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The Interplay between Ex-post Credit Risk and the Cycles: Evidence from the Italian banks

Anastasiou Dimitrios[†]

Abstract

The objective of this research is to empirically examine if both credit and business cycle affect the ex-post credit risk (i.e. non-performing loans) in the banking system of Italy. My sample includes 47 Italian banks for the period 1995Q1-2015Q1. The increase in NPLs post-2008 has put into question the robustness of many European banks and the stability of the whole sector. It still remains a serious challenge, especially in Italy which is one of the countries that has been hit by the financial crisis more than other economies. By employing Fixed Effects, Random Effects and GMM as econometric methodologies I find a positive (negative) association between credit cycle (business cycle) and NPLs. Higher NPLs in Italy are due to adverse macroeconomic conditions (i.e. downward phase of the business cycle) and due to excess credit (i.e. upward phase of the credit cycle). Another important finding is that the Italian NPLs have a symmetric sensitivity between both business and credit cycle. Such findings may be helpful for both senior bank loan officers and policy makers when designing macro-prudential as well as NPL resolution policies.

Keywords: Non-performing loans; Ex-post credit risk; Business cycle; Credit cycle; Macro-prudential policy; Italian Banks.

JEL classification: C23, C51, G21, G2, E32

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1. Introduction

The majority of studies regarding non-performing loans (NPLs) agree that NPLs constitute the number one ex-post credit risk, causing a lot of problems not only concerning banks' balance sheets but also concerning the whole economic activity of the country (Louzis et.al., 2010; Berger and DeYoung, 1997); that is the reason why I use the term ex-post credit risk instead of NPLs. In the recent literature of banking, the association between business cycle and credit risk has been examined for both macroeconomic and microeconomic management purposes.

Some studies argue that the possibility that the macroeconomic conditions impact on the portfolio riskiness of banks is disparate for each different phase of the business cycle. Marcucci and Quagliariello (2008) supported that the riskier the portfolios of banks are, the more cyclical are, implying that they are even more sensitive to business cycle. On the contrary, less risky bank portfolios are less cyclical, meaning that they are less sensitive to business cycle.

The procyclical nature of banks with the business cycle can be revealed by the following: After the peak of a cyclical upturn, when the downturn phase of the cycle starts, the creditworthiness of borrowers deteriorates, the profitability of customers worsens and NPLs are revealed. Therefore, losses will occur in the balance sheets of banks (cyclicality). As a consequence, my prior is that Italian banks would have greater (lower) levels of NPLs during worsening (improving) macroeconomic conditions. In particular, I expect that during expansionary (contractionary) phases of the business cycle less (more) NPLs are expected due to the improving (worsening) macroeconomic environment. So, a negative sign is expected between the business cycle and NPLs. In addition, during expansionary (contractionary) phases of the credit cycle more (less)

NPLs are expected due to increasing (decreasing) loan granting. So, a positive sign is expected between the credit cycle and NPLs

In Italy, the continuous increase in NPLs across the period 2008 and 2014 (reaching 19% in 2015) coincided with a fall of more than 20 % in investment in the tradable sector.¹ The reason why I choose to examine the case of Italy is twofold. First, because Italy (from a data perspective) has the most significant number of banks across all the EU countries and second, because of its high levels of nonperforming loans. Italy, Greece, Spain, Ireland and Portugal (also known as PIIGS or GIPSI) are these EU (peripheral) countries which have extremely high levels of non-performing loans.

During the last decades, policy makers and bank supervisors pay a growing interest to the behavior of banks, in order to examine their possible procyclical nature. The guarantee of the financial and macroeconomic stability it is a matter of high importance in order to understand to what extent and whether banks are influenced by the macroeconomy.

The need for a macro-prudential authority in an economy – along with the more traditional types of policy – derives from the procyclicality of the banks' NPLs with the credit cycle. To add to this effect, financial institutions correlate their balance sheets through interbank lending. If one bank goes bankrupt, then its net debtors in the system will incur in losses. This can trigger a chain reaction which could ensnare multiple banks and the ultimate "victims" being the depositors who lose their deposits. Both of these effects go unnoticed by both governments and banks. Thus, banks do not hedge against systemic risk properly and government authorities do not conduct the best policy towards financial stability.

