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Business Cycle and the Riskiness of Italian Firm: An Empirical Analysis

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Given the importance of the relationship between default rates and business cycles, we examine the ability of macroeconomic variables, explaining changes on the default rate of Italian companies. Via a VAR (vector autoregressive) model and an analysis of individual equations, we find a significant influence of short-term interest rates, and the growth rate of gross domestic product (GDP) in the euro area, on the default rate of Italian companies in the period 1985-2004. Using the selected macroeconomic variables, we build a credit cycle index (CCI) in order to infer the state of credit in the Italian market in future periods. The construction of this "credit cycle index" is based on a robust econometric structure with a minimum number of parameters and a minimum number of required data.

Keywords: credit risk, business cycle, econometrics, endogenous, estimation, ordinary least squares (OLS)

Introduction

What most influences the performance of a credit portfolio is the systematic risk (Jarrow, Lando, & Yu, 2000; Frey & McNeil, 2002; Lucas, Klaassen, Spreij, & Straetmens, 2001; Giesecke, 2003). In a loan portfolio, the level of risk is primarily represented through the credit cycle, which in turn is characterized by deterioration or improvement.

Despite this, the most popular portfolio models such as those of CreditMetrics (Gupton, Finger, & Bhatia, 1997) and CreditRisk (Credit Suisse, 1997) did not take into account the cycle and its effects on risk. An exception is the CreditPortafolioView (Wilson, 1997a, 1997b) model, which attempted to assess the relationship between the conduct of business failures and the macroeconomic indicators of the economic cycle. In fact, systematic credit risk factors are usually associated with macro-economic conditions. Empirical studies revealed that long-term trends of the average default rates of large company groups highly diversified between each other, relative to a given country are highly volatile and have cyclical factors.

It was recognized, indeed, that environmental factors may cause a correlation between the actual default rates of a set of companies (e.g., Asamow & Edwards, 1995; Wilson, 1997a, 1997b). This is evident both from theoretical models (Williamson, 1987; Kiyotaki & Moore, 1997; Bernanke, Gertler, & Gilchrist, 1999; Kwark, 2002) on the real business cycle, either by empirical evidence (Nickell, Perraudin, & Varotto, 2000; Bangia, Diebold, Kronimus, Schagen, & Schuermann, 2002; Kavvathas, 2001; Marcucci & Quagliarello, 2005).

The general conclusion of these models is that the probability of default tends to be higher in times of

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economic downturn. Hence, there is a general acceptance that the state of the economy of a country has a direct impact on the observed rate of insolvency.

In this work, we analyze the relationship between the default rate and the macroeconomic variable, examining how macroeconomic variables affect the movements in the default rates of Italian companies. Via a VAR model and an analysis of individual equations, we find a significant influence of short-term interest rates, and the growth rate of the GDP in the euro area on the default rate of Italian companies in period 1985 to 2004. Using the selected macroeconomic variables, we build a credit cycle index (CCI) in order to infer the state of credit in the Italian market in future periods. The paper is organized as follows.

In the second section, the difficulty of good correlation estimation between macroeconomic variables and default rates is explained. In the third section, a literature review of this item is made. In the fourth section, the data used for this work are presented. The empirical model and the results are presented in section five. The results are backtested in the sixth section. And the last section is the conclusions of the paper.

The Difficulty of a Good Correlation Estimation

The results obtained from the estimated correlation between macroeconomic variables and default rates are valid only if the statistical time series of default rates of loans are sufficiently long and sufficiently numerous groups. This, unfortunately, is not frequently found in banks.

One of the solutions which can be proposed is to perform an analysis of the correlations not on the bank’s internal data, but on very large databases, such as loans and credits of the whole system. Then, once we get the matrix of variances and covariance, apply this to the bank’s portfolio to assess the riskiness[1].

