

Business cycle effects on capital requirements: scenario generation through Dynamic Factor analysis

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Abstract

In this paper, we focus on the measurement of the measurement of the capital charges of a bank against expected and unexpected losses affecting the bank loan portfolio. In particular, we depart from the standard one factor model representation of portfolio credit risk, since we consider an heterogeneous portfolio, and we account for stochastic dependent recoveries. We estimate and identify the common (systemic) shock by fitting a Dynamic Factor model to a large number of macro credit drivers. In particular, we, first, consider the case of a systemic shock, interpreted as the state of the business cycle. Then, we disentangle the common shock in demand and supply innovations and we examine their impact on the bank capital requirements. The scenarios are obtained by employing Montecarlo stochastic simulation.

Keywords: Risk management, default correlation, Dynamic Factor

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Introduction

The proposed new Bank of International Settlement accord (known as Basel 2) provides for greater sensitivity of capital requirements to the credit risk inherent in bank loan portfolios. In light of the Basel 2 accord to reform the regulation of bank capital, there has been an extensive research on credit risk. The latter can be considered as a dominant component of risk for banks. The risk of an individual bank can be measured as the dispersion of future losses to its own portfolio driven by the obligors default. However, the focus of risk measurement is not on the standard deviation of the portfolio loss, but, given an highly asymmetric portfolio loss distribution, the emphasis is on the measurement of the Value at Risk (VaR). This is the minimum loss that a portfolio of credit exposures could suffer one out of one thousand years (if we choose the 99.9% percent rule and a year as the forecast horizon).

A crucial input of a portfolio credit risk model, PCR, is the appropriate characterisation of default correlations to obtain the bank loan portfolio distribution with the relevant percentile (e.g. the minimum capital requirement). Recent research suggests that the probability over upgrading, downgrading the credit quality of a borrower, vary with the business cycle. These are, for instance, the empirical findings, based upon transition matrices calculated using external ratings from Moody's and Standard and Poor's, of Nickell et al. (2000). Similar findings are in Bangia et al. (2000) who concentrate on the ratings of corporate borrowers and in Haldane et al. (2001) who focus on sovereign borrowers. Furthermore, the study of Jordan et al. (2002) and of Cateraineu-Rabell (2002), use transition matrices computed according to either Moody's data or to KMW style ratings. Their findings suggest swings, across the business cycle, in the minimum capital requirements (for a portfolio of 339 loans in a shared national credit program in the United States, the former study, and for a selection of banks in G10 countries, the latter study). Other studies, based upon time series data on internal ratings suggests similar conclusions. In particular, the study of Carling et al. (2001), find a substantial fall substantial improvement in the internal ratings ver the 1994-2000 period, and consequently, a fall in the capital charge of a large Swedish bank. This was found to be associated with the gradual improvement of the Swedish economy after the financial problems of the early 1990s. Segoviano and Lowe (2002), having access to time series data on the ratings assigned by a number of Mexican banks to business borrowers, find large swings in required capital. Finally, the study of Carpenter et al. (2001) conclude that in the Untied States there is very little cyclical impact on capital charges; on the other hand, Ervin and Wilde (2001) find large swings in the minimum capital requirements.

Also, the role of uncertain recoveries is important for the determination of Credit Risk VaR. The empirical study of Hu and Perraudin (2002) shows a negative correlation between probability of default and recovery rate. This finding can, for instance, be explained by observing that both default and recovery are found to depend on the state of the macro-economy (see the work by Gupton et al., 2000 and by Frye, 2000b).

In line with the aforementioned empirical findings, portfolio credit risk models account for the influence of the state of the business cycle on credit risk. The study of Shonbucher (2000), based upon the assumption of homogeneous portfolio, constant recovery and one common shock influencing the systemic component of firm asset values, has provided an analytic solution for the limiting portfolio distribution. However, given the heterogeneous nature of the portfolio under examination in this paper and the empirical evidence of stochastic dependent recoveries (provided by the aforementioned studies), we use stochastic simulation to quantify the risk associated to a bank loan portfolio. For this purpose, we follow the method put forward by Krenin et al. (1998) by generating scenarios through stochastic simulation to determine conditional default probability and conditional portfolio loss distribution. In order to account for default correlation, we average out across all scenarios and we obtain the unconditional portfolio loss distribution. We concentrate only on a “default mode” model, that is the model measures credit losses arising exclusively from the event of default. Given the heterogeneous feature of the portfolio under examination, we implement Monte Carlo simulation (which is standard in the proprietary models of Portfolio Credit Risk analysis). The novel aspects of the paper are described as follows. First, the macro scenarios are associated to common shocks identified (as aggregate demand and supply) and estimated by fitting a Dynamic Factor model to a large number of credit drivers. Secondly, we account for the impact of stochastic recoveries dependent on defaults.

The outline of the paper is as follows. Section 2 describes the basic definitions underlying the credit portfolio loss distribution. Section 3 describes the analytic solution to retrieve the unconditional loss distribution. Section 4 and 5 describe the stochastic simulation exercise and the Dynamic Factor modelling approach, respectively. Section 6 describes the empirical results. Section 7 concludes.

