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PROCYCLICALITY OF CREDIT RATING SYSTEMS: HOW TO MANAGE IT

by Tatiana Cesaroni*

Abstract

This paper evaluates the characteristics of a Point in Time (PiT) rating approach for the estimation of firms' credit risk in terms of procyclicality. To this end I first estimate a logit model for the probability default (PD) of a set of Italian non-financial firms during the period 2006-2012, then, in order to address the issue of rating stability (hedging against rating changes) during the financial crisis, I study the effectiveness of ex post smoothing of PDs in terms of obligors' migration among rating risk grades. As a by-product I further discuss and analyse the role played by the choice of rating scale in producing ratings stability. The results show that ex post PD smoothing is able to remove business cycle effects on the credit risk estimates and to produce a mitigation of obligors' migration among risk grades over time. The rating scale choice also has a significant impact on rating stability. These findings have important policy implications in banking sector practices in terms of the stability of the financial system.

JEL Classification: C32, E32, G24, G32.
Keywords: procyclicality, business cycle, financial stability, PiT rating system, long run probability default.

Contents

* Bank of Italy, DG Economics, Statistics and Research.

Introduction[1]

The deep economic and financial crisis that has recently affected many European countries has faced the problem of building up reliable credit rating systems to evaluate the degree of banking sector exposures and the financial risks in the Euro Area. To this purpose, the possibility of using banks' portfolio rating methodologies looking to the long term rather than the short run has been discussed in different contexts - the most known of these concerns the current debate on the role of rating agencies in producing credit risk default assessments able to take into account the effects of business cycle phases on obligors' creditworthiness.

This study contributes to such an important debate by describing and analysing the issue of setting up a rating system to estimate banks' portfolio credit risk that takes adequate account of business cycle conditions. More in detail it assesses both theoretically and empirically, the consequences of possible intervention measures into such a framework, aimed at reducing rating procyclicality (and gaining financial stability), in terms of rating consistency and accuracy.

A credit rating system can be defined as a procedure that assigns an individual Probability Default (PD) to each obligor on the basis of its financial soundness and/or the general macroeconomic conditions through a model and/or a set of rules. Obligors with similar individual PDs are then grouped (or mapped) into an ordinal rating scale consisting of different rating grades (or risk buckets) through a given function (or mapping algorithm). An average pooled PD is finally assigned to all the obligors sharing the same rating grade.

In monitoring a bank portfolio credit risk two main rating philosophies can be considered: the so-called "Point in Time (PiT)" and the "Through the cycle (TtC)" approaches. As we know, a PiT rating system produces an obligor Probability Default that is countercyclical and associated

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with macroeconomic short run variations. It means that the estimated obligor Probability Default (PD) will increase during recessions and decrease during expansions. The use of PiT PD can thus possibly amplify the procyclicality of the credit market and more in general of the financial sector. A TtC rating approach, on the contrary, produces a smoothed PD obtained by removing the cyclical factors in the data.[2] The smoothed PDs therefore reflect a long run credit risk profile of firms (obligors) and it appears more stable and less volatile over time. In this respect the building up of TtC rating systems to evaluate obligors' defaults (considering a long run perspective), would allow us to avoid undesirable procyclical effects on the banking and financial sectors due to the business cycle.

Although many banks and rating agencies already use a TtC perspective in evaluating probability defaults, in the Basel Regulatory framework[3] and more in detail within the Eurosystem credit assessment framework (ECAF)[4], a clear definition of what perspective a rating system should adopt in measuring PD associated with the obligors is not given and both PiT and TtC rating approaches are allowed.[5]

With regard to the rating philosophy choice, it is important to note that while from a bank risk management perspective the use of a PiT rating would ensure a better credit risk assessment, from a central bank monetary policy and macroprudential point of view a TtC approach would produce better results in terms of countercyclical monetary policy objectives and containing the procyclical effects on the financial system. The central bank monetary policy operations are in fact based on the amount of financial assets eligible as collateral[6] that eventually depends on the portfolio credit rating philosophy that is adopted as well as the macroprudential policies aiming to reduce procyclicality that are based on TtC financial reporting and risk measurement.

In a TtC rating philosophy, PD estimates are supposed to reflect a "long run average", i.e. an average PD over both economic expansions and recessions.[7] In this view the average PDs assigned to the obligors by the mapping algorithm are free from short run variations and more stable over the years. However, in dealing with TtC ratings we should keep in mind the trade off between the loss

[2] The smoothing techniques usually applied are based on moving averages or judgmental procedures.
[3] BIS (2010) Basel Committee on Banking Supervision's Guidance for national authorities operating the countercyclical capital buffer.
[4] The ECAF is a set of procedures, rules and techniques defined within the Eurosystem in order to achieve high credit standards for all the eligible assets within the Eurozone.
[5] Within the ECAF four main credit assessment instruments are used, namely ECAIs, IRBs, RTs and ICASs. Some of them use PiT perspectives while some others are more in line with a TtC view. This heterogeneity in the obligors' creditworthiness assessment can create inconsistency in comparison exercises between various credit assessments tools (i.e. benchmarking).
[6] If the PD increases, the effect on the amount of collateral pledged in the Eurosystem credit assessment framework is to reduce the quantity of eligible collateral, while if the PD decreases, the effect is an increase.
[7] The detection of TtC credit risk estimates free from cyclical fluctuations is not easy since, as documented in Cesaroni et al (2011), the length of a business cycle changes over time and the duration of expansionary and recessionary phases is asymmetrical and may even change over time.

of predictive ability due to the estimation of the true default rates (that are PiT) by means of a TtC model and the stability of ratings over time.

Indeed the credit cycle is strongly linked to the business cycle due to the fact that credit flows increase during expansionary periods and decrease during recessions. In the same way, the default rate data on obligors are also affected by business cycle fluctuations and thus are PiT. Consequently the econometric models used to predict borrowers' probability defaults (i.e. logit, probit models, or panel models) over a one-year horizon are usually PiT since they also contain the effects of the economic cycle. As a result, the predictive power of the true default rate is very high but the predicted PDs assigned to each risk bucket by the mapping algorithm, depending on the state of the economy, will vary considerably producing sometimes unnecessary fluctuations of obligors among risk buckets over time.[8]

To limit such fluctuations, a possible solution can involve the use of an ex post correction to PiT estimated default rates. For example, by applying a constant to rescale the PDs we can obtain smoothed PDs more in line with a TtC rating view. Another possibility would involve the use of robust risk buckets with an interval length able to limit obligors migration among them.

Given the relevance of procyclicality treatment and assessment for PiT ratings, this paper focuses on two objectives. First, it considers the use of countercyclical scaling factors to produce TtC credit ratings and evaluates the stability of the results in terms of obligors' migration among risk classes. Second it assesses the role played by the detection of rating buckets (i.e. risk buckets built using cluster analysis as opposed to risk buckets with fixed thresholds) in determining rating stability.

Paragraph 2 analyses the main causes and consequences of procyclicality in the financial system. Paragraph 3 describes the data set and introduces the econometric default probability model. Paragraph 4 discusses the rating trade off between accuracy and stability and formalizes it into TtC and PiT ratings systems. Paragraph 5 evaluates the impact of the ex post PD smoothing in terms of obligors' migrations over years and among risk classes and assesses the role of the rating scale definition on rating stability. The final paragraph draws some conclusions.

[8] The PiT rating philosophy can also be to a certain extent amplified by a "traffic light" approach based on a backtesting mechanism with an annual horizon.

2) Main causes of procyclicality in the financial system overall and in the financial regulatory framework.

2.1 Procyclicality in the financial system

The procyclicality of financial and banking systems is mainly linked to their lending activity. In periods of expansion, banks can underestimate their risk, relaxing their criteria to select obligors and reducing their capital buffers. On the contrary, during recessions a greater exposure to credit risk can determine a contraction of banks' assets through a reduction of granted credit lines. Since this mechanism increases the supply of credit during expansionary phases and reduces it during recessions, it can potentially contribute to amplifying cyclical fluctuations instead of counterbalancing them. As well documented in two seminal works (Kashyap, 2005 and Lowe, 2002), the procyclicality of the financial system and consequently of credit flows can be considered a usual phenomenon (as it mainly arises from the idiosyncrasy of banks funding and lending, asymmetric information etc.), nevertheless it should be adequately treated in order to avoid an increase of economic fluctuations and the occurrence of systemic risks.