The series that are available to banks are limited, partly because the nature of non-short-term credit risks prevent daily or monthly observations, being having considered to lengthen the horizon of historical analysis necessarily includes distortions due to structural modifications of long-term economies of production and consumption. Instead, the analysis of correlations needs a high abundance of data to distinguish “structural correlations”, related to strong phenomena, from the “temporary correlations”, valid only at certain periods so, in addition to the problem of being able to estimate the correlation between the losses of loans, it is important to be able to validate the hypothesis that the correlation between loans tends to remain stable over time.

The identification of macroeconomic variables that produce significant volatility in default rates to the economic cycle is important, because it can be used to condition the expected default rates and the matrix migration to the state of the economy. Then, macroeconomic variables can be inserted in forecasting internal rating systems.

Literature Review

The main question facing Nickell et al. (2000)[2] in their work is: given that the transition probabilities of the ratings vary for different borrowers at different times of the economic cycle, what are the causes of these variations?

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[1] A bank according to Basel II, in fact, may use both internal data and external data, but the population of exposures represented in the data, should be the same or at least be comparable with that of the actual exposure of the bank; the bank must also demonstrate that the economic and market conditions that underlie the data are consistent with the current situation and perspective.

[2] Helwege and Klieman (1996); McDonald and Van de Gucht (1999). The results of these two studies have benn confirmed and extended by Nickell et al. (2000).

The issue is faced calculating the non-conditional matrix and the conditional matrix of transition ratings in a standardized manner, and through a model “probit” logical in which the transitions are driven by realizations of a latent variable that incorporates a series of “dummies” by types of borrowers and the status of the business cycle.

The approach taken by Nickell et al. (2000) is to estimate the parameters by taking the entire universe of events of migration as a single sample, and considering the variables sector/area/state of the business cycle as dummy variables (the business cycle is considered by simply dividing the year into “favorable”, “normal” and “unfavorable”)[3]. The conclusions of this study confirmed what has previously been assumed. In fact, the authors found that the frequency of downgrade and default of counterparties to counterparts assigned to rating classes with a high risk increases in the early stages of economic downturn, it is less predictable and more contradictory than a second result obtained from their model, namely, for counterparts with better rating the impact of negative phases of the cycle seems to increase not only the probability of “downgrade” but also “upgrade”, thus affecting the volatility more than the direction of the rating process migration.

Bikker and Metzemakers (2005), using a panel of 26 Organization for Economic Co-operation and Development [OECD] countries over the period 1979-1999, found that the activity of the bank loan is highly dependent on the demand for money measured by cyclic variables, such as the rate of real growth, inflation, unemployment and real supply money.

Hackbarth, Miao, and Morellec (2006) developed a framework for analyzing the impact of macroeconomic conditions on credit risk and the choice of the dynamic structure of capital chosen by the company, demonstrating that this simple observation has a wide range of implications for business.

Closer to the Italian case we work on: Marotta, Pederzoli, and Torricelli (2005), applying a model developed by Pederzoli and Torricelli using the default data of Italian firms provided by the Bank of Italy.

The basic idea of the model is to use a measure of risk that grows just before a recession on the credit horizon, and vice versa decreases just before a period of expansion. The purpose of the proposed model is to include a forecast of the economic cycle in the measures of credit risk.

Other empirical studies incorporate macroeconomic variables in forecasting models of credit risk, such as the models proposed by H. Platt and M. Platt (1991) that attempted to isolate the dynamics of sectorial indices through the use of the “relative” value calculated by relating the obtained value by the company and that observed by the sector of membership.

Lennox (1999) used macroeconomic variables to improve the performance of the models of credit risk. The results look encouraging, both in terms of efficiency rating, and for the possibility of estimating the effect of a macroeconomic shock on the probability of company default.

A work of considerable importance for the analysis carried out here, and which draws on the empirical analysis, is that done by Zazzara and Rotondi (2005a). In their work, the ability of macroeconomic variables to explain the default rates of firms in the Italian banking market is examined. Via a VAR and analysis of individual equations, they found significant influences interest rates in the short term, the difference between potential GDP and real GDP (output gap), the real value of assets, and inflation on the default rate of Italian firms over the period 1990-2004. Using these macro variables, they built a “Credit Cycle Index” in order to infer the state of credit in the Italian market in future periods.