2. Credit Portfolio Loss Distribution

The credit portfolio loss L is given by:

$$L = \sum_{j=1}^N (D_j * L_j) \quad (1)$$

where N is the number of counterparts, D_j is a default indicator for obligor j (e.g. it takes value 1 if firm j defaults, 0 otherwise). Furthermore, the loss from counterpart j is given by:

$$L_j = \sum_{h=1}^H EAD_{hj} * LGD_{hj} \quad (2)$$

where EAD_{hj} is the exposure at default to the h business unit of obligor j . Finally, LGD_{hj} is the corresponding loss given default (equal to one minus the recovery rate, see below).

Since L is a random variable, it is crucial to retrieve its probability distribution to measure portfolio credit risk. For this purpose, from (1) and (2) we can observe that we need to consider as a random variable, at least one from D_j , EAD_{hj} , and LGD_{hj} . In this paper, we concentrate on the stochastic nature of defaults and loss given defaults, treating the exposures as deterministic. If the portfolio loss is uncertain in the future, then we can concentrate on few moments of the portfolio loss distribution. First, it can be relevant the measurement of the expected loss (e.g. the sample mean of the overall distribution). However, as in standard portfolio risk analysis, the standard deviation of the total portfolio loss is used to measure risk associated to the bank loan portfolio. However, given highly asymmetric credit portfolio loss distribution, it is customary to measure risk as the difference between the 99.9% percentile (as suggested by Basel 2) and the expected loss. This is the unexpected loss (economic capital). If the forecast horizon is a year, then the unexpected loss predicts the minimum loss (above the expected one) that can occur in one out one thousand years. Finally, if such an extreme event occurs, the loss is predicted by the expected shortfall, computed as the mean of the distribution values beyond the 99.9% percentile.

3. Stochastic PD's and Credit Portfolio Risk analysis

In this section we treat only defaults as stochastic random variables and we model them being dependent on the state of the business cycle. For this purpose, it is customary, in Portfolio Credit Portfolio Risk analysis, to implement a factor model specification for asset returns. In particular, the dynamics of the level of firm j 's asset value index is given by:

$$A_j = \beta_j U + \sqrt{1 - \beta_j} v_j \quad (3)$$

where U is a systematic risk shock affecting simultaneously every firm (parodying the state of the macro-economy) and v_j is an idiosyncratic (firm specific) risk shock. The two shocks in (3) are assumed to have independent standard normal distributions, implying that A_j has a standard normal distribution. The parameter β_j measures the effects of the common shock on the whole set of different obligors.

According to Merton (1974), a firm defaults when its asset value index falls below a threshold c_j . Specifically, define A_j as the level of firm j 's asset value index, which proxies the creditworthiness of obligor j . Let D_j symbolise the default event of firm j , then we can observe that:

if $A_j < c_j$, then $D_j = 1$; $D_j = 0$ otherwise.

The default boundaries c_j are pre-specified and obtained from the (unconditional) probabilities of default PD_j , given by:

$$PD_j = P(A_j < c_j) = \Phi(c_j) \quad (4)$$

where Φ is the cumulative standard normal probability distribution. From eq. (4) it is possible to retrieve the level of threshold c_j , which is given by $\Phi^{-1}(PD_j)$.

The main ingredients of a factor model for Portfolio Credit Risk analysis are the individual unconditional PD's (here obtained from the internal rating system of the bank) together with a measure of the asset correlation (measured by the cross product of the factor loadings in eq. (3)). These two inputs are all we need to measure default correlation. Intuitively, negative realisation of

the common shock can lead the asset firm values of different obligors to fall below their corresponding threshold values and then lead these obligors into default.

3.1 Analytic solution for the Credit Portfolio Loss

The Basel II proposal (as of January 2001) for the determination of economic capital is based upon the Schonbucher (2000) analytic solution for the unconditional portfolio loss distribution. For this purpose, the author (op. cit.) implements the factor model specification described above. The starting point is the estimation of the probability of default conditional on a specific realisation of the common shock. Under the assumption of homogenous portfolio¹ (e.g., same exposure, probability of default, loading factor across obligors) and deterministic loss given default, the probability of default for firm j conditional on a realisation u of the common shock U is given by:

$$\begin{aligned}
 p(y) &= p\{[A_{j_t} < \Phi^{-1}(PD)] | U = u\} = \\
 &= P[\sqrt{\beta}u + \sqrt{1-\beta}v_j < \Phi^{-1}(PD)] \\
 &= P\left(v_j < \frac{\Phi^{-1}(PD) - \sqrt{\beta}u}{\sqrt{1-\beta}}\right) = \Phi\left(\frac{\Phi^{-1}(PD) - \sqrt{\beta}u}{\sqrt{1-\beta}}\right)
 \end{aligned} \tag{5}$$

Therefore, conditioning on a specific realisation of the common shock, we obtain independent defaults across obligors, and, as a consequence, the conditional probability of having exactly n defaults is:

$$p\{X = n | U = u\} = \binom{N}{n} \{p(u) (1 - p(u))^{N-n}\}$$

Furthermore, averaging out across the different realisations of the common shock, the unconditional cumulative distribution is:

$$p(X \leq n) = \sum_{m=0}^n \int_{-\infty}^{\infty} p(X = m | U = u) f(u) du \tag{6}$$

¹ More recently, Wehrspohn (2003) provides analytic closed form solution of the limiting distribution and of the credit portfolio loss, under the classical one factor model representation, relaxing the assumption of homogeneous portfolio.

