cyclicalities could be found. However, the Basel II framework is based on the Asymptotic Single Risk Factor approach, and it may not be obvious how to take into account different factor loadings in order to calculate TTC ratings in Basel II compliant IRBA models.

Even though companies' credit risks seem unit root processes, the simulations of section four demonstrate that the average credit risk of a representative loan portfolio may be stationary and therefore subject to transitory fluctuations. This paradox is explained by the entry and exit of debtors. Hence, it would be possible to make a cyclical adjustment to the portfolio after calculating the credit risk at the debtor level, at least if the portfolio is subject to a same kind of entry and exit of firms as the artificial economy of section four. On the other hand, it is not obvious why it would be useful to calculate the credit risk of each debtor by using highly sophisticated methods, and then to apply a coefficient that prevents the variation of the capital requirement of the bank. Choosing a suitable constant risk weight for the whole portfolio would yield the same result with much less work. A somewhat more sophisticated way to implement TTC ratings is to apply smoothing at the rating category level. Potential debtors can be ranked according to their PIT credit risk, and they can be assigned ratings according to the credit risk relative to other debtors. The number of debtors in each category is held broadly constant by tightening criteria during cyclical upturns and loosening them during downturns. The risk weight of each rating category is held constant irrespective of how the actual default probability of the category develops. This approach was tested in the simulations by Gordy and Howells (2006); they concluded that the cyclical behaviour of capital requirements under this TTC rating system depends on the cyclical development of banks' policies concerning new lending. However, it can be argued that even under this more sophisticated smoothing one runs the risk of making complicated calculations in order to obtain a predefined, exogenously given result. If half of the loan portfolio is always assigned the weight 1.2, and the other half the weight 0.8, the average risk weight obviously cannot differ from 1. It would be more meaningful to use all would-be borrowers in the economy as benchmark when debtors are assigned ratings, but the bank may have got limited access to the required information set.

Previous empirical literature has not reached a clear consensus view on the time series properties of the development of real GDP. Nelson and Plosser (1982) questioned the traditional view of GDP growth as a trend stationary process. Some authors claim that output grows as a unit root process whereas some others have reached the conclusion that long-term economic growth is a trend-stationary process (see Beechey and Österholm 2008). Moreover, there may be structural breaks in the development of GDP (Papell and Prodan 2004). The answer to the question on trend stationarity vs. unit root may depend on the era and the country (Gaffeo et al 2005). Interestingly, this literature is not often referred to in analyses on through-the-cycle ratings even though the credit cycle is almost by definition related to macroeconomics. Even though Koopman et al (2009) concluded that the statistical relationship between credit risks and macroeconomic variables appears weak, there must be some connection between the behaviour of real output and the credit risk of the corporate sector which produces most of the output in the economy.

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