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[3] Dummy variables for the four locations considered: U.S., UK, Japan, and Europe (including England), dummy variables for 10 industry categories, dummy variables for the current state of the economy and that which is expected (one year). See Nickell et al. (2000), p. 216.

Data Sample[4]

The data available for the preliminary univariate and multivariate analysis, in order to find the most important macroeconomic variables are yearly. We take 1985 as the starting year for our estimation period, since for the series of default rates are not available prior data. The default rate series cover all Italian companies. The default rates are a moving average, centered at three years. This allows an easier processing of such data.

Starting from a sample of 12 series of macroeconomic variables, we arrive at the selection of the most significant ones for our analysis.

The variables are:

(1) Public demand (public administration expenditure in real terms): DPA.

(2) Taxes paid by enterprises (share to GDP): TPE.

(3) Taxes paid by households (share to GDP): TPH.

(4) Social security contributions (share of GDP): SC.

(5) Wages and salaries per capita industry: WpC.

(6) Brent crude oil prices: PBC.

(7) Price index for non-energy commodities (USD currency): PNC.

(8) Change $/€: CH.

(9) US GDP: USGDP.

(10) Euro GDP: EGDP.

(11) GDP in developing countries (developing countries): DCGDP.

(12) Three-month interest rate: IR3.

Univariate analysis was based on the verification of the stationarity of data via the ADF (Augmented Dickey-Fuller) test on the levels, log-levels, first differences and second differences, and if shocks are permanent or stationary.

Multivariate analysis was based on the significance of the regressors and the correlation of errors. At this stage, the choice of variables to be used may be based on subjective assessments, perhaps guided by theoretical assessments or maybe just from the results highlighted by other studies. Then, thanks to the econometric work, it is possible to identify the optimal classification rule, identifying variables that can be eliminated as not relevant in determining the effectiveness of the model. It is noted, however, that almost all proposed studies on the subject have used iterative procedures that can identify the significant variables among a large set of selected variables.

After carrying out an iterative process in which all possible VAR models were estimated, including the first with five variables, then four and then three, and have felt the significance of all variables in the following estimates of ordinary least squares (OLS).

At the end of the analysis, we consider only the following variables: the default rate of Italian companies, such as the autoregressive term, the logarithm of GDP in the euro area and interest rates in the short term.

Estimation Methodology and Results

Starting from the papers of Zazzara and Rotondi (2005b), we build a credit cycle index of Italian

[4] Data provided by Prometeia Association—one of the largest Italian companies in financial and economic research.

companies. A two-stage approach is used. We start from the identification of macroeconomic variables, and via a VAR model, we find the number of variables to use and the lag.

The VAR approach avoids a structural model, modeling each endogenous variable in the system as a function of lagged values of all endogenous variables. The equation is:

$$Y_t = AY_{t-1} + \cdots + A_p Y_{t-p} + BX_t + \varepsilon_t \quad (1)$$

After careful analysis and various tests we choose among all the series of macroeconomic variables.

$$DR_t = \frac{DF_t}{PL_{t-1}}$$

where DR_t is the default rate;

LNR_t is loans not repaid at time t;

EL_{t-1} is the existing loans in time $t-1$;

IR_{short} = interest rates in the short term.

$LEGDP_{EURO}$ = the logarithm of gross domestic product in the euro area.

The estimated VAR model tells us that the best model is one that uses few variables with a single lag, this gets the most significance of the regression. Table 1 shows the statistical regression performed with the VAR. The first terms in parentheses are the "standard error" variable regression. The second terms in parentheses are the *t*-statistic.