Combining the assumption of homogeneous portfolio with the assumption of an infinitely granular portfolio (where each exposure is set to be equal to $1/N$, with large N), Schonbucher (2000) derives the analytical solution for the unconditional cumulative loss distribution:

$$P\left(\frac{X}{N} \leq x\right) = \Phi\left[\frac{1}{\sqrt{\beta}}\left(\sqrt{1-\beta}\Phi^{-1}(x) - \Phi^{-1}(p)\right)\right] \quad (7)$$

In particular, the Basel 2 computation for the unexpected loss is based upon considering the 99.9th percentile of the distribution in (7) and by fixing the loading factor $\beta = 0.2$.

3.2 Stochastic recovery

Recently, few studies, have taken into account the stochastic feature of the recovery rate as well as defaults. In particular, the dependence between the default events and losses given default is introduced through a single factor that drives both default events and recovery rates. The recovery rate is then modelled by specifying the collateral value distribution (for instance, Frye, 2000a uses a Gaussian collateral value, whereas Pykhtin, 2003, focuses on a log normal distribution). These studies provide a macro type of explanation of an inverse relationship between PD's and recoveries documented, for instance, in Hu and Perraudin (2002). In particular, given a negative cyclical downturn, collateral values as well as asset firm values would fall, and, as a consequence, there would be an increase in the number of defaults and a decrease in the number of recoveries (given their dependence on the collateral). The empirical studies by Altman and Brady (2002), and also by Altman, et al. (2003) find that not only the state of the business cycle, but also contract-specific factors, such as, seniority and collateral, seem to affect recovery rates. Therefore, in addition to a macro-side explanation, also a micro-side explanation has been put forward to explain the relationship between PD's and recoveries. In particular, in presence of an high number of defaults, there is an excess of supply of distressed debt bonds, depressing the price of these bond, and consequently, the corresponding recovery rate.

To our knowledge, at the industry level, the computation of Credit Risk Portfolio VaR does not fully account for the stochastic dependence of recoveries from default. Proprietary models employed in Credit Portfolio Risk analysis treat the recovery rate either as deterministic or as stochastic (modelled through a beta distribution), but independent from the probability of default. In

line with the study of Altman et al. (2002), we model stochastic dependent recoveries, by imposing a perfect rank correlation between the LGD and the default rate associated with the common shock scenarios. In particular, we sort (in descending order) the number of defaults for each common shock scenario, we associate the corresponding percentiles of rr obtained from inverting the beta distribution corresponding to the recoveries sorted in ascending order². For example, when the common shock scenarios produce the largest number of defaults, the recovery rate takes the smallest value. On the other hand, when the common shock scenarios produce the smallest number of defaults, the recovery rate takes the largest value.

4. Stochastic simulation

In this paper, in line with equation (3), we assume that both the common and the idiosyncratic innovations are standard Gaussian. However, we consider an heterogeneous portfolio, and we also treat recoveries as stochastic and dependent on default events. Finally, we also let two common shocks affect the systemic components of the creditworthiness indices. Therefore, we cannot use the analytic solution for the unconditional portfolio loss distribution given in (6) and we need to implement Montecarlo simulation for the generation of the asset returns according to the factor model specification given in (3). Comparing the simulated asset returns with pre-specified thresholds (given the availability of data regarding the one-year unconditional PD's, as explained above) we are able to detect whether, conditioning on a specific macro scenario and a specific realisation of the idiosyncratic shock, an obligor defaults. The common shocks driving the systemic component in (3) are estimated and identified by fitting a Dynamic Factor model, DF (see Stock and Watson, 2002) to a large dataset of macroeconomic variables: the credit drivers. In the section below we describe the model used to produce the scenarios.

5. Dynamic Factor model

As anticipated in section 4, the identification and estimation of common shocks is obtained by fitting a Dynamic Factor model to x_{nt} , which is the n dimensional dataset of credit drivers (see Stock and Watson, 2002):

$$x_{nt} = Cf_t + \xi_t \tag{7}$$

²The shape of the beta distribution depends on the parameters a and b , linked to μ and σ , which are the sample mean and std. deviation of the recovery rate, respectively as follows: $b = \{[\mu^* (\mu-1)^2]/\sigma^2 + \mu-1\}$; $a = (b*\mu)/(\mu-1)$.

the first addend of the r.h.s. of (7) is the common component for each credit driver given by the product of the r dimensional vector of static factors f_t and the $n \times r$ coefficient matrix of factor loadings. The factor dynamics is modelled as follows (see Forni et al, 2003):

$$f_t = \Gamma f_{t-1} + R u_t \quad (8)$$

where R measures the impact multiplier effect of the q dimensional vector of common shocks u_t on f_t .

