“Credit risk management and cyclicality of bank lending to non-financial corporations in Italy during the financial crisis: 2008-2012. A modeling study”

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SECTION 1. Macroeconomic processes and regional economies management

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Credit risk management and cyclicality of bank lending to non-financial corporations in Italy during the financial crisis: 2008-2012. A modeling study

Abstract

Credit to non-financial corporations in Italy is characterized, in the period June 2008-June 2012, by frequent and intense quarterly cyclical fluctuations (peak amplitude €39.2 billion). The amplitude of these fluctuations has been ascribed to the effects of Basel II accords during the financial crisis which, by imposing regulatory capital constraints on banks' lending on the basis of credit risk estimates, induces an excessive credit reduction during economic recession and an excessive credit growth during economic expansion. In order to mitigate these cyclical effects, various techniques of buffering have been advocated. The authors have tested the opposite null hypothesis that the interaction between new credit given and defaults from outstanding loans tends to a steady state. It has been tested a quasi-linear distribution with a Cyclical Sensitivity Parameter (CSP) parameterized on variation of new credit supply in excess or defect of the rate of default of outstanding loans. It is found that, in the period June 2008-June 2012, frequent fluctuations of the total credit used by non-financial corporations are strongly related to the interaction between the default rate of outstanding loans and the growth rate of new credit supply. It's concluded that credit risk management in Italy has been effective in parameterizing credit supply growth to outstanding credit reduction caused by defaulting loans within the Basel II regulatory framework. Basel III prospective point-in-time output buffers based on filtered Credit/GDP ratios and dynamic provisioning proposals should take into account this steady state pattern underlying frequent and intense credit cyclical fluctuations.

Keywords: frequent cyclical fluctuations, credit growth rate, default rate, retrospective forecasting, steady state function, cyclical sensitivity parameter.
JEL Classification: G32.

Background

Credit risk management has become one of the most relevant topics both for financial institutions and for scholars. Credit risk models have evolved from subjective analysis to accounting-based credit-scoring systems and measures of credit risk and risk concentration (Altman and Saunders, 1998) and their effects on capital allocation and shareholders' value in banking assessed (Resti and Sironi, 2012).

The European Commission with the Credit Risk Directives (CRD I, II, III and CCR/CRD IV) and Banking Authorities with Basel Accords on minimum capital requirements and countercyclical buffers (Basel II and III) are still carrying out a long process of formalization of credit risk management methods and guidelines in order to diffuse a culture of common rules at the continental level.

Monitoring, data collecting and analysis of economic and financial cyclicality is coordinated in the EU by Eurostat, with cyclical indicators[1] such as the Business Climate Indicator (BCI), the OECD Composite Leading Indicators (CLI), the Ifo Economic Climate Indicator, the DZ Euroland, the IARC, IESR and E-Coin published quarterly by Eurostatistics.

Eurostat has developed and implemented a set of guidelines for the statistical analysis of cyclical fluctuations (2003) and modern statistical tools (Sigma, 2009) to which we will refer in full[2].

As far as banks' regulatory capital is concerned, cyclicality and the potential effects of capital requirements standards on the flow of credit into the economy have been addressed by the Basel II Committee and Italy's Central Bank (Banca d'Italia)[3]. Banca d'Italia recommended using long-term data horizons to estimate probabilities of default (*PD*)[4], to introduce a downturn loss-given-default (*LGD*) estimate[5] and to introduce expected long-run loss rates (*EL*) in AIRB methods[6]. The Basel II Accord requires own estimates of *PD* and *LGD* to be no less than the long-run default-weighted average loss rate given default calculated based on the average economic loss of all observed defaults within the data source for that type of facility[7]. Coherently, the introduction of point-in-time output buffers based on a Hodrick-Prescott

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[1] Eurostatistics 12/2012, pp. 9-14ю

[2] Eurostat (2003), 3.2.

[3] Banca d'Italia (2006), *Nuove disposizioni di vigilanza prudenziale per le banche – Circolare n. 263 del 27 dicembre 2006.*

[4] See BCBS 2006, sub-sections 472, 502, 503, 504.

[5] See BCBS 2006, sub-section 468.

[6] See BCBS 2006, sub-section 367 and Table 6 page 236.