Table 1

VAR Estimation

	DR_t	T_{brev}	$LPIL_{EURO}$
DR_t (-1)	0.857553 (20.9909)	-0.966055 (-1.67830)	-11.99617 (-1.01158)
IR_{short} (-1)	0.246329 (4.93865)	0.607240 (0.86407)	-0.911236 (-0.06294)
$LPIL_{EURO}$ (-1)	-0.008187 (-2.97555)	0.020297 (0.52357)	1.046109 (1.30981)
C	0.003160 (1.83458)	0.010666 (0.43951)	0.221320 (0.44265)
R-squared	0.981412	0.776045	0.746792
Adj. *R*-squared	0.977694	0.731254	0.696150
Sum sq. resids	1.06E-05	0.002099	0.890716
S.E. equation	0.000839	0.011828	0.243682
F-statistic	263.9913	17.32594	14.74661
Log Likelihood	196.9403		
Akaike information criteria	-19.46740		
Schwarz criteria	-18.87091		

Notes. Sample (adjusted): 1986-2004; included observations: 19 after adjusting endpoints. Standard errors and t-statistics are in parentheses.

The *R*-squared has a very high value confirming the validity of the regression. In all the VAR models estimated with more variables and/or more "lags" we found problems of low significance of the regressors and multicollinearity. So, the first results of estimation indicate that for the construction of the CCI and, more generally, to explain the relationship between macroeconomic performance and the default rates of the loans, it is more efficient to work with a select few one-lag macro variables.

Figure 1 traces the impulse response function, the dependent variable (in our case, default rate), which corresponds to a shock in the standard deviation of each explanatory variable. As expected, the default rates respond negatively to an exogenous shock of the standard deviation of GDP in the euro area, but respond positively to a shock in the standard deviation of interest rates in the short term.

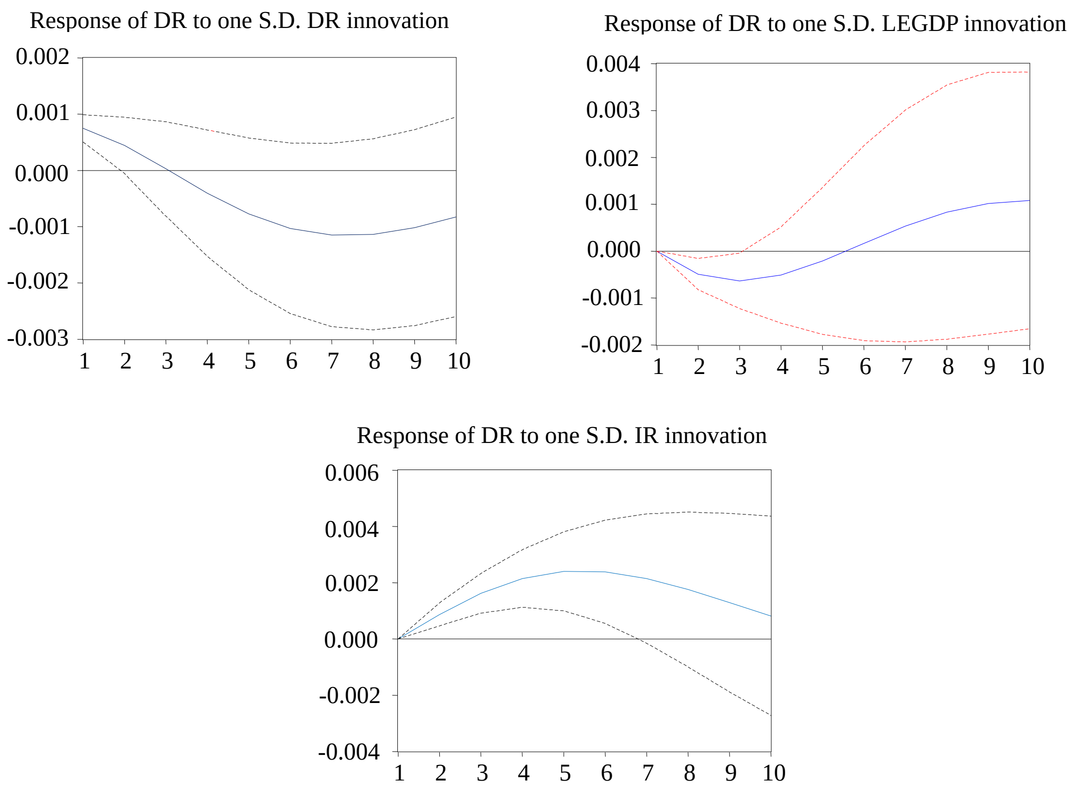

Figure 1. Responses on impulse function of DR.