5.1 Estimation and identification

The static factor space can be consistently estimated by either the generalised principal component estimator proposed by Forni et al. (2000) or the principal component estimator proposed by Stock and Watson (2002)³. In this paper we use the procedure proposed by Stock and Watson which (in case of a cross section dimension exceeding the time series dimension) gives a consistent estimator of the static factors f_t is given by :

$$f_t = \sqrt{T} W_n \quad (9)$$

where W_n is the $n \times r$ matrix having on the columns the eigenvectors corresponding to the first r largest eigenvalues of the covariance matrix of x_{nt} . In the second stage of the analysis, according to (7), we estimate, by OLS, a VAR(1) on the static factors f_t :

$$f_t = \Gamma f_{t-1} + \varepsilon_t \quad (10)$$

The structural form impact multiplier matrix R in (8) is given by KMH , where:

- 1) M is the diagonal matrix having on the diagonal the square roots of the q largest eigenvalues of covariance matrix of the residuals ε_t .
- 2) K is the $r \times q$ matrix whose columns are the eigenvectors corresponding to the q largest eigenvalues of covariance matrix of the residuals ε_t .

3) H is a $q \times q$ rotation matrix, which (in case of $q = 2$) is given by:

$$H = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$$

The identification of common shocks u_t in (8) is achieved by finding the rotation of the angle θ in H which complies with sign restrictions on the impulse response profile of the credit drivers x_{nt} :

$$C(I - \Gamma L)R \tag{11}$$

In eq. (11) a consistent estimate (for $n > T$) of the reduced form factor loading matrix C is obtained by regressing x_{nt} on f_t (see Forni et al., 2003). The sign restrictions used to identify R (and the common shocks u) are along the lines of Uhlig (2004). In particular, we select all the rotations of the angle θ that imply, over the 12 months forecast horizon of the impulse response profile, a negative impact of the first shock on the real industrial production index, IP, and a positive impact on the aggregate consumer price, CPI, index. Among the selected rotations, we pick the one delivering the lowest impact, in the first three months of the impulse response forecast horizon (in order to allow a delayed effect from the shocks), on the aforementioned series. This particular rotation would then identify a supply shock. If, for this particular rotation, the impulse response profile corresponding to the second shock implies a positive co-movement between CPI and IP series, then the second shock is identified as demand-side structural form innovation.

5.2 Simulation of the credit worthiness index

Given that the credit drivers used in this paper are observed at monthly frequency and the forecast horizon is a year, we need to project the static factors 12 step ahead. Since $\varepsilon_t = KMHu_t$ we can derive the h -step ahead projection of the static factors (with $h = 12$) by rolling forward the VAR(1) in (10):

$$f_{t+h} = \left[\Gamma^h f_t + \Gamma^{h-1} KMHu_{t+1} + \dots + KMHu_{t+h} \right] \tag{13}$$

³ More recently, Kapetanios and Marcellino (2003) have proposed an alternative method, based on a state space model to estimate a large dimensional Dynamic Factor model.

Once we obtain an OLS estimate of the $r \times 1$ vector of sensitivities coefficients β_j , by regressing the stock returns obligor j on the r estimated static factors, we are able to project the systemic component of the creditworthiness indices:

$$A_{j,t+h} = \beta_j f_{t+h} \quad (14)$$

We can observe from (13) and (14) that in line with multifactor models for asset returns, the systemic component (driven by the common shocks) can be split in two parts. The first, described the first addend in the r.h.s of eq. (13), is the predictable component, which is a function of current and past values of the common shocks. These values describe the information set available at time t when the rolling forecasts are produced. The remaining addends in (13) capture the unanticipated systemic component, given that they are a function only of future common innovations.

The unpredictability of the A_j is further enhanced by allowing an idiosyncratic (firm specific) disturbance to affect the asset returns. Consequently, the h step ahead projection of the firm j asset return is given by:

$$A_{j,t+h} = \beta_j f_{t+h} + v_j \quad (15)$$

where v_j is the idiosyncratic (firm specific) innovation.

Since we want to compare the results obtained under the simulation of the portfolio loss with those corresponding to the analytic solution (see above), we need to generate return series that are $N(0,1)$. For this purpose the systemic component has to be standardised, hence the final specification for the creditworthiness proxies is given by:

$$A_{j,t+h} = \sqrt{R_j^2} \beta_j \left[\frac{\Gamma^{h-1} R u_{t+1} + \dots + R u_{t+h}}{\Gamma^{h-1} R R' \Gamma^{h-1} + \dots + R R'} \right] + \sqrt{1 - R_j^2} v_j \quad (16)$$

where the R_j^2 are the goodness of fit measures obtained from the OLS regression of the stock returns on the static factors. In eq. (3) underlying the analytic solution of the portfolio loss, the projection of the asset returns is entirely static and, furthermore, it is difficult to interpret the common shocks, in case they are at least two. If we focus on eq. (16), then the (reduced form) dynamic multipliers given by the powers of Γ and the structural form impact multipliers matrix R

allow to account for the dynamics of the credit drivers and to identify the systemic shocks, respectively.