2.2 Procyclicality in the current financial regulatory framework

To ensure financial stability the main objective of the measures adopted under the financial regulatory framework over the last decade has been the control of possible systemic risks and contagion effects. The two major reforms that have contributed to controlling risk factors in the banking sector are the adoption of the International Accounting Standards (IAS 39) principles in 2005 and the Basel 2 Capital Requirements Directive introduced by the Committee on Banking Supervision in 2006. Both measures, although introduced to prevent risks related to the banking system, contain features that may perhaps intensify the procyclicality of the financial system.[9]

The main cause of procyclicality in the Basel 2 framework is the regulation of banks' minimum capital requirements. The Basel 2 Capital Accord links the minimum capital requirement to portfolio riskiness. Since the level of risk of the bank's assets, measured by obligors' ratings in the different rating grades, depends not only on their creditworthiness but also on the general macroeconomic conditions, mapping obligors by using a PiT rating system can produce an increase in the frequency of downgrading if economic conditions deteriorate.

To take this shortcoming into account, the Basel II Accord introduced the possibility for banks to use the TtC approach for their rating systems. With this mechanism the individual PiT PDs

[9] To address the regulation drawbacks that emerged during the 2007 crisis, the regulatory framework was furthermore modified, leading to the introduction of Basel 3 introduction and to a further revision of the IAS 39 principles, both of which are still in the implementation phase.

assigned to each obligor[10] can be corrected using smoothing techniques based on long run moving averages (at least five years, and in any case possibly an entire business cycle) in order to reduce their volatility.

Another element of regulation that can potentially trigger procyclicality in the financial system is the adoption of fair-value accounting (so-called market value) for the evaluation of all financial activities introduced under the International Accounting Standards (IAS 39). On the one hand the introduction of fair value allows us to achieve greater transparency with respect to the historical cost criterion, on the other hand it can introduce volatility in income and profits as well as in balance sheet items because the evaluation of assets is linked to short run market movements.

Given the drawbacks of procyclicality in the financial system, a strand of literature has been devoted to analysing and developing TtC credit rating systems. To this end Nickell et al (2001) estimate obligors' ratings (using a probit model) and analyse the stability of ratings with respect to obligors' sector, type, country, and business cycle in terms of migration within the transition matrix. Similarly, Bangia et al (2002) analyse the issue of credit risk procyclicality considering credit migration matrices free from business cycle conditions. By conditioning the migration matrix on two states of the economy (expansion and contraction), they show that the loss distribution of credit portfolios can differ significantly over the business cycle. Amato and Furfine (2003) study the degree of procyclicality of the ratings produced by Standard & Poors using annual data on US firms and conclude that there is little evidence of procyclicality in their ratings. Loffler (2004) analyses the properties of the TtC rating methodologies used by the main rating agencies using a market value model of default (i.e. a Value at Risk model) and concludes that the TtC rating is more stable than the PiT rating. To do this he separates transitory and permanent components in default frequencies of rating agencies using Kalman filter techniques. Valles (2006) estimates the probability default for a set of Argentinian obligors using a probit model and produces a TtC rating developing “stable risk buckets” obtained through cluster K-means methods in order to minimize the Chi-square criteria.

Kiff, Kisser and Schumacher (2013) study the TtC rating properties in terms of accuracy and stability. They consider a market value approach to risk default estimation and similarly to Loeffler they decompose the asset value of a firm into permanent and transitory components.

This paper extends the previous literature on rating procyclicality discussing and analysing possible ways of acting on PiT ratings in order to produce PDs in line with a TtC rating view. To this end I use a dataset of Italian bank borrowers, built taking information from the Bank of Italy’s Central Credit Risk Register and the Companies Register. Indeed, the main advantage of using a

[10] The use of TtC rating is not binding and banks can decide whether to use it or not.

TtC rating system is being able to take into account long run dynamics in the economy by reducing the impact of the business cycle on the probability default estimates and in the last analysis on the overall amount of credit available in the banking system.

3) The dataset and the logit model

In order to evaluate the characteristics of a PiT rating system in terms of procyclicality, I consider micro data on the defaults (adjusted bad loans) of obligors from the non-financial sector. The data come from the Bank of Italy's Central Credit Register (CR) and the Italian balance sheet database (CEBI/CERVED). In particular I use the one-year default probabilities of non-financial firms' obligors at the end of each year, which have an overall exposure towards the banking system that is greater than €75,000. The default definition is based on non-performing loans. According to this definition obligors are considered in default if it is unlikely that they will repay their bank debt and have been in arrears for more than 90 days. Furthermore, the default definition used is "system wide" meaning that it refers to the exposure of a given obligor towards the whole banking system and not only towards a single bank. In this respect the rating assigned to the obligor refers to the system as a whole and not to a given lender bank. The data spans from 2006 to 2012. The database has a changing number of observations year to year because some obligors are registered in the December of a given year but are not present in the December of another year.

To provide an initial descriptive analysis of the data, Table 1 reports the unbalanced panel of total debtors and the proportion of them in default at the end of the year, together with yearly GDP growth and spreads over the sample 2006-2012.

Table 1: Panel data description

Period	*Debtors**	*Default* debtors*	*Default rate(*100)*	*GDP growth (*100)*	*Spreads*
2006	205508	1541	0.75	2.20	0.97
2007	223321	1267	0.57	1.68	0.21
2008	243401	1385	0.57	-1.16	0.05
2009	257961	2448	0.95	-5.49	3.08
2010	266193	2251	0.85	1.70	3.23
2011	270201	2081	0.77	0.5	4.03
2012	268263	2147	0.80	-2.5	4.92

*Source: the Central Credit Register

Looking at the default rates dynamics over the years (Column 4) we can notice a peak corresponding to 2009. GDP growth is negative in 2008 and 2009 corresponding to the economic crisis. In 2012 GDP growth also registers negative growth although this is less pronounced than in 2009. Looking at the spreads we also note an increase in short and long term interest rate differentials starting from 2009.

A logit credit risk model was used to estimate and forecast the probability of default for the portfolios of Italian non-financial firms.[11] The estimated independent variable is the default d_{it} of a given firm taken from the Central Credit Register. The default takes a value of 1 if the obligor is in default at the end of the year and 0 otherwise. The model takes the form:

$$\log\left(\frac{PD_i}{1-PD_i}\right)=\beta_0+\sum_{j=1}^{k}X_{itj}+\varepsilon_{ijt} \qquad (1)$$

where PD_i represents the probability that firm i will fail and 1- PD_i represents the probability that firm will not fail. X is a set of explanatory variables containing firms' budget, financial and macroeconomic data.[12]

The explanatory variables can be divided into two groups: (i) financial variables related to the firms' structure, which changes over time and over individuals (dimension it) coming from the Italian Central Credit Register and from firms' balance sheets (ii) macroeoconomic variables (t dimension) that account for business cycle changes over time.

The first group includes:

- The amount drawn as a proportion of the amount granted (creditdr) by firms is a proxy of creditworthiness. The expected sign of the PD is positive (Source: Central Credit register).
- Number of times an account has been overdrawn in last five end quarters (overdr). This indicator represents a proxy of the firms' probability of default because the higher the number of times it has been overdrawn the higher the PD for a given firm (Source: Central Credit Register.
- Net financial expenditures/EBITDA (finexp): this indicator captures the firms' financial soundness. (Source: balance sheets).

[11] There are several ways to model default rates. Since in this context the dependent variable y shows a very low variability over time I choose to model the population of banks' obligors using a pooled logit.
[12] The model could also include a more complete set of financial firms' indicators. However the model specification is not the focus of the paper and it is functional to the procyclicality treatment.

- Age of firm (age): The expected sign is negative because a higher number of years that a firm has survived on the market will reduce the its likelihood of default. (Source: Central Credit Register).

The second group includes:

- GDP_Growth: this variable captures the effects of the business cycle across the economy on the probability default of a given obligor. The expected sign of the PDs is negative.
- Spreads: they are built as yearly long term interest rates minus short term interest rates. This variable, reflecting market expectations, allows us to take into account, albeit indirectly, the international environment.[13] The expected sign is positive because the higher the differential between long term and short term interest rates the higher the expected PDs.

