An exercise of stress-testing for the fleet usage and the loss-given-default in an operating leasing business

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***Abstract*—**The constantly increasing risk in today's global financial markets has emphasized the importance of correctly estimating future credit losses. Recent experience shows that underestimating the probability of default and the loss given default associated with financial transactions can threaten the stability of financial markets. Subsequent to calculation and estimation of these key risk parameters, stress testing has also gained importance in financial institutions with the introduction of Basel II. Although discussed from many perspectives, the predominant use for stress testing is in predicting how a portfolio would respond to changes in the macroeconomic environment. The present paper evaluates the impact of national and international macroeconomic shocks on the commercial fleet usage of a major operating leasing company. By analyzing the fleet usage under a range of macroeconomic scenarios over time, our research provides a dynamic framework for stress-testing the fleet usage and the expected and unexpected loss-given-default, with a number of foreseeable applications to financial stability related issues.

***Keywords*—**Loss-given-default, Macroeconomic variables, Regression, Stress-testing, Tail risks.

I. Introduction

LENDING institutions are aiming in maximizing their revenue, while limiting their losses due to default-either by avoiding default events in the first place or by recovering as much as possible when an obligor actually does become insolvent.

Driven by a competitive market and motivated by the new Basel Capital Accord [3], creditors have put a lot of effort into development and improvement of their methods to assess the creditworthiness of their obligors and to deduce the probability of default (PD). However, not only the probability of default but also the economic loss in the case of default has to be estimated to quantify credit risk and to calculate the Basel II capital requirements under the advanced approach. Subsequent to these aspects, stress testing has also gained importance in financial institutions with the introduction of Basel II. Although discussed from many perspectives, the predominant use for stress testing is in predicting how a portfolio would respond to changes in the macroeconomic environment. The future environment is encapsulated in a macroeconomic scenario for an extreme situation and then fed through a scenario-based forecasting model [6]. A stress test model must contain explicit macroeconomic factors. All stress test models are scenario-based forecasts. The most comprehensive use of stress testing has been in tradable instruments, whereas the technology for stress testing the loan book has historically lagged far behind.

A stress scenario includes economic downturns, depressing industry conditions, severe market risk events, different types of liquidity squeezes, solvency problems, and so on.

The plausibility of scenarios is important for the interpretation of the stress test results. Stress test results which show heavy losses for a financing company will more readily lead to counter-measures if decision-makers tend to regard the scenario as plausible. Plausibility standards should therefore exclude scenarios which are next to impossible and could for this reason undermine the credibility of stress test results. For this reason, correlations between risk factors are to be taken into account when identifying stress scenarios [17].

The stress tests implemented by the banks have registered some deficiencies lately. The amplitude and the severe current financial crisis has determined many banking institutions and supervising authorities ask if the stress tests used before this crisis were quite efficient and helped the banking sector to face this real challenge [7].

The financial crisis showed several lacks in the stress tests systems of the banks especially regarding the crisis scenarios and the methodologies used for crisis simulation.

In many banks, the stress tests were done only for specific activities or risks, without being considered an aggregation of results on the overall bank. Another issue is that most of the risk management methods, including stress simulations, use statistic data in order to assess the future exposures at risk. These data are based on long periods of economic stability and are not sufficient to identify a crisis. The banks underestimated the strong correlation between the lack of liquidities on the

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market and the financing pressure. Therefore, it is crucial to treat correctly the dependencies between different risks and integrate them on the overall financial group or bank [30].

Nowadays increasing global financial integration aims that many large financial institutions operate in many different economic areas and are active in lending in several countries. The balance sheets of large corporations and banks thus typically have a significant international exposure. Against that background, the assessment of the financial sector resilience needs to account for shocks that originate from the international environment rather than from the purely domestic macro-financial sources.

Examples of macroeconomic events with a global impact are:

- The multiple tightening of interest rates and bond market crash of 1994,
- The exchange rate mechanism crisis in September 1992 and its effect on the British pound, and
- The two major oil shocks of the 1970s.