[7] See BCBS 2006, sub-section 468.

filter of the macroeconomic credit-to-GDP gap[1] to reduce cyclicality during periods of excessive credit growth and promote cyclical dampening during periods of contraction is among the main goals of the ongoing Basel III reform[2].

Specifically Italy is characterized by the enduring effects of the 2007-2009 financial crisis in terms of actual and prospective negative GDP growth (-2.4% in 2012; -0.2% in 2013), growing sovereign Debt (≅ €2,000 billion) and a growing Debt/GDP ratio (≅ 1.25) ratio[3]. In the period June 2008-June 2012 the volume of outstanding loan facilities is characterized by frequent (frequency = 0.5 cycles/year) and intense (peak amplitude: mean = €39.2 billion; s.e. = €2.83 billion) quarterly cyclical fluctuations[4] in the minima to maxima[5] interval around the mean (€915.4 billion; s.e. = €3.59 billion) of the nominal total credit used by non-financial corporations[6] (Figure 1-A – Magnified Box).

The conflicting effects of cyclicality on the tradeoff between stability and timeliness in predicting probabilities of default and recovery rates have been analyzed by Altman, Brady, Sironi and Resti (2005), who observe that banks tend to react to short-term evidence. Regulation should therefore encourage the use of long-term average rates in AIRB systems. In Italy linear long-term predictions due to the frequent cyclical waveform fluctuation are statistically significant ($\hat{y} \cong y$ and $d\hat{y}/dx \cong dy/dx$) only every 8 quarters (4 phases, 2 years).

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Altman and Rijiken (2005) observe that agencies delay the timing of through the cycle rating migration estimates by 0.56 years at the downside and 0.79 years at the upside. This signifies that in Italy, with a phase period of 0.5 years, as we will see, in a period of economic downturn, agency ratings are systematically one phase late through the cycle.

Jarrow et al. (1997) provide a discrete time-homogeneous Markov chain transition matrix for the term structure of credit risk spreads which assumes a time step of one year. In Italy in the period 2008-2012 this time step corresponds to two phases of the cycle (1 year), rendering the assumption of time-homogeneity during such time step not statistically acceptable.

Gordy and Howells (2004) observe that credit risk adjusted portfolio management is based on time-homogeneous Markov transition processes, which are based on *ex-ante* probabilities of default which register all *expected* variation in the rating variables and register all *ex-post* variation as *unexpected*. Frequent cyclicality would systematically alter the ratio between unexpected and expected variation. Repullo et al. (2008, 2009, 2011) observe that higher buffers in expansions are insufficient to prevent a significant contraction in the supply of credit at the arrival of a recession, which in Italy has occurred in the period 2008-2012 every year.

Sironi and Resti (2012) observe that a modification of the current IFRS 39 concept of incurred loss with a principle of fair value and amortized cost could further increase the procyclicality of banks' credit policies. In Italy, 0.5-year phases render misleading through-the-cycle quarterly and half year estimates of fair values.

1. Research questions and methods

In this paper we have asked two research questions:

Q1 – is there a statistically significant linear relationship linking credit output fluctuations to default rates in the period June 2008 – June 2012? We argue that if such variation in credit supply is satisfactorily explained by independent variation in the default rates through the business cycle then cyclicality is satisfactorily explained by the endogenous relationship between credit and default rates, as it should be according to operating Basel II Accords. In other words, if the relationship is linear ($d^2y/dx^2 = 0$) it is not procyclical ($d^2y/dx^2 \neq 0$);

Q2 – given that Q1 linear relationship does exist, can we formulate a null hypothesis regarding the causes of such relationship which can be statistically analyzed and tested? In particular we will test the hypothesis that credit supply variation systematically converges to a steady state, i.e. credit supply is systematically increased or decreased in order to achieve credit steady state at a certain level.

[1] See BCBS 2010a, pages 8-14.

[2] See BCBS 2010a, page 1. Buffering and dynamic provisioning aim at tightening capital regulatory requirements during economic expansion, also with the purpose of limiting inflationary credit growth, and relax capital regulatory requirements during economic downturn in order to mitigate the procyclical effects of credit reduction during recession and credit growth during expansion.

[3] MINEF, Documento di Economia e Finanza 2012, II: Documento di analisi e tendenze di finanza pubblica.