Table 2 logit model over the period 2006-2012

Log likelihood = -59118.047			Pseudo R2 = 0.2338
default	Coef.	Std. Err.	z
gdpgrowth	-1.53013	0.3534616	-4.33
spread	0.09497	0.0055983	16.96
creditdr	4.21953	0.0885666	47.64
finexp	0.00492	0.0001741	28.26
overdr	0.76247	0.0054289	140.45
age	-0.01156	0.0009227	-12.54
cons	-10.5609	0.0844931	-124.99
LR chi2(6) = 36074.42	Prob > chi2 = 0.0000	Number of obs = 1734830	

Table 2 reports the estimated logit model over the period 2006-2012. The variables were selected on the basis of their economic relevance and statistical significance. The number of observation is 1,734,836. All the coefficients are significant at 1 per cent. Looking at the coefficient signs we can notice that as expected there is a negative relationship between the business cycle and the default rate. The spread is also significant and enters with the expected sign of the coefficient. Finexp and

[13] The differential between long term and short term interest rates reflects to some extent the market expectations of a country's ability to repay its debts. In this sense it represents a market based proxy of the default probability.

the number of accounts overdrawn coefficients are positive and explain an increase in the default probability, while age of the firm enters in the equation with a negative sign.

Table 3 Measures of model discriminatory power

Year	*Accuracy Ratio (AR)*
2006	0.90
2007	0.91
2008	0.91
2009	0.90
2010	0.90
2011	0.90
2012	0.90

To validate the model (i.e. to distinguish if the model correctly discriminates between obligors that have defaulted and those that have not defaulted), Table 3 reports the Accuracy Ratio (AR) statistics by year. The AR curve, which gives the percentage of times in which the model is able to predict the true default, ranges from 0.90 to 0.91 showing that the model has very good discriminatory powers.

4) Rating trade off between accuracy and stability

In setting up a reliable rating system, on the one hand we would like to obtain a credit risk model able to correctly predict obligors' default risk, on the other hand we would like avoid an excessive variability in the classifying obligors into the risk buckets of the rating scale over the years. We are hence faced with a trade off between accuracy and stability.

In fact, a desirable feature of a rating system is not only its predictive ability but also its capacity to stabilize obligors' migrations among risk categories and over time.

A PiT rating usually has a good predictive power but can potentially amplify obligors' migration among risk categories. A TtC rating, on the contrary, displays lower predictive ability but can improve rating stability.

The building up of a stable rating system would have the advantage of reducing financial system procyclicality and would help to counterbalance the effect of the business cycle on the banking system.

A credit rating system can generally be affected by procyclicality through the ***estimated PD*** itself ***that is PiT***. This feature determines a migration of firms among Credit Quality Risk buckets over the years that is to a certain extent affected by the effects of economic cycle and can potentially amplify procyclicality. Besides, the ***length of the intervals*** defining the risk buckets of the rating scale also plays a role in determining the rating stability because closer intervals increase the probability of obligors' migration among risk classes over time.

In order to assess and compare the characteristics of PiT and TtC ratings in terms of stability, in what follows I set up a possible formal definition of a PiT rating and of two alternative TtC rating definitions. The first one is based on smoothing the PDs. The second one is based on the definition of robust risk buckets.

Definition 1 *A PiT rating system is defined by (1) a function f assigning a PD to the obligors on the basis of macroeconomic conditions and information on their financial soundness; (2) A rating scale consisting in a discrete set of rating grades (or risk buckets); (3) A mapping algorithm that assigns each obligor to a given rating grade.*

Definition 2 *A TtC rating system is defined by (1) a function f assigning a PD to the obligors on the basis of macroeconomic conditions and information on their financial soundness; (2) An* **ex post smoothing** *to remove cyclical factors from the estimated PDs; (3) A rating scale consisting in a discrete set of rating grades (or risk buckets) (4) A mapping algorithm that assigns each obligor to a given rating grade.*

Definition 3 *A TtC rating system is defined by (1) a function f assigning a PD to the obligors on the basis of macroeconomic conditions and information on their financial soundness; (2) A rating scale consisting in a discrete set of* **robust** *rating grades (or risk buckets); (3) A mapping algorithm that assigns each obligor to a given rating grade.*

Definition 4 *A TtC rating system is defined by (1) a function f assigning a PD to the obligors on the basis of macroeconomic conditions and information on their financial soundness; (2) An* ***ex post smoothing*** *to remove cyclical factors from the estimated PDs; (3) A rating scale consisting in a discrete set of* ***robust*** *rating grades (or risk buckets) (4) A mapping algorithm that assigns each obligor to a given rating grade.*

In a rating system we can thus improve the stability acting on PD smoothing, the definition of rating grades or a combination both.

Proposition 1 *Assume a fixed rating space S= (R_1,R_2, …. R_{k-h},…,R_{k-1}, R_k) with probability intervals (j; j+m) defining each risk bucket R_{k-h}, then the probability of migration from bucket R_{k-h} to bucket R_{k-l} of obligor j in switching from an expansion (recession) to a recession (expansion) will be higher (lower) for PiT PDs than for TtC PDs.*

(See proof in the appendix)

The intuition for the above result follows from the fact that at firm level the PiT PD displays higher variability over time w.r.t. a smoothed TtC PD by definition. Under a recession, this fact determines an increase of the PD over time that is greater than under a TtC rating. This will cause more firms to migrate to the highest risk buckets (i.e. the worst obligors) during a recession and to the lowest risk buckets (i.e. the best obligors) during an economic expansion because it will be more common to have an estimated PD in t that moves from risk bucket t (i.e. during an expansion) to t+1 (i.e. during a recession).

Proposition 2 *Assume a fixed rating space S= (R_1,R_2, …. R_{k-h},…,R_{k-1}, R_k) with probability intervals (j; j+m); assume a more granular rating space S*= (R_1,R_2, …. R_{k^*-h},…,R_{k^*-1}, R_{k^*}) with Rk*>Rk, and (k*-h)< (k-h) for each R, the Probability of migration from bucket k*-h to bucket k*-l of obligor j over time will be higher under S* compared to S for both PiT and TtC PD* rating philosophies.

(See proof in the appendix)

Intuitively, the above result reflects the fact that shorter risk buckets will display lower probability thresholds and thus the frequency of overpassing that PD bucket from t to t+1 will be higher under S^*.

On the basis of the above definitions and propositions in what follows, I evaluate the removal of the procyclicality effects in a PiT rating system, both by applying an ex post smoothing of the PD and by considering robust risk bucket thresholds. With the first approach, cyclical factors are removed from the PDs by applying a scaling factor (varying over the years) making an ex post correction of PiT PDs at firm level. The resulting obligors PDs are in line with those obtained through a TtC rating, which allows us to control for business cycle effects on obligors migration among rating grades. With the second intervention measure, I consider robust risk buckets with thresholds that take account of lower PD variability over time. In this case the buckets are detected endogenously to the model through cluster analysis techniques.

Ex post PD smoothing

Let the probability default of a firm *i* at time *t* be $PD_i(t)$ with $0 < PD_i(t) < 1$. Let $S = (R_1, R_2, \ldots R_{k-h}, \ldots, R_{k-1}, R_k)$ be the rating space and $R_1, .. R_k$ the risk buckets (or rating grades) defining the rating scale. Each risk bucket *(R)* is represented by a probability interval *(j; j+m)* with $0<j<1$, $0<j+m<1$. The former risk buckets will correspond to the lowest probability default and thus will include the best obligors.

Let *N(t)* be the number of rated firms in a given year *t* and *n(t)* be the number of true defaulted firms in year *t*. The scaling factor can be computed as:

$$SF(t) = DR\_LR(t) \,/\, DR(t)$$

where *DR(t)* is the current default rate in year t given by *n(t)/N(t)* and *DR_LR(t)* is its long run average. The calibration produces a new weight for the probability default at firm level in each year *t* obtained by applying the corresponding scaling factor:

$$PD^{TTC}{}_i(t) = PD^{PIT}{}_i(t) * SF(t) \qquad (2)$$

where $PD_i(t)$ is the probability default of a given firm in year t and $PD_i^{TTC}(t)$ is the corresponding TtC correction, obtained by multiplying the PD at firm level with the scaling factor. In periods of expansion the *SF(t)* will be greater than 1 and will increase the $PD_i^{TTC}(t)$ of the obligors. In recessions the *SF(t)* will be less than 1 and will reduce the $PD_i^{TTC}(t)$ of the obligors. The countercyclical pattern of *SF(t)* allows us to smooth the business cycle effects on PDs.

The scaling factor (SF), given by the ratio of the long run default component for the total amount of obligors to the current total default rate, can be applied to the estimated obligors PDs at firm level coming from a PiT model. By multiplying the estimated PD at firm level with the SF, the predicted estimated PDs would be more in line with a TtC approach.