¹Source: Europa (2016)

The macro-prudential authority is tasked with internalizing the externalities that are the roots of all this while coexisting with the fiscal and monetary authority. So, macro-prudential authorities should take into consideration the evolution of both the business cycle and the credit cycle, when designing their macro-prudential policies and thus helping the fiscal and the monetary authorities to form their own policies.

The remainder of the paper is structured as follows: Section 2 includes a general literature review on the determinants of NPLs. In section 3 I present the data, the models and the econometric methodologies that I employed and in section 4 I report the estimation results. Finally, Section 5 concludes.

2. A Brief Literature Review

During the last decade, a remarkable literature on business and the financial (or credit) cycle of Italy has been written and particularly on the relationship between business cycle and ex-post credit risk (Quagliariello, 2006; Marcucci and Quagliariello, 2008). One recent study regarding the business cycles in euro-area is this of Konstantakopoulou and Tsionas (2011). Konstantakopoulou and Tsionas (2011) investigated on what degree the business cycles are synchronized for the Eurozone countries. Also, they tried to examine if there are any dynamic relationships developing between them (i.e. the business cycles).

Concerning the variables that affect ex-post credit risk, a plethora of literature exists. The vast majority of the literature examines which macroeconomic and/or bankspecific determinants influence the level of NPLs. To begin with, Berger and DeYoung (1997) implemented some Granger-causality tests in order to test four bank relatedmanagement hypotheses concerning the relationship between bank capital, loan quality and cost efficiency. Berger and DeYoung (1997) came to the conclusion that the moral hazard and bad management hypotheses were explaining a considerable part of problematic loans. Podpiera and Weill (2008) also estimated a Granger causality test in order to see the relationship between ex-post credit risk and cost efficiency, while Ghosh (2006) found that lagged leverage significantly affects NPLs. Kauko (2012) and Espinoza and Prasad (2010) using macroeconomic variables as explanatory variables, they found that NPLs rise with interest rates and fiscal and external deficits and decline with greater economic growth. Louzis et al. (2010) examined the variables that affect ex-post credit risk for each loan category (business, mortgage, and consumer) separately. Their findings show that NPLs are importantly related to macroeconomic variables and the quality of bank management. Cifter (2015) examined how bank

concentration influence NPLs. His results were ambiguous. Beck et al. (2015) found that the factors that affect NPLs are share prices, GDP growth, the exchange rate and interest rates. Nkusu (2011) found that a recrudescence in the macroeconomic conditions, such as sluggish growth, higher unemployment or decreasing asset prices is interrelated with high levels of NPLs. On the other hand, improving macroeconomic conditions reduce the ratio of NPLs. Messai (2013) had as main findings that the real interest rate and unemployment rate influence NPLs positively, while ROA has a negative effect on NPLs. Ghosh (2015) stated that the related variables that increase NPLs are liquidity risk, poor credit quality, larger capitalization, inefficiency cost, and the size of the whole banking industry as well as inflation, unemployment, and public debt. Chaibi and Friti (2015) compared the determinants of (NPLs) of commercial banks in France and Germany, during the period 2005–2011. They found that French banks are more susceptible to bank-specific determinants than the German banks.

Bofondi and Ropele (2011) focused on Italian banks for the period from 1990 to 2010. Their research was focused solely on the determination of macro factors affecting impaired business and household loans. Results for household loans recorded a positive relationship between NPLs and unemployment and interest rates, and a reverse relationship for GDP growth and real estate prices. Regarding businesses loans, they found a positive effect of unemployment and interest expense ratio to EBITDA, while a negative effect was related to the consumption of durable goods.

In a recent study Anastasiou, Louri and Tsionas (2016b) found that tax on personal income and output gap are two new in the literature variables which are found to significantly affect NPLs and should be taken into account when formulating macroprudential policies. In another study, Anastasiou, Louri and Tsionas (2016a) by employing both Fully Modified OLS and Panel Cointegrated VAR as econometric methodologies found that MIR interest rate margin is a crucial determinant of NPLs (positively affecting them). Another recent study is this of Vithessonthi and Tongurai (2016), who found that business cycles seem to mitigate the effect of financial markets development on banks risk.