[4] If a period is the duration of 1 cycle, the frequency is the number of cycles per period. The amplitude is the minima and maxima absolute values of the cycle. In our case: period=2 years, then frequency = 1/2 = 0.5 cycles/year. In physical notation, to which we refer in this paper, a cycle has 4 phases: $dy/dx > 0$ $d^2y/dx^2 > 0$, $dy/dx > 0$ $d^2y/dx^2 < 0$, $dy/dx < 0$ $d^2y/dx^2 < 0$, $dy/dx < 0$ $d^2y/dx^2 > 0$, 1 minimum $dy/dx = 0$ $d^2y/dx^2 > 0$ and 1 maximum $dy/dx = 0$ $d^2y/dx^2 < 0$. The phase period is equal to the cycle period/4.

[5] In a discrete distribution a maximum is determined when $y(t) > y(t-1)$ and $y(t) > y(t+1)$, a minimum when $y(t) < y(t-1)$ and $y(t) < y(t+1)$ and a steady state when $y(t) = y(t-1)$ and/or $y(t) = y(t+1)$.

[6] Italy Central Bank, Statistical Bulletin III-2012, Information on Customer and Risk, Default Rates for Loan Facilities and Borrowers, TDB30486: Quarterly default rates for loan facilities – Distribution by Customer Sector of Economic Activity and Total Credit Used: Non-financial Corporations – Reporting Institutions: Banks, Financial Companies and Other Institutions Reporting to the CCR.

We have analyzed Italy's Central Bank Statistical Bulletin's quarterly default rates for loan facilities (credit used) in the period March 1996-June 2012: Information on customer and risk, default rates for loan facilities and borrowers (TDB30486); Quarterly default rates for loan facilities; Distribution by customer sector of economic activity and total credit used: Non-financial corporations; Reporting institutions: Banks, financial companies and other institutions reporting to the Central Credit Registrar.

Coherently, we have defined:

ABD = Adjusted bad debts refer to the total loan exposure of borrowers who, for the first time in the reference quarter, meet one of the total loans outstanding when a borrower is reported to the central credit register: a) as a bad debt by the only bank that disbursed credit; b) as a bad debt by one bank and as having an overshoot by the only other bank exposed; c) as a bad debt by one bank and the amount of the bad debt is at least 70% of its exposure towards the banking system or as having overshoots equal to or more than 10% of its total loans outstanding; d) as a bad debt by at least two banks for amounts equal to or more than 10% of its total loans outstanding;

TCU = the amount of total credit used by all the borrowers covered by the central credit register and not classified as adjusted bad debtors at the end of the previous quarter. The *TCU* does not include the credits that, in the given quarter, have been transferred to institutions not reporting to the central credit register;

d = The default rate of loan facilities in a given quarter is represented by the ratio between the amount of total credit used by borrowers who become adjusted bad debtors (*ABD*) during the quarter in question and the amount of credit used by all the borrowers covered by the central credit register and not classified as adjusted bad debtors at the end of the previous quarter (*TCU*);

L = Loans refer to loans disbursed by banks to non-banks calculated at face value (until September 2008 at book value) gross of adjustment items and net of repayments. The aggregate includes mortgage loans, current account overdrafts, loans secured by pledge of salaries, credit card advances, discounting of annuities, personal loans, leasing (from December 2008 according to the IAS17 definition), factoring, other financial investments (e.g. commercial paper, bill portfolio, pledge loans, loans granted from funds administered for third parties), bad debts and unpaid and protested own bills. The aggregate is net of repurchase agreements and, since December 2008, net of stock exchange repos and gross of correspondent current accounts, performing loans.

We have analyzed data with a modified Bayesian technique called "Retrospective Forecasting" utilized by Shaman and Karspeck (2012a, 2012b) to predict flu epidemics in New York City on the basis of fluctuating outcomes. The technique assumes retrospectively perfect knowledge of future parameters i.e., the posterior parameters and other state variables are reset to an initial distribution before commencing each reiterative forecast form the present into the past (Backward Calculation)[1] which, as we will see, will determine, in our case, the Cyclical Sensitivity Parameter ς (*little sigma*) of the system. Consequently under the hypotheses of the statistical model, we assume that a credit manager at time *t* had perfect information of period *t*, *t+n* default rates and we will test the goodness of fit of the Steady State Function and the sensitivity to cyclicality of credit supply through an estimate of the parameter ς (*little sigma*) with a chi-square test.