To explain the effects of PD smoothing on the mapping algorithm I consider risk buckets with fixed thresholds; the mapping algorithm (*MA)* that assigns an obligor *i* at time *t* to a given risk bucket under a PiT rating will be represented by the following function:

$$\underset{K-H}{F}\left(PD_i\right)_i^{PIT}(t) = 1 \qquad if\,(j< PD_i^{PIT}(t) =<j+m)\ \ and\ 0 \text{ otherwise} \qquad (3)$$

In the case of smoothing, the mapping function will be the same but the argument will be $PD_i^{TTC}(t)$.

$$\underset{K-H}{F}\left(PD_i\right)_i^{TTC}(t) = 1 \ if \quad (j< PD_i^{TTC}(t) =<j+m) \text{ and 0 otherwise} \qquad (4)$$

Or equivalently:

$$\underset{K-H}{F}\left(PD_i\right)_i^{TTC}(t) = 1 \ if\,(j< PD_i^{PIT}(t) * SF(t)=<j+m) \text{ and 0 otherwise} \qquad (5)$$

Overall a scaling factor *SF(t*) of less than 1 will reduce the obligors' PDs and thus it will increase the number of firms in the lowest risk buckets (in which "the best obligors" are placed). A scaling factor greater than 1 will work in the opposite direction. Namely, it will determine higher individual

PDs and thus it will reduce the number of firms in the lowest rating classes and will imply a migration of obligors towards the highest risk buckets.

It is important to note that from a theoretical point of view since the true realized defaults are the PiT ones, the backtesting should be also conducted on PiT PDs without any correction for the business cycle. Once the model has passed the backtesting,[14] the scaling factor correction should have the single task of smoothing the business cycle effects of obligors migrating among classes. The ex post correction allows us to conduct the usual model diagnostics on the PiT model and to make an ex post adjustment of PDs in order to avoid excessive obligor variability across the risk categories in the wake up of mapping, achieving stability improvements[15]

Risk Buckets' length and rating stability

Another possibility to manage procyclicality is to act on risk bucket length.[16] A greater length of risk intervals for example, could determine a higher concentration of obligors only in a few buckets reducing the possibility to differentiate changes in the obligors creditworthiness.

A mapping involving greater risk buckets would determine greater migration of the obligors towards the better risk categories during recessions compared to smaller risk buckets but at the same time wouldn't guarantee the proper granularity of the intervals that is a desirable property of a rating system. An optimal solution would require the selection of robust risk buckets to achieve the desired trade off between stability of obligor migrations over time and accuracy (namely, the possibility to appropriately differentiate obligors' creditworthiness).

One possible way of identifying risk buckets that are robust to cyclical fluctuations is to determine them endogenously to the model by partitioning the estimated PDs through cluster techniques (See Foglia et al, 2001 and Valles, 2006). This method has advantages and disadvantages; on the one hand it allows us to estimate risk buckets consistent with the pool of obligors under examination, but on the other hand it does not allow us to make a comparison with the ratings evaluated on the basis of different obligor pools.

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[14] In this context the backtesting is meant as a procedure used to validate the results of the rating model in terms of pooled PDs. It operates through a comparison of the average PD in each rating grade with the true realized default rate.

[15] The correction of a PiT PD estimate can be made using a scaling factor to correct the cyclical factors in line with the production of a TtC approach. Such a constant can be considered as a kind of weight able to rescale the estimated PD at obligor level.

[16] A greater length of intervals will determine a lower probability of obligors' migration among risk buckets over time.

5) Empirical results

In what follows I analyze the impact of PD smoothing and the rating scale definition on the rating stability of non-financial firms' portfolios (and thus on the mitigation of procyclicality). To this purpose, I assess the effects of the two methodologies in terms of obligors' migrations among risk classes.

5.1 Effects of PD smoothing on rating stability

The removal of the cyclical component of the PD to detect its long run behavior can be done by using the time series techniques usually applied for detrending purposes (moving averages, HP filters, unobserved component models, polynomial detrending ect.). In this paper, given the yearly frequency of the data and the short sample length (7 years), I apply the simple mean of default rates (DR_MEAN) over the period.[17] The ratio between the DR_MEAN and the current default rate (DR) represents the "so-called" scaling factor (SF_MEAN). To perform a sensitivity analysis, I also compare the results of SF_MEAN application to obligors' PDs with those of SF_MAX obtained considering the ration between the maximum default rate of the sample (DR_MAX) and the current default rate.[18] Using these two long run default views, we can built two countercyclical scaling factors. Obviously, the scaling factor based on the maximum default rate as long run component[19] will give more conservative results in terms of backtesting by construction with respect to the scaling factor based on the average default rate.

To give an intuition of the differences in applying the two hypothesis of long run defaults. Graph 1 reports a comparison between the annual default rates (blue line) and the two default rates long run components used to built the scaling factors: DR_MEAN (green line) and DR _MAX (red line).

Looking at the dynamics of the current default rate over years, we notice an increase in the default rate in 2009, corresponding to the deep recession following the global financial crisis, when it reached its maximum value (DR_MAX). The average default rate (DR_MEAN) roughly corresponds to defaults experimented in 2006 and in part in 2011.

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[17] The choice of smoothing based on the average of yearly data gives more consistency to the analysis since I consider the same data frequency that I use in the paper for the model estimates. In banking practice another possibility would be to use quarterly default rates from the Central Credit Register and to estimate the scaling factors on the basis of higher data frequency (i.e. use of last quarter scaling factor for a given year) however the results are fairly similar.

[18] The maximum default rate over the period can be interpreted as the long run default rate component. This hypothesis can be considered analogous to the Wharton school method for estimating the degree of plant utilization which takes the maximum value of the capacity utilization in a sample as its long run component.

[19] The scaling factor is built considering the maximum peak over the period (in this case 2009) as long run default rate.

Graph 1 Comparison between current (DR), average (DR_MEAN) and maximum(DR_MAX) default rate.

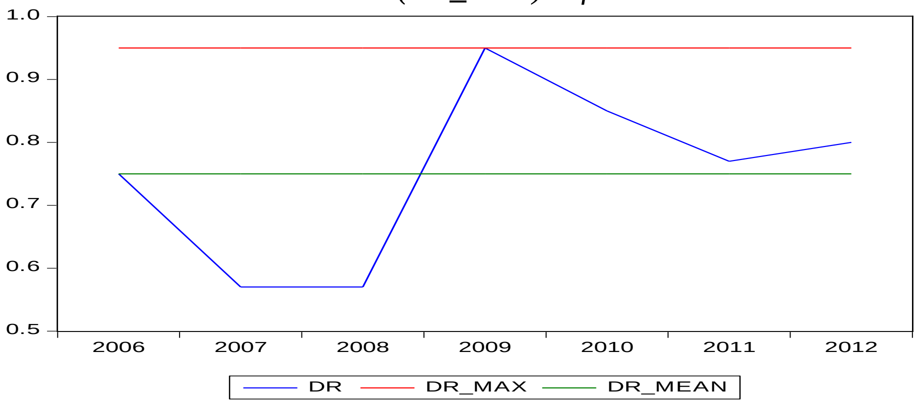


Table 4 reports the scaling factor when the long run default rate is obtained by using: the average DR (SF_MEAN) and the maximum DR corresponding to a Bottom (most extreme) hypothesis (SF_MAX). In order to ensure consistency of scaling factors I calculated them from the static pool used to estimate the model, namely the true portfolio default.

Table 4 Scaling factors based on the ratios between DR_MEAN (or DR_MAX) and current DR

YEAR	*SF_MEAN*	*SF_MAX*
2006	1.000	1.267
2007	1.322	1.674
2008	1.318	1.669
2009	0.791	1.000
2010	0.887	1.123
2011	0.974	1.233
2012	0.937	1.187

Looking at SF_MEAN we can see that while before 2009 the values are greater than 1, starting from 2009 the values became less than 1, this produce an individual PD increase (at least in the first risk bucket) before 2009 and a PD reduction after this date.

A preliminary evaluation of the scaling factors' effects on the PD microdata, can be obtained by comparing the distribution of firms among risk buckets before and after their application with respect to a given year. In fact, even if the total number of defaulted obligors by year (considering both the TtC and the PiT approaches) does not change, the distribution of obligors' default rates among the rating grades (risk buckets) will change.

In order to evaluate the effects of applying scaling factors to obligors' migration among risk buckets Tables 4,5,6,7,8,9 and 10 in the appendix report the backtesting for the years 2006-2012. Each table compares the results produced by PiT PDs, and TtC PDs obtained applying the scaling factor based on the average default rate (SF_MEAN), and a TtC PD obtained applying a scaling factor based on the maximum default rate of the period (SF_MAX).