To summarise, in the empirical analysis described below, we, first, consider the analytic solution for the portfolio loss obtained assuming that the asset returns follow the stochastic process given by (3). Then, we consider the simulation of portfolio loss, assuming that the asset returns dynamics is given by (16). In particular, we distinguish among three different cases. The first involves the assumption that there is only one common shock (interpreted as the state of the business cycle) driving the systemic component. In the second and third case we fix the dimension of u_t to two and we consider the marginal contribution to the overall portfolio loss due to either a supply or a demand shock. For this purpose, the first column of the structural form dynamic multipliers would identify the supply shock and the second column of the structural form dynamic multipliers would identify the demand shock.

Finally, we follow Krenin (1998) suggestions on how to deal with the replications in the simulation experiment. More specifically, we carried out 1000 simulations for each scenario, and conditional on each scenario we carried out 1000 simulations for the idiosyncratic component of each obligor creditworthiness index. This gives one million observations and by sorting them in ascending order we are able to obtain the unconditional portfolio loss distribution.

5.3 Comparison with the existing methods.

It is important to observe that existing portfolio credit risk models involved in the generation of macro scenarios through Montecarlo simulation rely on eq. (13) to project the systemic component for the creditworthiness indices. However, two are the main differences with the method proposed here. First, the shocks u are as many as the number of the observed credit drivers (see either Credit Portfolio View approach developed by Wilson, 1997, or the method suggested by Pesaran et al., 2004). In our method there are only few shocks underlying the dynamic of credit drivers. Secondly, the impact multiplier matrix R in equation (8) is diagonal in Wilson (1997) and lower triangular in Pesaran et al. (2004)⁴. We argue that the aforementioned identifying schemes are arbitrary. Consequently, we appeal to sign restrictions to identify the u 's. Finally, our preference of fitting a Dynamic a Dynamic Factor model rather than a VAR to the credit drivers can be explained as follows. First, the exogeneity assumptions used by Pesaran et al. (2004) to handle a relative large number of macro-variables characterising cannot be applied to our dataset (given that most of the

time series we consider are specific to only one country: Italy). Second, as shown in Giannone et al. (2003), the impulse response profile of macro-aggregates (whose observations are contaminated by measurement error) implied by equilibrium business cycle models, is better proxied by the impulse response profile (especially, in the short and medium run) estimated from a Dynamic Factor than the corresponding profile obtained by fitting a VAR to the empirically observed data. This can be explained by, first, acknowledging that the rank reduction feature of the system of endogenous variables is preserved by a DF model and, by also considering that the extraction of the factors is obtained by minimising the noise (which captures the measurement error) to signal ratio.

Finally, the last remark regards the simulation experiment suggested by Pesaran et al. (2004) which is based upon the joint draw of shocks to the credit drivers and specific to each firm (e.g. idiosyncratic innovations). This simulation procedure can be implemented only when the number of obligors is relatively small. However, in this paper, we deal with a large portfolio of obligors (see section 6.1), and we follow the suggestion of Krenin et al. (198) regarding the generation of different scenarios (see section 5.2).

6. Empirical analysis

6.1 Data

We consider a corporate portfolio, describing the exposures of an Italian bank towards corporate small and medium sized enterprises, SME. Specifically, in this portfolio, there are 270.000 claims which according to the different type of instruments (such as receivables, trade credit loans, and financial letters of credit) are associated with 150.000 counterparts, which gives 53 billions Euro regarding the committed amount and 31 billions Euro regarding the drawn amount. The obligors with marginal exposure have been grouped in homogenous clusters in terms of rating and economic sector. This allows to consider a portfolio with 9912 obligors (with cluster and non-clusters) which gives a total exposure of 44 billions of Euro. To summarise, we consider an heterogeneous portfolio consisting of 9912 sub-portfolios, with obligors treated identically within each sub-portfolio, but with probability of default, exposure and sensitivity differing across the sub-portfolios.

The data span (monthly frequency) under investigation corresponds to the period after the introduction of EMU, starting in January 1999 and ending in May 2003. We now describe the data regarding the proxy for the creditworthiness index and for the credit drivers.

Given that most of the obligors are non floated in the stock market, we assemble the counterparts in twenty large clusters corresponding to the following Italian MIB sub-sectors stock price indices: Food/Grocery, Insurance, Banking, Paper Print, Building, Chemicals, Transport/Tourism, Distribution, Electrical, Real Estate, Auto, Metal/Mining, Textiles, Industrial Miscellaneous, Plants/Machinery, Financial Services, Finance/Part, Financial Miscellaneous, Public Utility, Media. The returns on these stock indices are used to proxy the creditworthiness indices of each obligor.