We have assumed an LGD = 1; the hypothesis is reasonable in the framework of the analysis since recovery rates affect, at time of recovery, the credit supply to the economy, and such effect will be "seen" in the total credit used and in the credit growth rate.

Under these assumptions, we have defined the variable *f* as:

f = The credit growth rate determined as:

$$f\ ;\ \left[\frac{L_{t+\delta,t+n}}{TCU_{t+\delta}\left(1-d_{t+\delta,t+n}\right)}\right]_{\delta\to n}.$$

The credit growth rate is asymptotically equal to the amount of loan facilities disbursed in period *t*, *t+n* divided by the total credit used at the beginning *t* of the period which will survive (1-*d*) to the end *t+n* of such period. The variable *f* assumes that the credit risk manager possesses perfect information regarding *d* and therefore will not grant new loans or additional loans *L* to borrowers which will default in the same period;

δ = The sliding time parameter *δ* accounts for the fact that the nearer the credit risk manager gets retrospectively to time *t+n*, the more perfect information becomes and thus the retrospective forecast;

ς = the cyclical sensitivity parameter (CSP).

In other words, the CSP is determined through repeated backwards iterations as the parameter that solves the implicit Steady State Function (Equation 1) for *X* = *d* and *Y* = *f* given:

$$\left[\frac{\prod_{t=0}^{T-1}\left(1-d_{t+\delta,t+1}\right)\left(1+f_{t+\delta,t+1}\right)}{\left(1+\varsigma\right)^{T-1}}\right]_{\delta\to n}\ ;\ 1 \qquad (1)$$

[1] See also Backward Calculation in Eurostat (2003); 3.2.

We can now formulate the null hypotheses that:

Q1: $H_0^{Q1}: f = \beta_1 + \beta_2 d + \varepsilon$: the credit supply growth is a dependent variable linked by a linear relationship with the default rate;

Q2: $H_0^{Q2}: \frac{d}{1-d}; (\varsigma = 0)$: the credit supply growth or decline rate is explained by the default rate alone and is not sensitive to exogenous cyclicality. As an alternative, we will test and that the credit supply growth or decline rate is not explained by the default rate alone and is sensitive to exogenous cyclical positive or negative factors.

We have utilized Mathematica 8 and Statistical-Graphical Integration with Mac OS X Datagraph 3.1.

2. Findings

The findings are summarized in Equation 2. In synthesis, we accept the null hypothesis H_0 that the frequent fluctuations of the total credit used by non-financial corporations *TCU* in the period June 2008-June 2012 can be explained satisfactorily with a quasi linear relationship by the independent variable "default rate": $F_X = \{f \mid d\}$ with $\varsigma \approx 0 = 0.0014743$ and a chi-square of 0.4509 (n = 17). In the preceding period March 1996-June 2008, credit has grown in excess of the period default rates at a significant and steady rate of 2.1% ($\varsigma \neq 0 = 0.02068$) with a chi-square of 1.063 ($n = 49$).

Equation 1: Steady State Function (SSF): Distribution of Credit Supply Growth f given the Default Rate d and the Cyclical Sensitivity Parameter ς.

$$F_X(f|d) = \begin{cases} \frac{d + 0.0014743}{1-d} \; if \; [t_{jun08}, t_{mar12}] \\ \frac{d + 0.02068}{1-d} \; if \; [t_{mar96}, t_{jun08}) \end{cases} . \qquad (2)$$

All evidence, discrete distributions and statistical tests have been summarized in Fig. 1, 2 and Table 1.

Figure 1-A. The total credit used by non-financial corporations *TCU* in the period March 1996-June 2012 has been divided into 2 sub-periods. The first period from March 1996 to June 2008 excluded, and the second period from June 2008 included to June 2012. The starting date of the second period has been chosen so as to comprise a total period of 4 years, the period during which the total credit used (mean = €915.4 billion; s.e. = €3.59 billion) reveals 8 phases (n-1 quarters) and 2 cyclical fluctuations (I and II). Real total credit utilizes as basis March 1996 = 100, with a yearly non-adjusted inflation of 2.06% from March 1996 to June 2008 and 1.91% from June 2008 to June 2012.