The mapping is achieved by assigning the individual PDs to each risk class according to a fixed grading scale used within ECAF system. This scale is given by the following probability intervals: (0; 0.03) (0.03; 0.1) (0.1; 0.4). An average PD given by the ratio between the number of defaulted firms and the number of firms in this class is then assigned to the obligors in the same grading class.

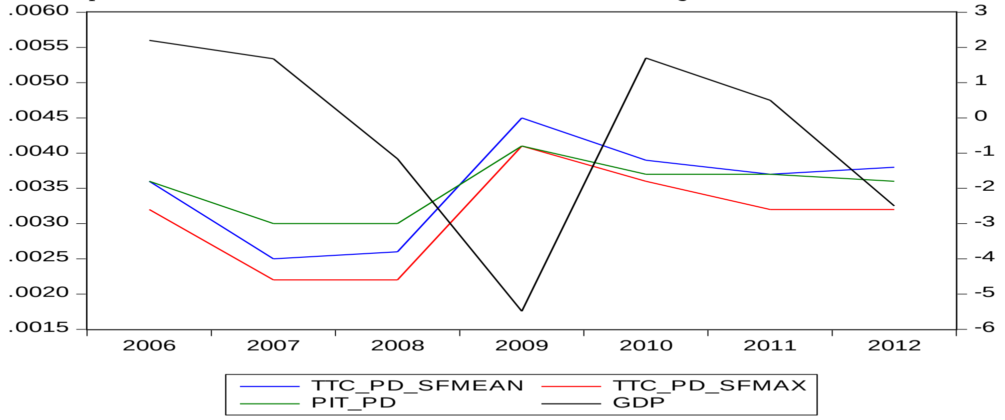
Observing the results concerning the PiT PDs in the sample 2006-2012 we can see that the average default probability for each rating bucket increases during recessions and decreases during expansionary periods showing a procyclical effect of the PiT rating system. In particular the number of obligors being classified in the highest risk bucket (0.1- 0.4) rises from 103 in 2008 to 585 in 2009 (the year corresponding to the maximum peak of the crisis).

Looking at the smoothing corrections, as expected, results concerning 2009 (year of maximum negative GDP growth) show a migration of obligors in the lowest risk classes when a TtC PD scaling factor (SF_MEAN) is considered. The results concerning 2010, 2011 and 2012 obtained by applying a scaling factor mean (SF_MEAN) greater than 1 also move in the expected direction. The number of firms in the lowest risk buckets declines significantly producing TtC PDs.

As expected the scaling factor corresponding to the bottom hypothesis (SF_MAX) determines a shifting of obligors into the worst risk categories greater than is the case for the average scaling factor of all the years considered. Comparing the backtesting results for the two three-year periods 2006, 2007, 2008 and 2010, 2011, 2012 we note a decrease in the number of obligor defaults in the first risk bucket when shifting from PiT to TtC ratings with a bottom hypothesis of scaling factor (SF_MAX).

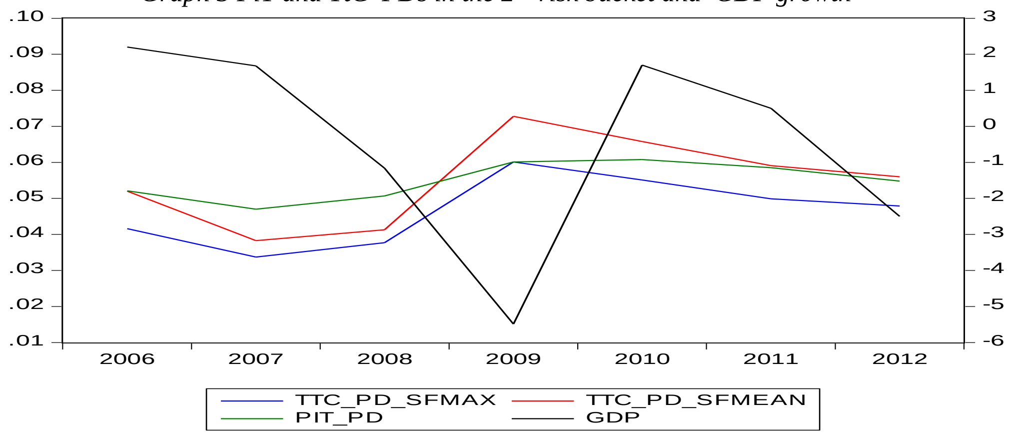
To give a more immediate view of the PD rescaling effects, Graphs 2 and 3 display the variation of PiT PDs and, TtC PDs obtained with SF_MEAN and SF_MAX over the years together with the yearly growth rate of GDP in the first and second risk buckets respectively.

*Graph 2 PiT and TtC PDs in the 1st risk bucket and GDP growth **



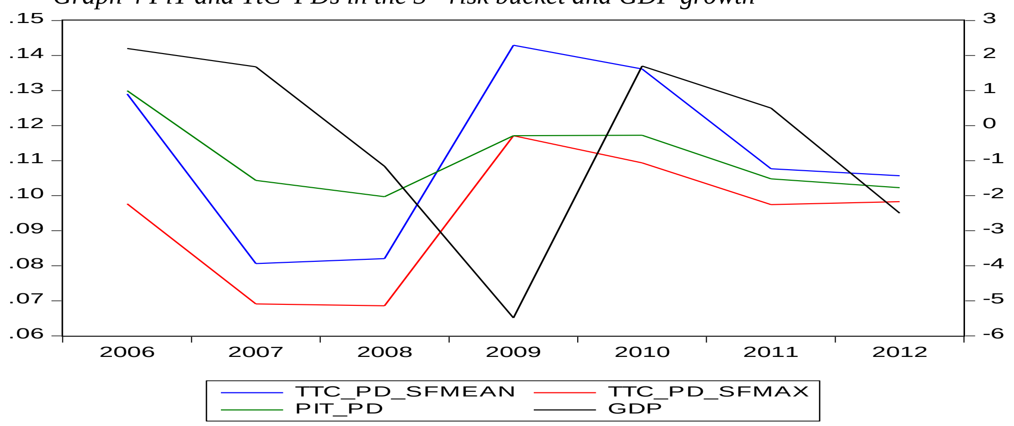
*PiT_PD: Point in Time PD,
TtC_PD_SFmean: PD Through the cycle obtained with the application of scaling factor mean.
TtC_PD_SFmax:PD Through the cycle obtained with the application of scaling factor max.
Left scale Probability of default; Right scale GDP.

*Graph 3 PiT and TtC PDs in the 2nd risk bucket and GDP growth **



*PiT_PD: Point in Time PD.
TtC_PD_SFmean: PD Through the cycle obtained with the application of scaling factor mean.
TtC_PD_SFmax: PD Through the cycle obtained with the application of scaling factor max.
Left scale Probability of default; Right scale: GDP.

*Graph 4 PiT and TtC PDs in the 3rd risk bucket and GDP growth**



*PiT_PD: Point in Time PD.
TtC_PD_SFmean: PD Through the cycle obtained with the application of scaling factor mean.
TtC_PD_SFmax:PD Through the cycle obtained with the application of scaling factor max.
Left scale Probability of default; Right scale: GDP.

Overall, the results show a significant sensitivity of obligors' migrations among risk buckets over time. The findings also indicate that the use of TtC PDs free from business cycle movements (the so-called stressed scenario) produces significant smoothing in terms of firms allocations among risk classes over time and contributes to reducing business cycle effects on obligors' ratings.

Looking at the PDs in 2009 we find an increase in the average PD obtained using the SF_MEAN. in both first and second risk buckets. However looking at the number of defaulted firms (Table 8) we can note that the obligors in the first and second risk buckets increase from 972 to 1097 and from 891 to 1068. This evidence confirms an improvement in the obligors classification when PDs are smoothed with respect to the PiT mapping. This is important because PD smoothing contributes to reducing the overall procyclicality of the rating system, the credit cycle and, in the last analysis, it can enhance the financial system stability.

5.2 Effects of rating scale definition on rating stability

The granularity of the rating scale[20] plays a very important role in achieving rating accuracy and stability[21]. A rating scale that is too granular would produce a good classification of obligors but also a very high variability of obligor' classification over time, thus reducing the rating system stability.