Stress tests are an important risk management tool that has been used for a number of years now, both by banks as part of their internal risk management practices and by supervisors to assess the resilience of banks and of financial systems in general to possible shocks. This method is also called *scenario analysis* and it consists of specific scenarios of interest in order to assess possible changes in the value of the portfolio.

II. Pleading for Advanced Testing Methodologies

The new landscape of capitalism, known as the *market economy*, is far more sophisticated and complicated than previous versions have been. In fact, compared with banking in the post-World War II years, market economy sophistication has increased by more than a factor of ten. This change affects the way we look at the world, at our business and at the information we receive, and also at the use we make of such information. Data analysis pertaining to economic conditions and financial transactions has been always based on *statistics* (noun, singular), making use of *probabilities* and studying what might lie behind a distribution. But our notions of what that distribution may be have changed. In classical testing procedures the prevailing concept is that of the *normal distribution* characterized by a mean *(x),* the so-called true value; standard deviation *(s)*, the measure of dispersion; and *skewness* and *kyrtosis*. The twenty-first century brought along the need for *stress tests*, which is a quantum jump in data analysis. Experienced analysts know that the normal distribution hypothesis is a near-sighted approach that can lead to significant errors [7].

Many real-world situations are simplifications made through mathematical formulae, known as *models*. Bankers, traders and analysts need models to gain an idea of future movements in prices or other variables, to prognosticate the impact of market changes on their investment and to exercise control over exposure. A model, however, must adequately represent the relevant structural relationships between the variables that it addresses. This is not always achievable because of:

- Model uncertainty, and
- Data uncertainty.

Model uncertainty refers to a lack of knowledge about the most crucial variables that should be chosen. It also reflects limited knowledge about the exact transmission mechanism that characterizes the economic, financial or technical environment under study.

Data uncertainty denotes incomplete and unreliable information about developments affecting the chosen variables up to the current observation period. In addition, the data being collected may not be accurate, or fail to include extreme values, yet advanced type analysis target these outliers in particular [7].

The lack of extreme values that have low frequency, but high impact, is one of the most significant factors in creating the false belief that a distribution of events is normal, whereas in reality it is not. Fig. 1 provides an example from credit risk. *Spike* is an extremely short-lived price movement in the spot market. Spikes can also be created by a market disturbance, when the worst feared by economists, investors and analysts continues to worsen. This long-tail distribution must be studied through *stress testing*.

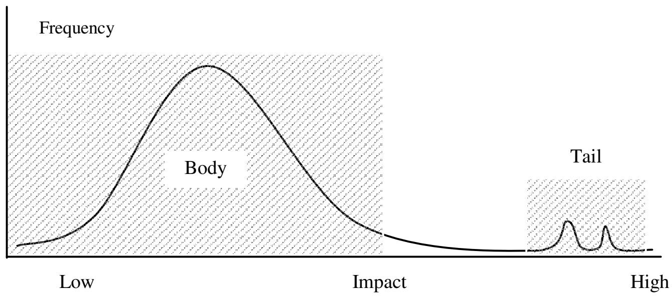

Fig. 1 A distribution of credit risk can be divided into a body, which is almost normally distributed, and a tail with own characteristics.
Source: Adapted by authors from [7]

Stress tests cover a range of methodologies. Complexity can vary, ranging from simple sensitivity tests to complex stress tests, which aim to assess the impact of a severe macroeconomic stress event on measures like earnings and economic capital. Stress tests may be performed at varying degrees of aggregation, from the level of an individual instrument up to the institutional level. Stress tests are performed for different risk types including market, credit, operational and liquidity risk. Notwithstanding this wide range of methodologies, the turmoil has highlighted several methodological weaknesses. At the most fundamental level, weaknesses in infrastructure limited the ability of banks to identify and aggregate exposures across the bank. This weakness limits the effectiveness of risk management tools - including stress testing.

The kind of approach (top-down or bottom-up) to be used in the stress test will be primarily determined by the availability of data to the supervisory authority. Both approaches have strengths and weaknesses.