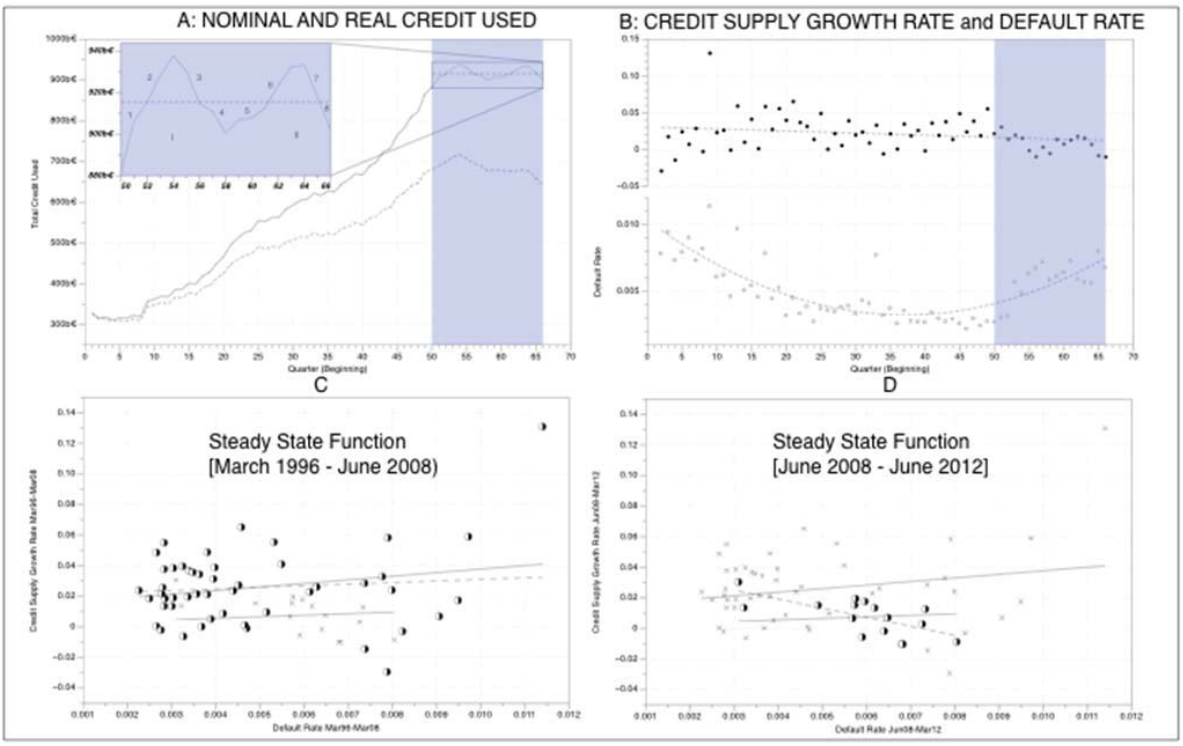
Figure 1-B. We have divided the Credit Supply Growth Rates (f) and the Default Rates (d) of the period March 1996 – June 2012 into 2 sub-periods. The first period from March 1996 to June 2008, and the second period from June 2008 to June 2012. The concave-upward (convex downward) quadratic fit reveals a significant ($R^2 > 0.5$) $R^2 = 0.64628$ for the default rate time series and linear regression a non-significant $R^2 = 0.05019$ for the credit supply time series. From a time series perspective, credit growth appears stable vs. default rates declining and then growing again.

Figure 1-C. Linear regression of credit supply rates as a function of default rates by Ordinary Least Squares (OLS) from March 1996 to June 2008 reveals a $R^2 = 0.0451$ and $\chi^2 = 0.9904$ (Table 1). Null hypotheses H_0 (lower solid line) and H_1 (upper solid line) testing of the observed credit growth rates vs. the expected rates following the SSF reveals a steady state parameter of $\varsigma = 0.02068$ with a $\chi^2 = 1.063$ (Table 1). In synthesis, in the period March 1996-June 2008, credit has grown in excess of the period default rates at a significant and steady rate of 2.1% ($\varsigma \neq 0 = 0.02068$) with a chi-square of 1.063 ($n = 49$).