To assess the effect of the rating scale adopted on rating stability I consider two different grading scale definitions. The first one is based on fixed thresholds external to the model (0.0 - 0.03) (0.03 - 0.1) and (0.1 - 0.4), the second is based on a cluster k-means algorithm that considers the Euclidean distance criterion between observations. The k-means algorithm is a non-hierarchical method that groups all the obligors' PDs into a predetermined number of clusters on the basis of their similarity to a given measure (i.e. distance, correlation). The observations in the same cluster, being more similar, are expected to have a minimum "within" variance. Concerning the choice of the criterion for measuring the distance between observations, I have found two approaches using cluster techniques for identifying robust risk buckets: Foglia et al (2001) and Valles (2006). The first paper uses the Euclidean distance criterion while the second paper uses a distance criterion based on a chi square minimization.[22]

[20] Granularity refers to the number of risk classes considered in a grading scale.
[21] See Foglia et al, 2001 for a comparison of the effects of different grading scales on IRB systems.
[22] I do not have any a priori on the distance criterion, so in the paper I have chosen the Euclidean distance between observations because it is simple and intuitive. However this aspect does not represent the focus of the paper.

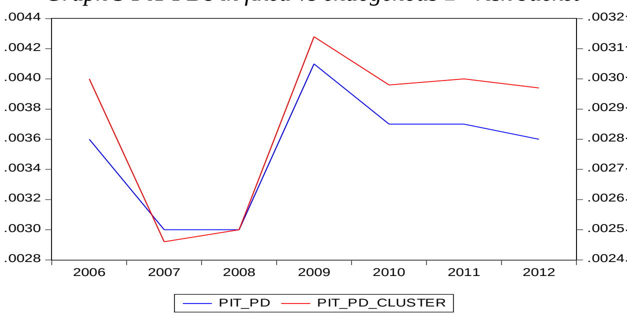
It is important to notice that the cluster k-means algorithm, is based on obligors' PDs information over the whole sample 2006-2012, and thus should produce thresholds buckets that, to a certain extent, are robust to obligor fluctuations.

After setting the number of clusters at three[23], I carried out the k-means algorithm on the estimated PDs. The grading scale defined by the cluster algorithm identifies the following risk bucket thresholds: (0 - 0.0213) (0.0213 -0.0741) (0.0741 -0.257).

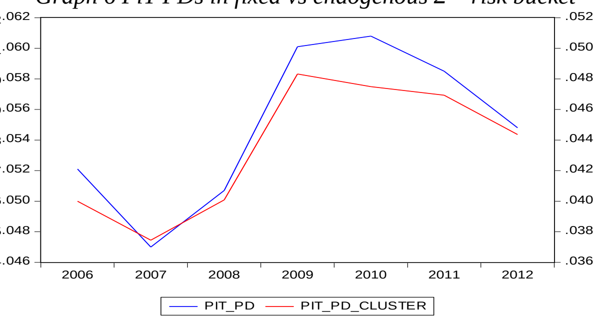
The mapping algorithm described in (2) and (3) was then applied in order to determine the distribution of obligors among the new risk buckets. Tables 12-18 in the Appendix report the distribution of the obligor' PiT PDs among the new risk buckets selected with the cluster analysis.

To analyze the effects of "robust" bucket detection in terms of stability graphs 5 and 6 compare the distribution of PiT default rates in the first and second risk buckets based on fixed thresholds with Point in Time PD distribution (PiT_PD) among first and second "endogenous risk buckets thresolds" obtained with the cluster analysis (PIT_PD_CLUSTER).

*Graph 5 PiT PDs in fixed vs endogenous 1st risk bucket**



*Graph 6 PiT PDs in fixed vs endogenous 2nd risk bucket**



*PiT_PD: Point in Time PD,
PiT_PD_CLUSTER: Point in Time PD included into risk buckets obtained with cluster analysis.
Left scale:Point in Time PD; Right scale: PiT_PD_CLUSTER

The results show that the application of the previous scaling factors to a more granular grading scale[24] produces, including in this case, a significant smoothing of obligor migrations among risk buckets.

Looking at the graphs we can see that the distribution of obligors over time both in the first and second buckets displays lower variability in the case of PDs mapped into robust risk buckets.

A further possibility of managing procyclicality in a rating system is to consider a "hybrid TtC system" that acts both on PD smoothing and on risk buckets length (see Table 12-18 Columns 4-9).

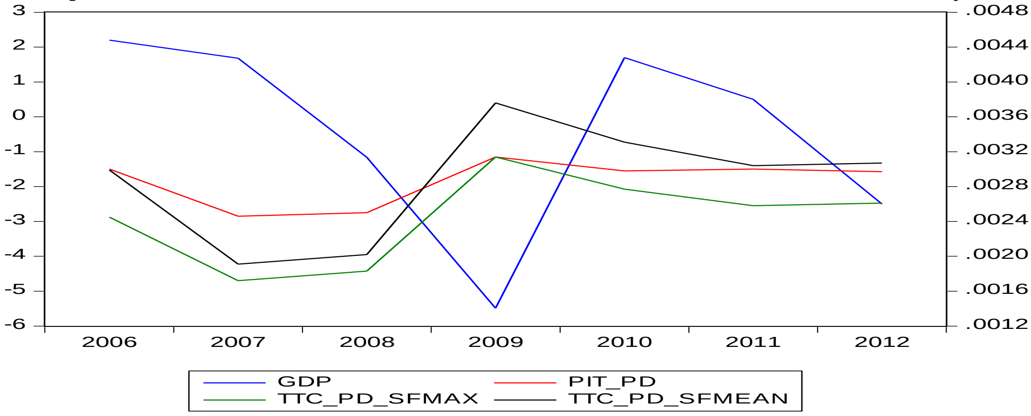
To assess the impact on rating stability of this last TtC rating approach, Graphs 7 and 8 show the

[23] The number of clusters was chosen in order to compare the results with the number of fixed rating grades. Even if the risk buckets that I consider are the same the rating space obtained with the cluster analysis is more granular because the PDs intervals are shorter.

[24] The overall interval length considered in the cluster rating scale spans from (0 - 0.257) rather than (0-0.4).

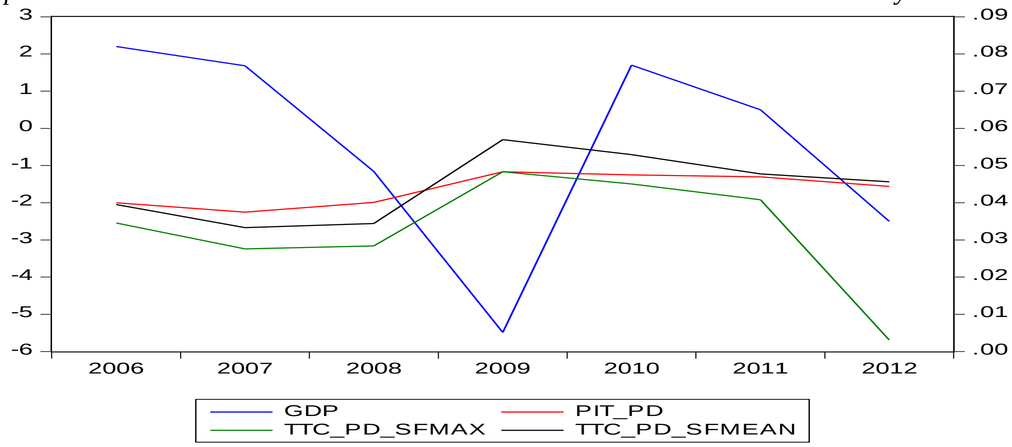
effects of the application of the original scaling factors to the PiT PDs mapped in the "robust" risk buckets obtained through cluster analysis. Graph 7 displays the dynamics into the first risk bucket while graph 8 reports the dynamics of PDs into the second risk bucket.

Graph 7 PiT and TtC PDs in the 1st risk bucket thresholds obtained with Cluster Analysis



*PiT_PD: Point in Time PD,
TtC_PD_SFmean: PD Through the cycle obtained with the application of scaling factor mean.
TtC_PD_SFmax:PD Through the cycle obtained with the application of scaling factor max.
Left scale: GDP; Right scale: Probability of default.

Graph 8 PiT and TtC PDs in the 2nd risk bucket thresholds obtained with Cluster Analysis



*PiT_PD: Point in Time PD,
TtC_PD_SFmean: PD Through the cycle obtained with the application of scaling factor mean.
TtC_PD_SFmax:PD Through the cycle obtained with the application of scaling factor max.
Left scale: GDP; Right scale: Probability of default.

The results show that even in this case the smoothing improves of the obligors' classifications, placing them in the lowest buckets - a more marked effect compared with using fixed rating scales. In 2009 the number of firms classified into the first risk bucket increases from 725 to 886.

To give a more straightforward description of a rating system stability over the cycle, Table 19 in the Appendix reports the percentage variation of the initial cohorts of obligors under a PiT rating before and after the application of scaling factors for both fixed and endogenous risk buckets.