3. Models, Methodology and Econometric Estimation

The bank data for NPLs used in this paper collected from the BankScope Database provided by DataStream Professional on a quarterly basis. I have an unbalanced panel dataset with 2.218 observations and a sample of 47 Italian banks for the period 1995Q1-2015Q1.

Given that data for business and the credit cycle do not exist, I created them from other series/data. So, I utilized real GDP and credit to private nonfinancial sector from domestic banks in order to obtain the business and credit cycle respectively. I collected data for real GDP and credit to private nonfinancial sector from domestic banks in Italy from the DataStream Professional Database.

In order to obtain the two types of cycles, I separated each series' cyclical components from their trends. The literature provides a plethora of ways to do this. A popular method, especially used in macroeconomics², is the Hodrick-Prescott filter (HP filter, hereafter). However, in this study I employed the Christiano Fitzgerald filter (CF filter, hereafter), firstly proposed by Christiano and Fitzgerald (2003). The core difference between the two filters is that while HP filter needs a specific assumption for the time range of a variable's cyclical part, the CF filter works with a hypothesis on the

² Nilson and Gyoamai, 2011.

range of the range. Furthermore, the CF filter asymptotically converges to the ideal filter, which theoretically considers an infinite amount of observations on the series.

More specifically, in order to obtain the business and the credit cycle I followed the methodology of Drehmann et.al. (2012). In particular, I took real GDP and credit to private nonfinancial sector from domestic banks, and through the CF filter I obtained the cyclical component and trend, by decomposing each variable. These cyclical components stand for the business cycle and the credit cycle respectively. The reason why I utilized real GDP instead of nominal GDP is simply because I am interested in real values of gross domestic product and not in changes driven by inflation.

According to Drehmann et.al. (2012), it is speculated that there exist two levels of frequencies where a cycle may be detected, the short-term and the medium-term. The short-term is thought to cover frequencies between 1 and 8 years (4 and 32 quarters in our data). The medium-term may last anywhere between 8 and 30 years or between 32 and 160 quarters respectively. Due to the relatively short time-period coverage that I have, I examine only how the short-term cycles influence the Italian banks' non-performing loans.

Regarding the variables that I used in the econometric model, as dependent variable I have nonperforming loans as percentage to total loans and as explanatory variables I employed the cyclical (or short-run) component from the decomposition of the real GDP, namely the business cycle (BC hereafter) and the cyclical component from the decomposition of credit to private nonfinancial sector from domestic banks, that is the credit cycle (CC hereafter).

In figures 1 and 2 we can observe the Italian business cycle and credit cycle respectively, for the period 1995Q1-2015Q1.

*****Insert figures 1 and 2 here****

In figures 3 and 4 we can see the evolution of the total Italian credit to private nonfinancial sector from domestic banks and the total Italian real GDP respectively.

*****Insert figures 3 and 4 here****

As a first step, I examined all variables for unit roots. I employed both the Augmented Dickey Fuller (1979) (ADF test) and the Phillips-Peron (1988) (PP test). The results can be found at table 1. None of the variables were found to be unit root and therefore all of them are stationary at level.

*****Insert table 1 here*****

I estimated two kinds of models. One static model using both Fixed Effects and Random Effects and one dynamic model using GMM.

The under-estimation models are the following:

Static model:

$$NPL_{i,t} = \beta_0 + \delta_1 C C_t + \delta_2 B C_t + \varepsilon_{i,t} \tag{1}$$

Dynamic model:

$$NPL_{i,t} = \beta_0 + \gamma NPL_{i,t-1} + \delta_1 CC_t + \delta_2 BC_t + \delta_3 CC_{t-1} + \delta_4 BC_{t-1} + \varepsilon_{i,t}$$
(2)

where, i, t, NPL, CC and BC stand for both models Italian banks, time (quarters), non-performing loans, credit cycle and business cycle respectively.

According to the Hausman test, the Fixed Effects approach is more appropriate method. In order to estimate the dynamic model, I employed the difference Generalized Method of Moments, firstly proposed by Arellano and Bond (1991). As instruments I

used the first lagged variables for both the dependent variable and the explanatory variables. These instruments are in line with the results of the Sargan test.