Figure 1-D. Linear regression of credit supply rates given the default rates by OLS from June 2008 to June 2012 reveals a $R^2 = 0.4367$ and a $\chi^2 = -0.2064$ (Table 1). Null hypothesis H_0 (lower solid line) testing of the observed credit supply rates vs. the expected rates following the SSF reveals a steady state parameter $\varsigma = 0.0014743$with a $\chi^2 = 0.4509$ (Table 1). In synthesis, from June 2008 to June 2012, credit growth rates are linearly negatively correlated to default rates but appear to be significantly fluctuating around the Steady State Function with null cycle sensitivity.

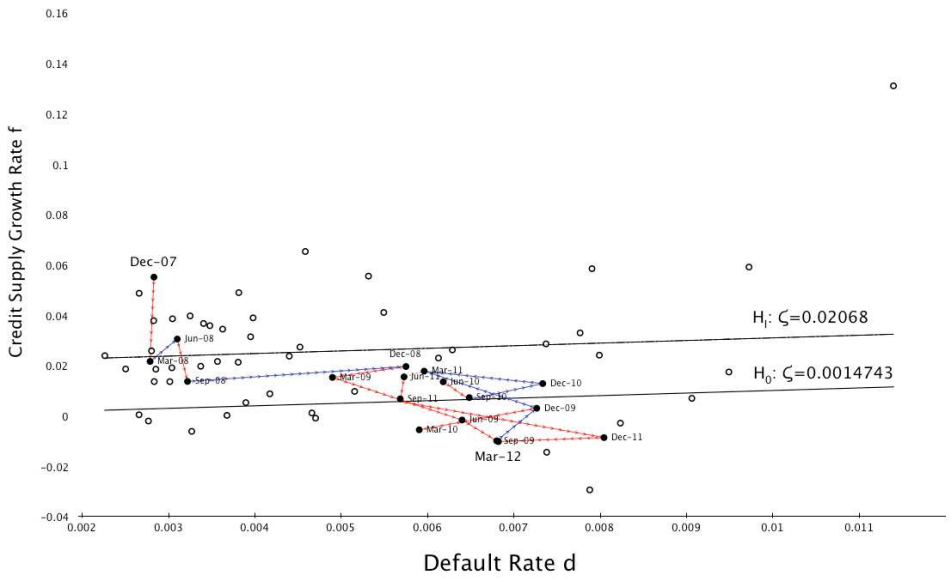
In synthesis, in the two periods, both OLS linear regression and SSF explain significantly the dependency of the credit supply growth rate from the default rate. However, Figure 2 explains the frequent fluctuations of the total credit used by non-financial corporations in the period June 2008-June 2012 in terms of the function $F_X\{f|d\}$ with a Steady State Parameter $\varsigma = 0.0014743$.

The heuristic path of adjustment of credit growth rate in the period June 2008-June 2012 to the Steady State Function $\varsigma = 0.0014743$ has been shown in Figure 2.



Sources: Banca d'Italia TDB30486, ISTAT, Ministero dell'Economia e delle Finanze.
Legenda: A: Solid line – Nominal quarterly (beginning) total credit used; Dotted line – Real quarterly (beginning) total credit used (Base March 1996 = 100); B: Circles: quarterly credit supply rates. Hollows: quarterly default rates – Time series – March 1996-June 2012; C: Quarterly credit supply rates and default rates – OLS (dashed line) and SSF (upper solid line) – March 1996-June 2008; D: Quarterly credit supply rates and default rates – OLS (dashed line) and SSF (lower solid line) – June 2008-June 2012
Statistics: Mathematica 8 and Mac OS X Datagraph 3.1.

Fig. 1. 1-A, 1-B, 1-C, 1-D



Sources: Banca d'Italia TDB30486, ISTAT, Ministero dell'Economia e delle Finanze.
Legenda: Solid line: Steady State Parameter SSE.
Circles: [June 2008 – June 2012].
Hollows: [March 1996 – June 2008).
Arrows Blue: Credit Supply Growth Rate -dy/dt > 0.
Arrows Red: Credit Supply Growth Rate - dy/dt<0.
Statistics: Mac OS X Omnigraph Pro v22.29.