We consider a large number of credit drivers. First, in line with CreditMetrics (1997), we consider financial variables, given by the MSCI stock price indices for a number of sectors (e.g. Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health, Financials, Information Technology, Telecommunications, Utilities) corresponding to different geographical areas (World, US, Europe, Emerging Markets). We also add to the stock prices data (which are the only ones considered by CreditMetrics, 1997), other financial, nominal and real macroeconomic credit drivers.

The other financial variables considered are the short term and long term interest rates in Italy (e.g. one, two, three, six, nine, twelve months Italian interbank rates; the MSCI Italian government bond yields for the following maturities: one to three years; three to five years; five to seven years; seven to ten years; over ten years).

The nominal variables are the consumer prices, CPI, and the producer prices, PPI. In particular the CPI indices considered are for all items (e.g. aggregate), and for different following aggregate goods: clothing and footwear; communications; education; electricity and other fuels; energy; food; furnishing; health; restaurants and hotels; insurance; recreation; transport. The PPI Indices are for all items and for the following sectors: basic metals; chemicals; consumer goods durable; non durable; electricity, gas and water, supply; electricity, gas, steam and hot water; energy; food, beverages and tobacco, intermediate goods; machinery and equipment; mining and quarrying; motor vehicles; publishing, printing and reproduction; textiles and raw materials.

The real credit drivers considered are given by the real seasonally adjusted (real) indices for aggregate industrial production and for the following sectors: investment goods, intermediate goods, energy, manufacturing, food, textiles, leather, wood, paper, coke, chemicals, rubber, non metals, metals, machinery, electricity, other, furniture, energy. Finally, among the set of real economic variables, we also include the real effective exchange rate.

The CPI and PPI series have been de-seasonalised by employing monthly deterministic dummies. Stationarity has been achieved by taking the first order differences. Finally, each series in the dataset have been standardised to have zero mean and unit variance.

6.2 Clustering

It is important to observe that in the portfolio under examination (see below), some obligors sharing common features are aggregated in clusters. Each of these clusters contains a large number of obligors, each with a small contribution. In order to estimate the conditional losses for each cluster, we apply the Law of Large Numbers, hence the whole distribution collapses into a single value: the corresponding expected loss. As for the large number of obligors organised in non-clusters and given their relative large exposure, we use Montecarlo simulation to obtain the corresponding conditional portfolio loss distribution. Furthermore, in each scenario, the sum of losses deriving from default of the non cluster obligors (obtained through simulation) and the expected loss from the clusters gives the (conditional) portfolio loss distribution. Finally, the Montecarlo simulation has been based upon the simplifying assumptions that: a) we do not account for the use of financial collateral and of credit risk mitigation techniques; b) we consider the year as the reference temporal horizon; c) we do not consider claims maturing in a period less than a year.

6.3 Credit risk measurement

Standard AIC and BIC criteria to select the number of static factors cannot be employed since they rely on the minimisation of a penalty function only of the time series dimension. Therefore, we employ the method suggested by Bai-Ng (2002), which involves the minimisation of a penalty function depending on both the cross section and time series dimension, and the number of static factors, r , is found to be equal to four. As for the estimation of the sensitivities β of the multifactor model for the asset returns, we use *OLS*, and the the corresponding R^2 are given in Table 1. Employing the scenario generation described in section 5, we obtain the simulated loss distributions. As we can observe (see Fig. 1-6) the shape of the unconditional loss distribution is asymmetric and highly skewed to the right.

From the Figures below and Tables 2 and 3 (numbers are in millions of Euros) we can draw the following conclusions. First, by comparing the second and third column of Table 3, we can observe that the Basel II measure of the unexpected loss (obtained from the analytic solution described in equation (7)) approximates closely the economic capital obtained from the simulated loss distribution relaxing only the assumption of homogeneous portfolio. Secondly, by comparing results in Tables 2 and 3, we can observe that the consideration of stochastic dependent recovery

shifts to the right the unconditional loss distribution, implying high values for the expected loss, unexpected loss and expected shortfall. Finally, If we disentangle the common shock in two structural shocks: aggregate demand and aggregate supply, then we can observe that the demand shock has an higher impact on the credit risk measure of interests (see the fourth and fifth column of Table 2 and Table 3). This holds for both the case of constant and of stochastic dependent recovery. This last finding can be explained by taking into account that two are the type of recession scenarios driven by the identified common shocks. The first, driven by a demand shock, is a deflationary type recession scenario, given that both output and prices fall. The second recession scenario is driven by a supply shock, and it is described by a fall in output and increase in the price level. In this case, the increase in the price level, redistributing wealth from lenders to borrowers (and, also decreasing the level of real interest rates), can mitigate the depressive effect on the firms cash-flows driven by a fall in output. Consequently, the supply shock can have a less severe impact on the financial health status of the obligors, and on the overall risk associate to the bank loan portfolio.