From the supervisory standpoint, the top-down approach calls for a stress test structure that is both common (in terms of tools and methodology) and standard (applied identically to all participating entities). This normalized structure allows a test to be defined which is applied coherently and consistently regardless of the type and number of banks taking part in it. The use of a proprietary and joint framework applied uniformly for all participants yields results free from the arbitrariness and heterogeneity caused by internal differences in the methodology, calculations, importance and type of business of each individual institution. The main weakness of this approach coincides with the main strength of the bottom-up alternative: the richness of the individual information and the level of detail available to institutions, which enables a much more accurate perception (specific characteristics of their risk profile) of the impact that a particular shock would have. This greater level of detail, as compared with the uniformity of the common method, is the trade-off that must be weighed up when deciding which approach to use.[2]

The most complete stress exercise would undoubtedly be one in which the data available to the supervisory authority and to the individual institutions are fairly similar.

The exercise would be carried out by the authority (top-down approach) for the system as a whole. Simultaneously, the participating banks would carry out exactly the same type of test (the same assumptions and shocks) as the supervisor. These results would then be aggregated (bottom-up approach) and examined for convergence between those obtained in one and the other approach. Ideally it would be found that the exercise carried out by the authority replicates the results reported by the individual institutions using their own methodology.[2]

A recent survey of stress testing practice made by the Committee on the Global Financial System [8] shows that most stress tests are currently designed around a series of scenarios based either on historical events, hypothetical events, or some combination of the two.

Most risk management models, including stress tests, use historical statistical relationships to assess risk. They assume that risk is driven by a known and constant statistical process, i.e. they assume that historical relationships constitute a good basis for forecasting the development of future risks.[4]

Historical scenario stress testing is required by the Basel Committee, seeking to quantify potential losses based on re-enacting a particular historical market event of significance. Scenario shocks that determine the impact on portfolio valuation are taken from observed historical events in the financial markets. The first question in choosing a historical period for stress testing is which periods to choose. A historical event may be defined in one of two ways. In the first, the event is defined relative to a well-known crisis period (such as for example the Asian crisis of 1997). In the second, the event is defined by examining the historical record of moves in market risk factors relative to some user-defined threshold level of shocks. The second approach will no doubt also turn up events that correspond to most well-known crises, but may identify other event periods as well, depending on the particular risk factors whose histories are being scanned for large movements. The former approach is more prevalent.[25]

But history does not conveniently present the risk manager with a template for every plausible future market crisis (though the sample size of crises does keep increasing with time). For this reason, it may be desirable to create a hypothetical economic scenario as a stress test. Ideally, a hypothetical scenario is based on a structural model of the global financial markets (perhaps with a 'real' or physical goods and services component, too), in which the specification of a parsimonious set of market shocks provided as inputs to the model will result in a complete specification of responses in all markets. Well, in most cases that is not going to happen. Still, it is good to keep that ideal in mind when constructing an economic scenario, because it is very easy to make a bad scenario by ignoring cause, effect and co-determination in economic relationships.[25]

As a conclusion, historical scenarios try to re-create a particular economic environment from the past while hypothetical scenarios can represent a complete, but not yet experienced, economic situation. Creating scenarios based on historical data uses an intuitive approach, since it is plausible that a similar event happened in the past may occur again but, at the same time, it may lose its relevance in time because financial systems and markets are continuously changing.

On the other hand, hypothetical scenarios permit a more flexible approach of potential events, risk managers being more focused on anticipating particular events to which a portfolio may be vulnerable. We consider that both techniques need practical expertise and resource costs because of the difficulty of estimating the likelihood of an event.