Fig. 2. Credit supply growth rate fluctuations around the exogenous steady state parameter ζ in the period June 2008-June 2012

Table 1. Robustness of ordinary least squares (OLS) linear regression and steady state function (SSF) of P{X=f|d}

	[March 1996 – June 2008)		[June 2008 – March 2012]	
	OLS	SSF	OLS	SSF
N	49	49	17	17
ς		0.02068		0.0014743
Intercept	0.0144		0.0429	
σ Intercept	0.0084		0.0114	
X Intercept	-0.0061		0.0072	
Slope	2.3395		-5.9255	
σ Slope	1.5873		1.8665	
Correlation	0.2124		-0.6608	
R^2	0.0451		0.4367	
σ	0.0245	0.0247	0.0087	0.0125
s for residual	0.0247	0.0249	0.009	0.0129
Chi-squared	0.9904	1.063	-0.2064	0.4509

Sources: Banca d'Italia TDB30486, ISTAT, Ministero dell'Economia e delle Finanze.
Statistics: Mac OS X Datagraph 3.1 and Mathematica 8.0.

3. Interpretation

Credit risk management in Italy is characterized, in the period June 2008-June 2012, by frequent (frequency = 0.5 cycles/year) and intense (peak amplitude: mean = €39.2 billion; s.e. = €2.83 billion) quarterly cyclical fluctuations in the minima to maxima interval around the mean (€915.4 billion; s.e. = €3.59 billion) of the nominal total credit used by non-financial corporations. Such frequent and intense credit output fluctuations are frequently ascribed to exogenous Basel II cyclical effects and, consequently, output-based point-in-time Credit/GDP buffering or dynamic provisioning advocated. We have tested the opposite null hypothesis that such fluctuations in credit growth are entirely explained by a quasi-linear continuous Steady State Function (SSF) of the actual default rates parameterized with a Cyclical Sensitivity Parameter (CSP) of credit supply variation in excess or defect of the rate of defaulting loans. We have found that, in the period June 2008-June 2012, with a CSP of 0.00147 and a chi-square of 0.4509 (n = 17), the frequent fluctuations of the total credit used by non-financial corporations are significantly explained by variation of the independent variable "default rate", with no significant evidence of positive or negative cyclical sensitivity of the credit supplied. We conclude that credit risk management in Italy has been effective in parameterizing credit supply growth to default rates within the Basel II operating framework. Basel III prospective point-in-time output buffers based on filtered Credit/GDP ratios and dynamic provisioning proposals should take into account this steady state statistical pattern underlying frequent and intense credit cyclical fluctuations.

Conclusions

Basel II Accords have introduced regulatory capital requirements for banks based on an assessment of the risk of their credit portfolio. As the 2008 financial crisis began, new hypotheses on some dysfunctional effects of these requirements were generated, among which the hypothesis that Basel II capital ratios induce excessive credit reduction during economic recession and excessive credit growth during economic expansion. This effect seems particularly manifest in Italy where, in the period June 2008-June 2012, credit to non-financial corporations has been characterized by frequent and intense quarterly cyclical fluctuations (peak amplitude €39.2 billion). Among the proposed solutions by the Basel III accords is a mitigation of these cyclical effects with various techniques of buffering. This research proposes an alternative model which attempts to explain past cyclical fluctuations of banks lending to non-financial corporations in Italy during the financial crisis 2008-2012 in terms of variation in the default rate of loans alone. More specifically, we have generated the null hypothesis that the interaction between new credit given to non-financial corporations tends to a steady state by offsetting defaults from previous periods. We have tested a quasi-linear distribution with a Cyclical Sensitivity Parameter (CSP) parameterized on variation of new credit supply in excess or defect of the rate of default of outstanding loans. We have found that, in the period June 2008-June 2012, frequent fluctuations of the total credit used by non-financial corporations are strongly related to the interaction between the default rate of outstanding loans and the growth rate of new credit supply. We conclude that credit risk management in Italy has been effective in parameterizing credit supply growth to outstanding credit reduction caused by defaulting loans within the Basel II regulatory framework. Basel III prospective point-in-time output buffers based on filtered Credit/GDP ratios and dynamic provisioning proposals should take into account this steady state pattern underlying frequent and intense credit cyclical fluctuations.

Limits

As Gordy (2003) observes credit risk is idiosyncratic to the obligor, and what we define as a cycle is really a composite of a multiplicity of cycles tied to location, period and sector. Therefore this model suffers from the same limits as the Credit/GDP cyclical buffers, i.e. a single-factor model cannot capture any clustering of default rates due to heterogeneous sensitivity to smaller-scale components of the macro cycle.

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