Selecting the macro variables, we monotonically transform the default rates. The transformation is as follows:

$$\text{Logit}(DR_t) = \text{Ln}(\frac{DR_t}{1-DR_t}) = \alpha + \sum_i \beta_i \times X_{i,t\text{-}j} + \varepsilon_t \quad (2)$$

We transform the variable GDP:

$$D(\text{Ln}GDP) = \text{Ln}(GDP_t - GDP_{t-1}) \quad (3)$$

where D refers to the first difference, and Ln to the natural logarithm, so we turned the GDP series in the first difference of its natural logarithm.

We make this change for several reasons. First because we are not very interested in how the levels of GDP affect the default rate but rather than the GDP growth rate influences the default rate. The transformation in first differences is performed for a better stabilization of the variable and to make it more significant in the regression.

As shown above the natural logarithm of $\left(\frac{DR_t}{1-DR_t}\right)$ is linearly regressed with macroeconomic explanatory variables $X_{i,t-j}$. The β_i coefficients are therefore estimated using the method of ordinary least squares (OLS).

Table 2

Regression Analysis

Variable	Coefficient	Std. error	t-statistic	Prob.
C	-1.192346	0.162762	-7.325686	0.0000
Logit(DRt) (-1)	0.754341	0.040127	18.79895	0.0000
IR_{short} (-1)	4.940155	0.438420	11.26808	0.0000
$DLGDP_{EURO}$ (-1)	-0.158821	0.040396	-3.931564	0.0015
R-squared	0.986202	Mean dependent var.		-3.727850
Adjusted R-squared	0.983245	S.D. dependent var.		0.242755
S.E. of regression	0.031423	Akaike info criterion		-3.889449
Sum squared resid.	0.013823	Schwarz criterion		-3.691588
Log likelihood	39.00504	F-statistic		333.5380
Durbin-Watson stat.	1.927173	Prob (F-statistic)		0.000000

Note. Included observations: 18.

The statistical regression in Table 2 shows that the t-statistics of the coefficients are all significant, except the constant. Both the R-squared and the adjusted R-squared have very high values, and then the f-test statistic strongly rejects the null hypothesis of no significance of the estimate as a whole.

After estimating the equation above, it standardizes the Logit function and adds a minus sign before the equation, in order to obtain a new variable:

$$Z = -\frac{\text{Ln}\left(\frac{DR_t}{1-DR_t}\right) - \mu_{\text{Ln}\left(\frac{DR_t}{1-DR_t}\right)}}{\sigma_{\text{Ln}\left(\frac{DR_t}{1-DR_t}\right)}} \tag{4}$$

The variable Z represents the Credit Cycle Index and indicates the status of credit divided by all the borrowers during the period t.

By construction, the index is zero when the value of all macroeconomic series is exactly equal to the average over the estimation period.

The CCI is rather positive or negative when the macroeconomic series differ from their mean.

In particular, it is positive in the good times of the cycle (implying a lower probability of default) and negative in the bad times (implying a higher probability of default). See Figure 2.