The role of stress testing in risk management is significant for all the decision makers. At the managerial level, stress tests enable a comparison of risks across different asset classes and exposures, and highlight the need for risk limits and controls. At the executive level, stress tests provide a way of comparing the risk profile of the institution with the risk appetite of the owners, helping to guide decisions on the optimal allocation of capital within the institution. For all levels of management, stress tests can help to determine if the return on a particular product or position is commensurate with the level of risk.[14]

The progressive use of stress tests will foreseeably help banks and financial authorities to understand better the consequences of possible future events and, in particular, to assess their impact more accurately. This will have to be achieved by a commitment to step up the development of these tests and raise their accessibility and frequency of use, both by the more specialized and active institutions and by others focused on more traditional types of business, while avoiding over-simplification of the exercise or a mere description of routine processes that has no subsequent utility. The aim is to anticipate the impact of difficult situations, whatever their origin, potentially able to alter the stability desired by the supervisory authority. Consequently, an estimate can be made of the resilience that the banking system will show if certain hypothetical shocks become real events. Hence, the results of stress tests can and should: (1) add value to the internal control exercised by banks in the course of risk management, (2) serve as a basis for fostering prudential techniques of protection against adverse situations, and (3) facilitate prevention and early warning and response tasks to deal with these adverse situations.[2]

III. STATISTICAL APPROACH TO LINEAR REGRESSION MODEL

In this paper, we use a linear regression model to build the predictive model for the recovery rate, and hence LGD. We study the relationship between two observed variables with the aim of predicting the value of the response variable when a new value of the auxiliary one is observed. The standard mathematic equation is:

$$y_i = \beta_0 + \beta_1 x_{i1} + e_i. \quad (1)$$

The dependent variable (y_i) must be a metric variable (e.g. the recovery rate). The independent variables (β_i) can be both metrics and dummy (binary variables coded 0 or 1).

Linear regression is a statistical technique which offers correct response if and only if some assumptions are tested. In most cases, the analyst ignores verifying these assumptions, which is a serious mistake, because in this case, the results can have different values comparing to real life.

The most important function of regression analysis is the prediction. Using regression, we can predict the value of the dependent variable, by simply manipulating the values of independent variables.

The basic assumptions of linear regression are:

i) *Linearity*. If the relationship between independent variables and the dependent variable is not linear, the results of the regression analysis will *under-estimate* the true relationship.

ii) *Homoscedasticity*. For each value of x, the errors around the prediction point must have the same value of the standard deviation. This means that the standard deviation does not vary with the values of the explanatory variables

iii) *Normally distribution of variables,* which implies a continuous and normally distributed target variable. Non-normally distributed variables can distort relationships and significance tests.

iv) *Variables are measured without error.*

The reality is described by probability modelling, where the end result is an estimate of *p(Good)*:

$$P(Good)_i = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} + e_i \quad (2)$$

and our prediction about reality will use the determinist model: $\dot{y} = a + bx$, where $\dot{y}$ is the predicted value.

The probability for each record i, is the sum of a constant and the products of a series of weights β_j and variable values x_{ij}, where the variables take on different values for each record, and the weights differ for each variable j (the error term e_i is ignored). The problem arises because many of the assumptions mentioned above do not hold true. The most problematic are "normally distributed error terms" and "homoscedasticity", because the result only has two possible values, 0 and 1. This is exaggerated further because the predicted values often fall outside the 0 to 1 range [20].

The accuracy of the model depends on how well the regression line fits with real data. This matching is evaluated by considering one statistics: standard error, defined as standard deviation (s_e) of the estimation error:

$$s_e \sqrt{\frac{\sum \left(\hat{Y}_i - Y_i\right)^2}{n-1-k}} \quad (3)$$

Where s_e is the standard error, e the error term, n is the number of instances and k is the number of explanatory variables.

A large standard error indicates that the observed values are distanced from the regression line, and so it is less representative for real data. Consequently, the predicted values are affected by larger errors.

Another statistical indicator often used is the coefficient of determination (R^2) which, expressed as a percentage, shows how the variance of the dependent variable is explained by the estimated equation:

$$R^2 = 1 - \frac{\sum \left(\hat{Y}_i - Y_i\right)^2}{\sum \left(\overline{Y} - Y_i\right)^2} \quad (4)$$

The coefficient of determination can be interpreted also as follows: how much the forecasting of y values improves by considering the estimated model.

Linear regression is the most obvious predictive model to use for recovery rate (RR) modelling. But the error component of the linear regression model for predicting the recovery rate does not satisfy the random variable assumptions because the distribution of the recovery rate tends to be "a bathtub shape" [15].