After the estimation of the above models, I examined whether the following hypotheses hold:

Hypothesis 1: H_0 : $\delta_1 = \delta_2 = 0$

If we do not reject the null hypothesis, this would provide evidence that Italian NPLs are sensitive neither to BC not to CC. So, the desirable outcome of this hypothesis would be a clear rejection of it.

Hypothesis 2: $H_0: \delta_1 = \delta_2$

If we accept the null hypothesis, this would suggest that Italian NPLs have a symmetric sensitivity between both BC and CC.

4. **Results**

In table 2, we can see the estimated coefficients and their corresponding robust standard errors for all models, both static and dynamic. More specifically, in table 2 model 1-FE and model 1-RE refer to the first static model which was estimated by Fixed and Random Effects correspondingly. Model 2 refers to the dynamic model with the GMM estimation.

*****Insert table 2 here****

In general, all of the estimated coefficients have signs compatible both with the relevant literature and economic theory as well. I found a clear rejection of the first testable hypothesis for all models, implying that Italian NPLs are sensitive both to BC

and to CC and thus BC and CC are both important and significant factors which influence the Italian NPLs.

Starting with the static model, in both Fixed and Random Effects approaches, CC found to exert great impact on the level of NPLs, since its coefficient is significant at 0.01 significance level. BC also found to have the proper sign and to negatively affect Italian banks' NPLs. In absolute terms, the coefficient of CC found to be greater than the corresponding coefficient of BC and thus the CC seems to have a greater impact on the evolution of the NPLs than the BC. However, this is not confirmed by the results of the second hypothesis that I tested, since in all models I found that he null hypothesis of the second testable hypothesis is not rejected (again for all types of models) and thus we can infer that Italian NPLs have a symmetric sensitivity between the impacts of both BC and CC.

With respect to the dynamic model, the one lagged period NPL found to be significant at 0.01 level of significance and it also found to exert great influence on the current values of NPLs, as it was expected. The coefficient of the current period BC did not found to have any significance. On the contrary, the one period lagged BC found to exert only some significance at 0.10 level. With respect to the coefficient of CC and the coefficient of one period lag CC, they both found to be statistically significant at 0.05 level, implying that both of them have a significant positive impact on the Italian NPLs. In general terms, once again, all variables BC, CC and their corresponding one period lags found to carry the proper sign.

As a consequence, the main findings confirm my prior that Italian banks would have greater (lower) levels of NPLs during worsening (improving) macroeconomic conditions. In particular, I found that during expansionary (contractionary) phases of the business cycle less (more) NPLs are expected due to the improving (worsening) macroeconomic environment. In addition, during expansionary (contractionary) phases of the credit cycle more (less) NPLs are expected due to increasing (decreasing) loan granting.

5. Conclusions

In this paper I investigated the role of business cycle and credit cycle as potential determinants of NPLs. As far as my knowledge, this is the first empirical study which attempts to examine if the two major cycles of an economy play role on the evolution of the Italian banks' NPLs. I employed both a static and a dynamic model, using Fixed Effects, Random Effects and difference GMM as estimation methods.

With respect to the two kinds of cycles, both BC and CC found to exert great significance on the static and on the dynamic model. Another important finding is that the Italian NPLs have a symmetric sensitivity between both BC and CC. I strongly believe that such findings could foster a macro-prudential approach to financial stability.

In terms of future research, this study could be expanded by examining other types of cycles such as the political cycle or/and stock market cycle. Furthermore, other econometric methodologies and alternative decomposition methods for real GDP and for credit to private nonfinancial sector from domestic banks could be implemented.

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Tables

Table 1: Unit roots tests		
Panel B: Fisher type AI	DF Unit roots test	
Variable Name	Probability values	
NPL	0.003	
CC	0.000	
BC	0.000	
Panel B: Fisher type P	P Unit roots test	
Variable Name	Probability values	
NPL	0.008	
CC	0.001	
BC	0.000	
Notes: (a) Variables NPL, CC, BC stand for non-perf respectively. (b) The null hypothesis is that the under-ex PP stand for the Augmented Dickey Fuller test and the b Source: Datastream, Own estimations	xamination variables are unit root. (c) ADF and	