7. Conclusions

The aim of this paper is the measurement of the capital requirements for a bank, by taking into account, especially, the role played by the business cycle on default probabilities and loss given defaults. In order to account for interdependencies of defaults across different obligors, we focus on the unconditional portfolio loss distribution. In particular, since we depart from the homogeneous portfolio and constant recovery assumptions, our measures of the capital requirements are obtained from the simulated (unconditional) portfolio loss distribution. The macro scenarios are obtained by fitting a Dynamic Factor model to a number of macroeconomic credit drivers. The choice of this model is motivated by taking into account its good approximation (in the short-run) of the dynamics implied by equilibrium business cycle models (see Giannone et al. 2003). As for the identification of the systemic shock, we consider, first, the case of a single common shock (interpreted as the state of the business cycle) underlying the dynamics of the different credit drivers. Then, we disentangle the common shock in aggregate demand and supply innovations in order to assess their impact on the bank capital requirements for the chosen forecast horizon. We find evidence of capital requirements sensitive to the business cycle. Specifically, the empirical results suggest that, in line with Altman et al. (2002), ignoring the main feature of recoveries (as stochastic and dependent on default), can imply serious under provision of minimum capital requirements (especially in presence of macro-economic shocks identified as demand side innovations).

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Table 1: R² from the multifactor regressions

Food/Grocery	0.21
Insurance	0.44
Banking	0.57
Paper Print	0.27
Building	0.49
Chemicals	0.36
Transport/Tourism	0.23
Distribution	0.27
Electrical	0.58
Real Estate	0.30
Auto	0.30
Metal/Mining	0.19
Textiles	0.46
Industrial Miscellaneous	0.07
Plants/Machinery	0.36
Financial Services	0.33
Finance/Part	0.37
Financial Miscellaneous	0.37
Public Utility	0.53
Media	0.61

Table 1: credit risk measures with constant recovery

	analytic: impact of common shock	simulation: impact of common shock	simulation: impact of demand shock	simulation: impact of supply shock
Expected Loss	330	348.57	340.67	335.94
Unexpected Loss	2418.53	2711.90	4682.29	3841.66
Expected Shortfall	-	4047.75	5874.96	4349.66

Note: numbers are in millions of Euros

Table 2: credit risk measures with stochastic dependent recovery

	simulation: impact of common shock	simulation: impact of demand shock	simulation: impact of supply shock
Expected Loss	534.45	532.16	509.94
Unexpected Loss	9593.14	8376.73	6886.07
Expected Shortfall	11694.21	10412.04	7703.47