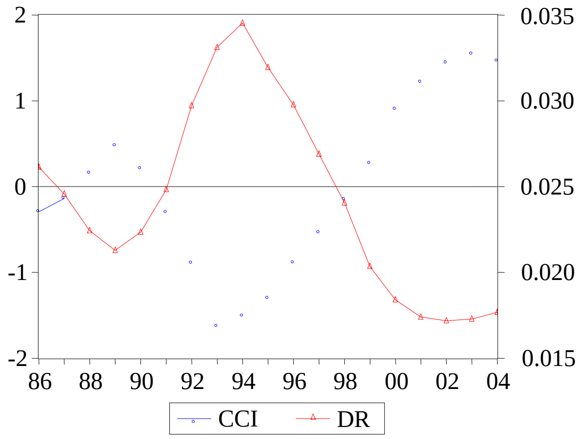

Figure 2. Relation between DR and CCI.

Visual inspection of the Figure 2 (where CCI = CCI estimated, and DR = the default rate in the period observed) above shows an inverse relationship between the default rate and the CCI credit, as assumed in the construction of the index. You can see how the CCI approximates quite well to the trend of default rate in Table 3.

Table 3

Comparison Between Actual CCI and CCI Estimated

Years	Actual	Estimate	Years	Actual	Estimate
1987	-0.14994	-0.24479	1996	-0.99943	-0.87965
1988	0.252228	0.081049	1997	-0.54895	-0.49671
1989	0.482398	0.448169	1998	-0.05439	0.031501
1990	0.269926	0.32977	1999	0.678005	0.381685
1991	-0.19697	-0.31965	2000	1.119023	0.878269
1992	-0.99049	-0.87652	2001	1.367896	1.290381
1993	-1.47174	-1.53971	2002	1.421929	1.216358
1994	-1.65872	-1.62648	2003	1.394831	1.30301
1995	-1.31222	-1.39476	2004	1.298784	1.41808

Table 3 shows in the “Actual” column the actual values of the index for each year of the sample, and the “Estimate” column the estimated value. You can see that there is a close proximity of the values for each year of the sample and as for the large majority of the observations the two measures have the same sign, it is very important to note the change of sign, the estimated CCI approximates well two on three, the third anticipate the observation in one year.

Backtest and Forecast

After building our CCI, we test the robustness of our approach through statistical backtest measures. In particular, we ensure the foresight of our credit cycle index, both “in-the-sample” and “out-of-the-sample”.

We use the widely used statistical error “Theil Inequality Coefficient”[5].

$$TIC = \frac{\sqrt{\sum_{t=1}^{n} \frac{(\lambda - y)^2}{n}}}{\sqrt{\sum_{t=1}^{n} \frac{\lambda_t^{\,2}}{n}} + \sqrt{\sum_{t=1}^{n} \frac{y_t^{\,2}}{n}}} \tag{5}$$

where:

$\lambda_t =$ Expected value of the credit cycle index at time *t*;

$y_t =$ Realized value of the credit cycle index at time *t*;

$n =$ Number of periods.

$\sqrt{\sum_{t=1}^{n} \frac{(\lambda_t - y_t)^2}{n}}$, the numerator is known as the root mean squared error of the forecast. This coefficient varies from 0 to 1, where 0 indicates a perfect “fit”.

Figure 3 shows an almost alignment of the curve representing the expected CCI (ESTIMATE) with that achieved (TRUE). Some small difficulties in the final estimation where the credit cycle index follows a slightly different trajectory than the credit cycle index achieved.

5 It provides a measure of how well a time series of estimated values compares to a corresponding time series of observed values.

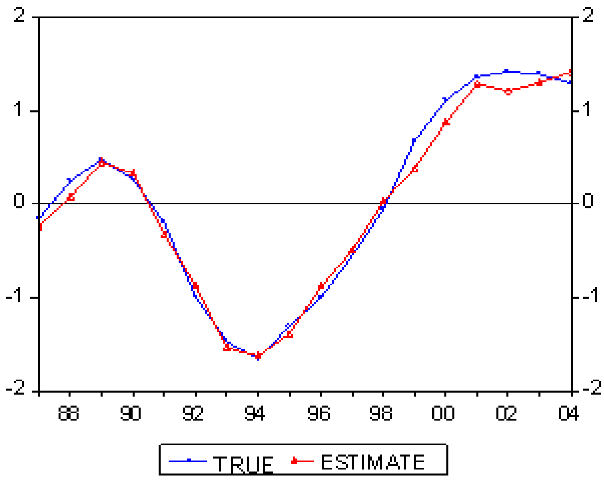

Figure 3. Comparison between actual CCI and CCI estimated.