	Static Model 1-FE	Static Model 1-RE	Dynamic Model 2-GMM
NPL _{it-1}			0.768***
	-	-	(0.032)
CCit	0.016***	0.015***	0.004**
	(0.002)	(0.003)	(0.001)
BC _{it}	-0.003*	-0.004*	-0.001
	(0.004)	(0.004)	(0.001)
CC _{it-1}	-	-	0.004**
			(0.001)
BC _{it-1}	-	-	-0.002*
			(0.001)
Constant	4.287***	4.062***	1.098***
	(0.021)	(0.051)	(0.127)
		nostics	
R ²	0.104	0.071	-
Observations	2,218	2,218	2,122
Number of panel id	47		
	6	hypotheses lity values)	7
Ηο: δ ₁ =δ ₂ =0	0.000	0.000	0.000
Ηο: δ1=δ2	0.069	0.062	0.031
	stering on banks are in parenthe		0.05 and * p-value<0.1. (b) Robus BC stand for non-performing loans

Figures

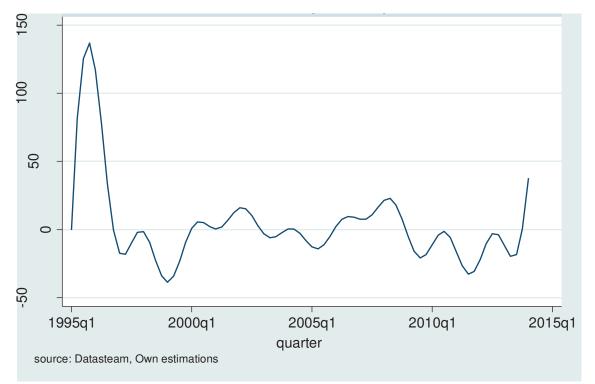


Figure 1: Cyclical Component from Real GDP, 1995Q1-2015Q1

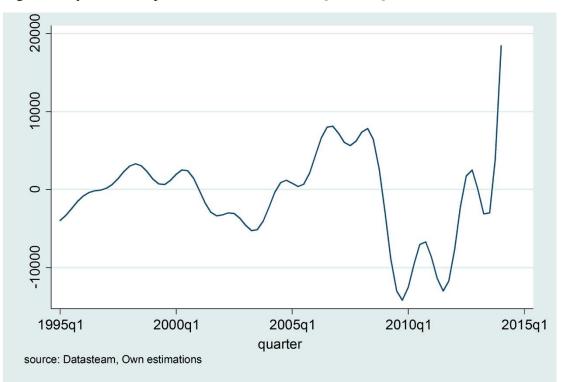


Figure 2: Cyclical Component from Credit, 1995Q1-2015Q1

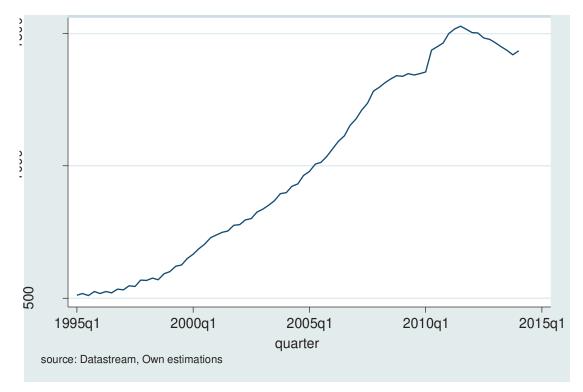


Figure 3: Total Credit to Private Nonfinancial Sector from Domestic Banks, 1995Q1-2015Q1

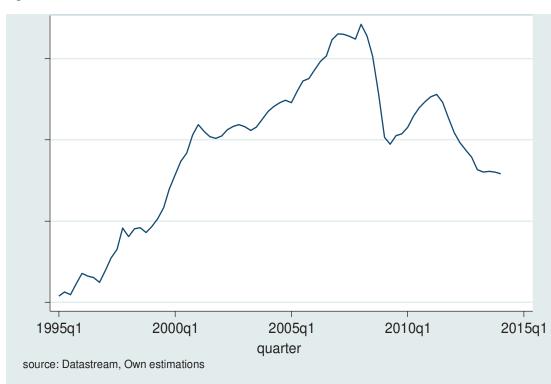


Figure 4: Real Gross Domestic Product, 1995Q1-2015Q1