The results show that the number of obligors migrating to the highest risk class decreases sharply during the 2009 recession when using a scaling factor mean. The result holds considering both fixed and endogenous risk buckets. The results also indicate that the smoothing produces a more equal distribution of firms among risk grades when endogenous risk buckets are considered.

Overall, the results indicate that both ex post PD smoothing and a robust risk buckets detection can reduce the procyclicality of the ratings and thus improve their stability over time. Both the techniques analyzed represent a useful tool for central bankers dealing with collateral eligibility issues and macro-prudential regulation as well as for risk managers in private banks. Both methods used to reduce procyclicality into the rating systems present advantages and shortcomings. For example the PD smoothing let the PDs to be less procyclical but at the same time reduces the predictive power of the model. Analogously, the use of endogenous risk buckets would allow to obtain a more suitable classification of obligors within a given bank's portfolio, but does not allow us to compare an obligor' PD distribution with that one of another financial institution because the mapping would be based on a different rating scale. The sensitivity of obligors migration into the transition matrix to the smoothing parameters (i.e. scaling factors and risk buckets length) also leads to considerations about the optimal choice of the degree of smoothing and the granularity of the scale used. In practice the level of PD smoothing and rating granularity should be chosen following criteria based on the desired level of the eligible collateral or the a desired risk target.

Conclusions

A PiT rating system used to evaluate obligors' default probability contains several mechanisms potentially able to exacerbate financial system procyclicality. After analysing the main shortcomings of a PiT rating system, I discuss possible improvements lines. Among the various solutions, I explore both the effects of ex post corrections of PiT PDs on the allocation of obligors to the different risk buckets and the adoption of various rating scale definitions.

The empirical results show that a PiT system without any mechanism to correct for procyclicality produces an allocation of obligors to the risk buckets that is at least to a certain extent affected by the business cycle.

The findings also show that, an ex post correction of PiT probability default based on countercyclical scaling factors taking into account of the long run dynamics of firms' defaults allows us to obtain a PD at firm level that is more in line with a TtC rating perspective. Since from a theoretical point of view the validation of a rating system should operate on PiT PDs (the predicted default rates are PiT), the use of an ex post smoothing of the estimated PDs represents a way to make a TtC mechanism operational without losing the possibility of conducting the usual diagnostics on a PiT model.

The impact of an ex post correction obtained using scaling factors and evaluated in terms of firms' migrations among risk buckets, indicates that the number of firms migrating in the lowest classes is lower during expansions and higher during recessions. Overall, the results show that ex post smoothing can reduce the stability problems linked to PiT rating systems. However, given the different degree of variability in firms' migration among risk buckets after the scaling factor correction, the choice of optimal smoothing procedure is still open.

To assess the effects of adopting a particular rating scale on rating stability I also considered two different grading scales. The first one is based on fixed thresholds external to the model, the second detects the rating bucket thresholds through a cluster analysis. With this second approach the rating bucket thresholds are detected endogenously to the model using cluster techniques.

Overall, the results show that a procyclical rating policy can be mitigated both by performing ex post smoothing and by using robust risk bucket thresholds. These findings have important implications both for banking supervision purposes (evaluating the amount of eligible collateral available in the banking sector, prudential regulation, deposits management) and for the stability of the financial system.

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Appendix1

Proposition 1 *Assume a fixed rating space S= (R_1,R_2, …. R_{k-h},…,R_{k-1}, R_k) with probability intervals (j; j+m) defining each risk bucket R_{k-h}, then the probability of migration from bucket R_{k-h} to bucket R_{k-l} of obligor j in switching from an expansion (recession) to a recession (expansion) will be higher (lower) for PiT PDs than for TtC PDs.*

The intuition for the above result follows from the fact that at firm level the PiT PD displays higher variability over time w.r.t. a smoothed TtC PD by definition. Under a recession, this fact determines an increase of the PD over time that is greater than under a TtC rating. This will cause more firms to migrate to the highest risk buckets (i.e. the worst obligors) during a recession and to the lowest risk buckets (i.e. the best obligors) during an economic expansion because it will be more common to have an estimated PD in t that moves from risk bucket t (i.e. during an expansion) to t+1 (i.e. during a recession).

CASE OF RECESSION in t+1

Proof:

Without loss of generality assume a mapping algorithm that considers a rating space S with only two risk buckets R1 (0, j) and R2 (j,1) with 0<j<1. Assume a PiT rating system. The corresponding transition matrix of the obligors from t to t+1 will be:

Transition matrix under a PiT rating system

	t+1		
t	R1 (0,j)	R2 (j,1)	
R1 (0, j)	N_1^1	N_1^2	*N1(t)*
R2 (j,1)	N_2^1	N_2^2	*N2(t)*
	N1(t+1)	*N2(t+1)*	*N(t)= N(t+1)*

Let the frequency of migration from bucket R1 to R2 under a PiT rating system be:

$$f_i^{PIT}(t) = N_1^2 / N_1(t)$$

where $f_i^{PIT}(t)$ is the marginal transition frequency from rating 1 to rating 2 in 1 period. N_1^2 is the number of firms that move from R1 to R2 and $N_1(t)$ is the total number of obligors belonging to rating R1 at the beginnings of the period *(t).* Assume also that *t* is an year of expansion and *t+1* an year of recession.

Now assume a TtC rating system with the same mapping algorithm *M* and the same rating space *S*. The corresponding transition matrix of the obligors from t to t+1 will be:

Transition matrix under a TtC rating system

	t+1		
t	R1 (0,j)	R2 (j,1)	
R1 (0, j)	$N*_1^1$	$N*_1^2$	*N*1(t)*
R2 (j,1)	$N*_2^1$	$N*_2^2$	*N*2(t)*
	*N*1(t+1)*	*N*2(t+1)*	*N*(t)= N(t+1)*

Let the frequency of migration from bucket 1 to 2 under a TtC rating system be:

$$f_i^{TTC}(t) = N*_1^2 / N*_1(t)$$

Since in recession SF>1, *PDTtC<PDPiT* by definition, the number of firms assigned to R1(0,j) under PiT will be <= to those under TtC, thus *N1(t)=>N*1(t).* Since by definition of frequency $N*_1^2 <= N*_1(t)$. In a recession it follows that $f_i^{PIT}(t) >= f_i^{TTC}(t)$.

****

Proposition 2 *Assume a fixed rating space S= (R_1,R_2, …. R_{k-h},…,R_{k-1}, R_k) with probability intervals (j; j+m); assume a more granular rating space S*= (R_1,R_2, …. R_{k^*-h},…,R_{k^*-1}, R_{k^*}) with Rk*>Rk, and (k*-h)< (k-h) for each R, the Probability of migration from bucket k*-h to bucket k*-l of obligor j over time will be higher under S* compared to S for both PiT and TtC PD* rating philosophies.

Intuitively, the above result reflects the fact that shorter risk buckets will display lower probability thresholds and thus the frequency of overpassing such bucket PD from t to t+1 will be higher under *S*.*

CASE OF RECESSION *(PD(t+1)>PD(t))*

Proof: In case of a S rating space the scale the mapping algorithm will be:

- PIT case:

$f_{K-H}\left(PD_i\right)_i^{PIT}(t) = 1$ *if* $(k-h < PD_i^{PIT}(t) =< k-l)$ and 0 otherwise. Under S* we will have:

$$f_{K-H}\left(PD_i\right)_i^{PIT}(t) = 1 \quad if \quad (k^*-h < PD_i^{PIT}(t) =< k^*-l)$$

Since $(k^*-l) < (k-l)$ the PD_{S^*} (t) of obligor i under S* will be <= to PD_S (t) of obligor i under S

- TTC case:

$$f_{K-H}\left(PD_i\right)_i^{TTC}(t) = 1 \; if(\, k^*-h < PD_i^{PIT}(t) * SF(t) =< k^*-l)$$

The condition for moving from bucket *k*-h to bucket k*-l will be* $SF(t) < \dfrac{k^*-h}{PD^{PIT}(t)}$

Since the probability interval $(k^*-l)<(k-l)$ by definition, we will have $SF^*(t) < SF(t)$.