Note: numbers are in millions of Euros

Figure 1: Unconditional loss distribution: common shock and constant recovery

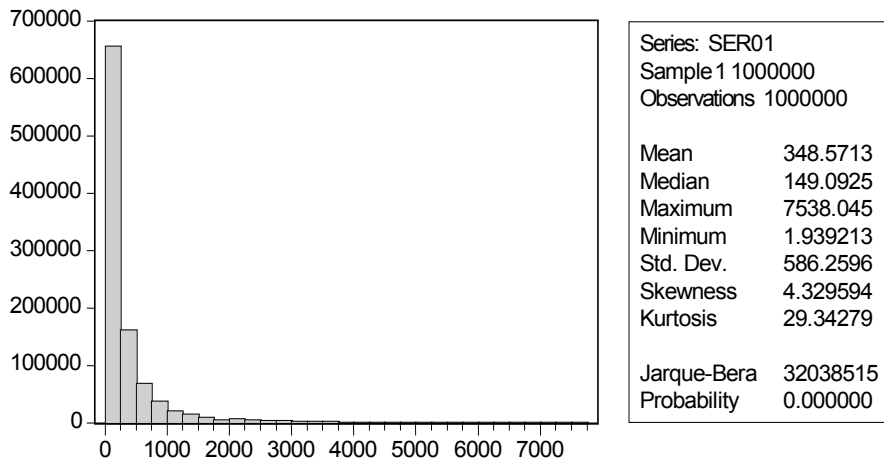


Figure 2: Unconditional loss distribution: demand shock and constant recovery

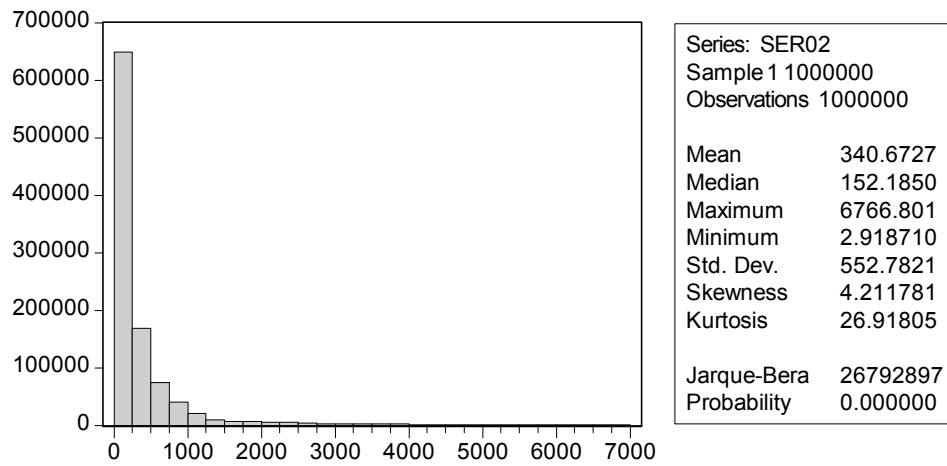


Figure 3: Unconditional loss distribution: supply shock and constant recovery

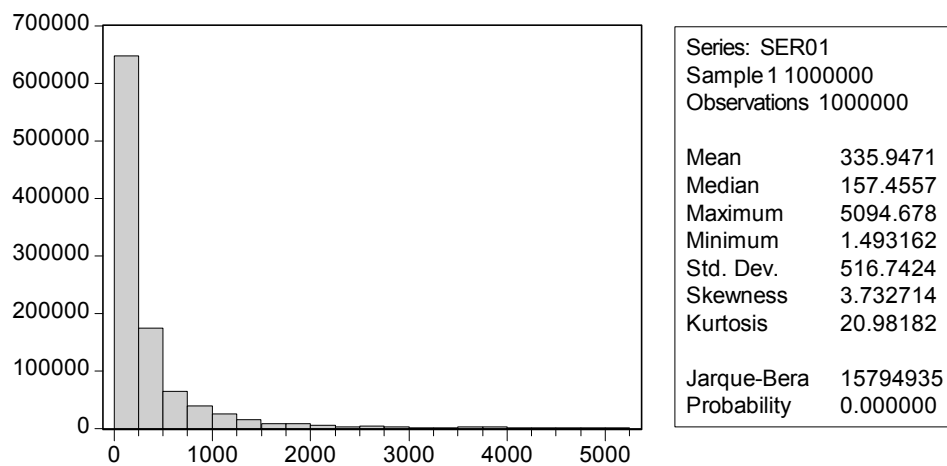


Figure 4: Unconditional loss distribution: common shock and stochastic dependent recovery

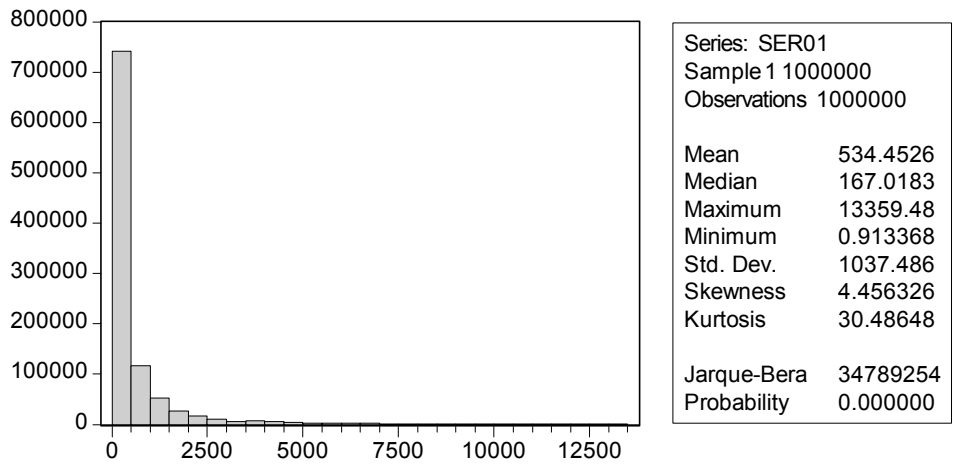


Figure 5: Unconditional loss distribution: demand shock and stochastic dependent recovery

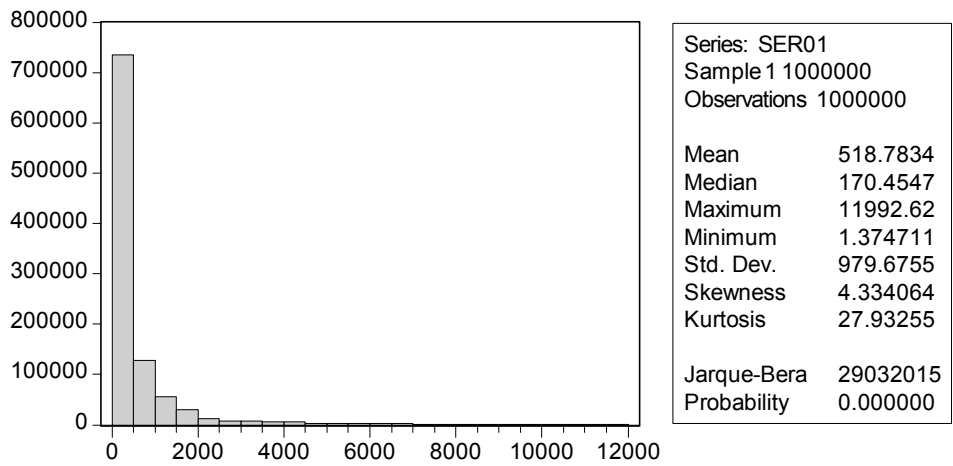


Figure 6: Unconditional loss distribution: supply shock and stochastic dependent recovery