Table 4 shows a good performance with a good “fit” between the expected CCI and CCI realized. These results are also due to annual data. To “backtest” the model better more representative quarterly data that best suite this type of phenomena would be useful, but, unfortunately, we do not have such data.

Table 4

Report of the Robustness of CCI

Sample Period	Tail inequality	Same sign of index	Same sign of index in change
1985-2004	0.072	95%	66%

Now we try to prove the robustness of our CCI estimating out-of-the-sample. To do this, we divide the sample period (1985-2004) in two, with the first being from 1985 to 2002. We estimate the coefficients as carried out by the regressing Equation (1), and using these estimate the credit cycle index in period (2002-2004). See Figure 4.

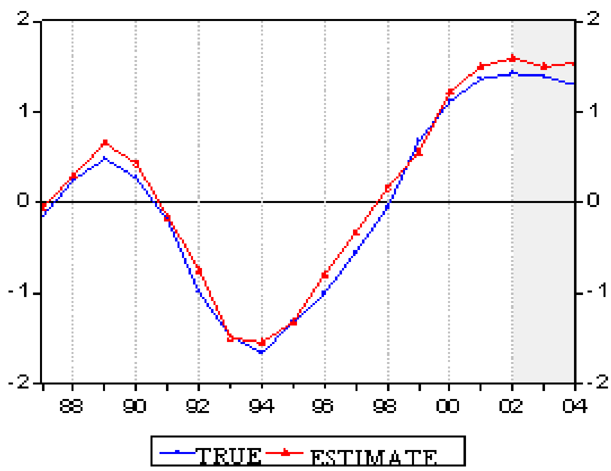

Figure 4. Comparison between estimated value out of the sample and true value.

Figure 4 compares the CCI estimated with the actual, and we can see how the two measures did not substantially differ, and make a good forecast out-of-the-sample.

Conclusions

The estimation of credit risk should reflect all the information available to the analyst, the best assessment of the risk of incurring in a crisis within the time period. This forecast should include not only indicators of risk based on history, but also prospective information. Models that estimate the probability of insolvency in the literature mainly consider historical data, primarily financial ratios. Therefore, it is clear that their effectiveness is conditioned by the reliability of accounting and the possibility that the historical values are really indicative of the future prospects of the company. The availability of market values is therefore particularly important to assess the riskiness of a business: if the financial markets are efficient, the prices that they suffer from properly express all the information available to traders and, therefore, incorporate the expectations of the future dynamics of the company. However, for most of the loans of Italian banks, the lack of values of the shares or bonds issued by enterprises, makes it impossible to directly estimate the credit risk on the basis of market values. However, it is extremely interesting to note the integration of financial information with macro-economic information in order to take into account expectations about future trends in the assessment of creditworthiness.

For these reasons, we have tried to highlight which relationships exist between the cyclicality of the economy and credit risk.

In this work, we analyze the relationship between the default rate and the macroeconomic variable, taking as a starting point a paper by Zazzara and Rotondi (2005b), where they examined how macroeconomic variables affect the movements in the default rate of Italian companies. Unlike the two authors, we have carried out research about the influence of macroeconomic variables that are totally independent of findings of these authors, following the analysis via a VAR models. As a result, we have found that the best method possible is the use of few variables (since even the few observations available to us) with just one “lag”.

The second stage of the analysis led us, after the transformation of the representative variable of the default rates, to regress with the macroeconomic variables selected with an autoregressive term.

Finally, we used the estimated coefficients found by the ordinary least squares regression for the construction of a “Credit Cycle Index” in order to infer the credit status of Italian companies. We backtested the index by a tail inequality index and we used it to make forecast. The index produces good and consistent results, both in the sample and out of the sample.

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