However, linear regression has many strengths, such as:

- It is the most widely used method, being also easy to understand.
- Using a linear regression model is usually much faster than methods such as neural networks.
- Linear regression models are simple and require minimum memory to implement, so they work well on embedded controllers that have limited memory space.
- By examining the magnitude and sign of the regression coefficients (β) you can infer how predictor variables affect the target outcome.

IV. THE MODEL AND THE SCENARIOS

A. Model description

One of the main determinants of credit risk is macroeconomic developments that prove too adverse to the strategic plan of an enterprise, hence the need to study them ex ante. Typically, a baseline scenario of a macro stress test for the banking industry assumes that the economy will move downwards and a bank's lending, as well as its inventoried loans positions, will go through a low point.

This type of stress testing based on macroeconomics has gained increasing acceptance in recent years, as many institutions expanded their quantitative market risk management systems into the credit business, in preparation for Basel II implementation. In this process, they developed scenarios in which risk parameters are selected from different categories of exposure, including both market and credit domains.

For Finance lease products, the impact of stress scenarios on residual values has to be reflected in the stress test results - either in terms of loss on sale, reduction from expected case gains, or impairments (see details below). For Operating Leases the same is generally true.

Impairment condition (Covered under FAS 144, Paragraph 7): "1) Impairment is a condition that exists when the carrying amount of a long-lived asset (asset group) exceeds its fair value.

2) An impairment loss shall be recognized only if the carrying amount of a long-lived asset (asset group) is not recoverable and exceeds its fair value.

3) The carrying amount of a long-lived asset is not recoverable if it exceeds the sum of undiscounted cash flows expected to result from the use and eventual disposition of the asset."

Estimates of future cash flows used to test recoverability (FAS 144, Paragraph 16):

"Estimates of future cash flows used to test the recoverability of a long-lived asset (asset group) shall include only the future cash flows that are directly associated with and that are expected to arise as a direct result of the use and eventual disposition of the asset (asset group). Those estimates shall exclude interest charges that will be recognized as an expense when incurred."

Fair Value (Covered under FAS 157)

Par. 5: "Fair Value is the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date"

Par. 6: "A fair value measurement is for a particular asset or liability. Therefore, the measurement should consider attributes specific to the asset or liability, for example the condition and/or location of the asset or liability and restriction, if any, on the sale or use of the asset at the measurement date." [13]

Thus, the implementation of the above mentioned requirements in our leasing environment means to calculate:

(Undiscounted cash flows renting over the holding period + Undiscounted Residual Value) Vs. NBV (5)

In other words to calculate the ratio:

(Sum of Future Cash Flows (Revenue - Cost) + Residual Value)/Net Book Value (6)

If the ratio is:

- Lower than 1, it means the asset is impaired and brings a loss to the business in the situation of a sale of assets;

- Higher than 1, it means the sale of the asset brings a profit to the business in the situation of a sale.

For our exercise it is important to build a statistical model that relates the macroeconomic factors in the stress tests to changes in asset value and to other key impairment assumptions, such a rental rates. The amount of stress introduced should be explained in terms of a demonstrated relationship between the values of the macro-variables making up the stress scenario, and the impact on key variables used in the impairment analyses.

The analysis sample has 3,288 operating leasing (rental) contracts through which a number of 38,153 commercial vehicles were leased to corporate customers across 15 European countries. The fleet usage analysis was done over a period of 10 years (Jan-2000 to Dec-2010), by comparing the number of vehicles leased with the total fleet of the leasing company.

In parallel, historical macroeconomic data on similar time span has been gathered on Eurozone Gross Domestic Product (GDP) and Industrial Production (IP), Inflation, Unemployment, Interest rates from Global Insight[1] and Moody's Analytics[2].