Appendix 2

Fixed rating buckets

Table 5 Backtesting year 2006

2006	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**
0.0 -0.03	191457	697	0.0036	191453	697	0.0036	188478	604	0.0032
0.03- 0.1	12612	657	0.0521	12590	655	0.0520	12966	540	0.0416
0.1 -0.4	1439	187	0.1300	1465	189	0.1290	4064	397	0.0977
>0.4									
Total	**205508**	**1541**	**0.0075**	**205508**	**1541**	**0.0075**	**205508**	**1541**	**0.0075**

Table 6 Backtesting year 2007

2007	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**
0.0 -0.03	210842	625	0.0030	207689	523	0.0025	204322	442	0.0022
0.03- 0.1	11511	541	0.0470	12196	467	0.0383	13789	465	0.0337
0.1 -0.4	968	101	0.1043	3436	277	0.0806	5210	360	0.0691
>0.4									
Total	**223321**	**1267**	**0.0057**	**223321**	**1267**	**0.0057**	**223321**	**1267**	**0.0057**

Table 7 Backtesting year 2008

2008	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**
0.0 -0.03	230871	699	0.0030	227536	583	0.0026	223722	484	0.0022
0.03- 0.1	11497	583	0.0507	12269	507	0.0413	14516	547	0.0377
0.1 -0.4	1033	103	0.0997	3596	295	0.0820	5163	354	0.0686
>0.4									
Total	**243401**	**1385**	**0.0057**	**243401**	**1385**	**0.0057**	**243401**	**1385**	**0.0057**

Table 8 Backtesting year 2009

2009	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**
0.0 -0.03	238135	972	0.0041	241316	1097	0.0045	238135	972	0.0041
0.03- 0.1	14828	891	0.0601	14662	1068	0.0728	14828	891	0.0601
0.1 -0.4	4995	585	0.1171	1980	283	0.1429	4995	585	0.1171
>0.4									
Total	**257961**	**2448**	**0.0095**	**257961**	**2448**	**0.0095**	**257961**	**2448**	**0.0095**

Table 9 Backtesting year 2010

2010	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**
0.0 -0.03	247836	924	0.0037	249346	969	0.0039	245959	875	0.0036
0.03- 0.1	14612	888	0.0608	14371	945	0.0658	15414	849	0.0551
0.1 -0.4	3744	439	0.1173	2475	337	0.1362	4819	527	0.1094
>0.4									
Total	**266193**	**2251**	**0.0085**	**266193**	**2251**	**0.0085**	**266193**	**2251**	**0.0085**

Table 10 Backtesting year 2011

2011	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**
0.0 -0.03	253736	929	0.0037	254093	944	0.0037	250156	806	0.0032
0.03- 0.1	12385	725	0.0585	12276	725	0.0591	14264	712	0.0499
0.1 -0.4	4075	427	0.1048	3827	412	0.1077	5776	563	0.0975
>0.4									
Total	**270201**	**2081**	**0.0077**	**270201**	**2081**	**0.0077**	**270201**	**2081**	**0.0077**

Table 11 Backtesting year 2012

2012	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**-1**	**-2**	**-3**	**-4**	**-5**	**-6**	**-7**	**-8**	**-9**
0.0 -0.03	249799	909	0.0036	250916	956	0.0038	246423	790	0.0032
0.03- 0.1	13678	749	0.0548	12935	725	0.0560	15663	750	0.0479
0.1 -0.4	4781	489	0.1023	4410	466	0.1057	6175	607	0.0983
>0.4									
Total	**268263**	**2147**	**0.008**	**268263**	**2147**	**0.008**	**268263**	**2147**	**0.008**

Cluster rating buckets aggregation (K means algorithm)

Table 12 Backtesting year 2006

2006	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
0.0 - 0.0213	187133	559	0.003	187128	559	0.003	182909	448	0.002
0.0213-0.0741	13572	537	0.040	13571	536	0.040	15953	551	0.035
0.074-0.257	4803	445	0.093	4809	446	0.093	6646	542	0.003
>0.257									
Total	**205508**	**1541**	**0.0075**	**205508**	**1541**	**0.0075**	**205508**	**1541**	**0.0075**

Table 13 Backtesting year 2007

2007	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
0.0 - 0.0213	207048	509	0.002	202395	386	0.002	199171	342	0.002
0.0213-0.0741	12605	472	0.037	15300	510	0.033	16393	452	0.028
0.0741-0.257	3668	286	0.002	5626	371	0.066	7688	463	0.002
>0.257							69	10	0.145
Total	**223321**	**1267**	**0.0057**	**223321**	**1267**	**0.0057**	**223321**	**1267**	**0.0057**

Table 14 Backtesting year 2008

2008	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
0.0 – 0.0213	226792	566	0.002	221698	448	0.002	218379	399	0.002
0.0213-0.0741	12751	511	0.040	16066	553	0.034	17298	491	0.028
0.0741-0.257	3858	308	0.080	5637	384	0.068	7634	487	0.064
>0.257							90	8	0.089
Total	**243401**	**1385**	**0.0057**	**243401**	**1385**	**0.0057**	**243401**	**1385**	**0.0057**

Table 15 Backtesting year 2009

2009	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
0.0 – 0.0213	231192	725	0.003	235925	886	0.004	231191	725	0.003
0.0213-0.0741	19040	920	0.048	16535	942	0.057	19041	920	0.048
0.0741-0.257	7726	803	0.104	5498	620	0.113	7726	803	0.104
>0.257									
Total	**257961**	**2448**	**0.0095**	**257961**	**2448**	**0.0095**	**257961**	**2448**	**0.0095**

Table 16 Backtesting year 2010

2010	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
0.0 – 0.0213	241698	720	0.003	244144	808	0.003	239721	664	0.003
0.0213-0.0741	17731	842	0.047	16852	892	0.053	18717	843	0.045
0.0741-0.257	6763	689	0.102	5196	551	0.106	7742	743	0.096
>0.257							12	1	0.083
Total	**266193**	**2251**	**0.0085**	**266193**	**2251**	**0.0085**	**266193**	**2251**	**0.0085**

Table 17 Backtesting year 2011

2011	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	DR	Companies	Default	DR	Companies	Default	DR
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
0.0 – 0.0213	248201	744	0.003	248563	756	0.003	244438	631	0.003
0.0213-0.0741	15512	728	0.047	15333	732	0.048	17532	715	0.041
0.0741-0.257	6483	609	0.094	6300	593	0.094	8107	716	0.088
>0.257							119	19	0.160
Total	**270201**	**2081**	**0.0077**	**270201**	**2081**	**0.0077**	**270201**	**2081**	**0.0077**

Table 18 Backtesting year 2012

2012	PiT PD			SF_mean_PD_correction			SF_max_PD correction		
Range of PD	Companies	Default	**DR**	Companies	Default	DR	Companies	Default	DR
Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
0.0 -0.0213	244135	724	0.003	245059	752	0.003	240990	629	0.003
0.0213-0.0741	16929	751	0.044	16470	751	0.046	18223	718	0.039
0.0741-0.257	7197	672	0.003	6732	644	0.003	8893	778	0.003
>0.257							155	22	0.142
Total	**268263**	**2147**	**0.0080**	**268263**	**2147**	**0.008**	**268263**	**2147**	**0.0080**

Table 19 Percentage of obligors among risk buckets after the scaling factor smoothing both in fixed and endogenous risk buckets

		Fixed risk buckets			**Endogenous risk buckets**		
		% obligors	**Sf_mean**	**SF_max**	**% obligors**	**Sf_mean**	**SF_max**
2006	1RB	100	100.00	98.44	100	99.99	97.74
	2RB	100	99.83	102.81	100	99.99	117.54
	3RB	100	101.81	282.42	100	100.12	138.37
2007	1RB	100	98.50	96.91	100	97.75	96.20
	2RB	100	105.95	119.79	100	121.38	130.05
	3RB	100	354.96	538.22	100	153.38	209.60
2008	1RB	100	98.56	96.90	100	97.75	96.29
	2RB	100	106.71	126.26	100	125.99	135.66
	3RB	100	348.11	499.81	100	146.12	197.87
2009	1RB	100	101.34	100.00	100	102.05	100.00
	2RB	100	98.88	100.00	100	86.84	100.00
	3RB	100	39.64	100.00	100	71.16	100.00
2010	1RB	100	100.61	99.24	100	101.01	99.18
	2RB	100	98.35	105.49	100	95.04	105.56
	3RB	100	66.11	128.71	100	76.83	114.48
2011	1RB	100	100.14	98.59	100	100.15	98.48
	2RB	100	99.12	115.17	100	98.85	113.02
	3RB	100	93.91	141.74	100	97.18	125.05
2012	1RB	100	100.45	98.65	100	100.38	98.71
	2RB	100	94.57	114.51	100	97.29	107.64
	3RB	100	92.24	129.16	100	93.54	123.57

RB =Risk Bucket

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