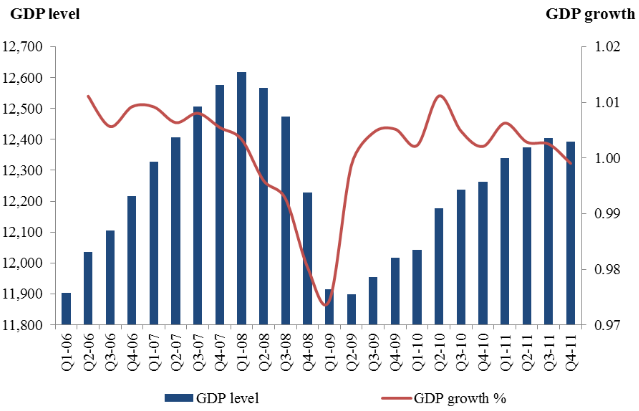

Fig. 2 GDP for Eurozone - historical data and forecasts

Source: Data were collected Global Insight and Moody's Analytics and were processed by the authors

Historically, Gross Domestic Product (GDP) and Industrial Production (IP) show similar trends Fig. 3 . However, GDP is projected a slower-paced recovery than Industrial Production. Additionally, GDP recovery is slowed by other sectors with slow 2009+ recoveries, such as Retail.

[1] See http://www.ihs.com/products/global-insight/index.aspx

[2] See www.economy.com.

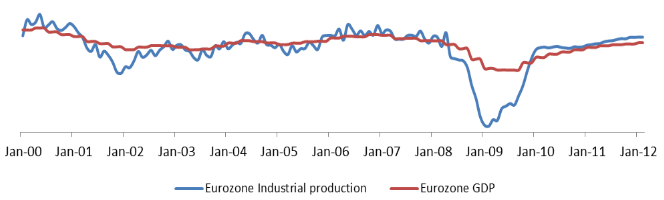

Fig. 3 GDP and Industrial Production historical data and forecasts
Source: Data were collected Global Insight and Moody's Analytics and were processed by the authors

Based on the macroeconomic data and the historical data regarding the fleet usage in our sample we have built several regression models between the fleet usage and the macroeconomic variables indicated above.

Conclusions and observations following the regression exercises are the following:

- Statistical relationship metrics indicate a good match between the fleet usage and the GPD, as graphically illustrated also by Fig. 4 ;
- Statistical relationship metrics indicate a weaker fleet usage relationship with IP versus GPD;
- IP shows a steeper decline as well as a faster and sharper recovery;
- The resulting model projects more extreme scenarios at peak and throughout the cycle.

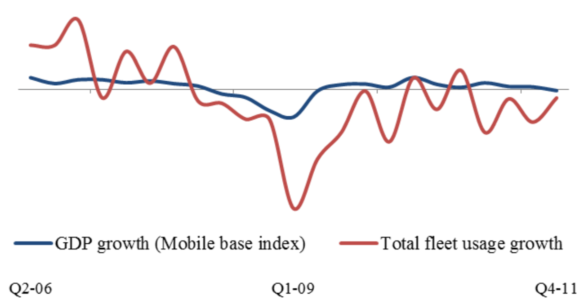

Fig. 4 GDP growth and Fleet usage growth historical data and forecasts
Source: Data were processed by the authors.

Every situation, no matter how bad it may be, can have a worst case. This worst case is not necessarily a catastrophe but, invariably, it leads to a salient problem; one to which senior management of the company must devote its full attention. In business, industry and government, a worst case is generally an event of low probability, but very high impact.

B. *Scenarios description*

Our stress-test is based on 3 scenarios: baseline, first stress and second stress with the following descriptions:

The *baseline* scenario is mainly based on the Autumn 2010 European Commission Forecast [31] and foresees a continuation of the economic recovery currently underway in the EU. GDP is projected to grow by around 1.7% in 2010-11 and by around 2% in 2012. A better than expected performance so far underpins the significant upward revision to annual growth in 2010 compared to the spring forecast. While the recovery is becoming increasingly self-sustaining at the aggregate level, progress across Member States remains uneven, with the recovery set to continue advancing at a relatively fast pace in some, but to lag behind in others. This reflects differences in the scale of adjustment, challenges across economies and ongoing rebalancing within the EU and euro area.

First stress scenario**:**
- 2011: Economic stimulus proves to be temporary and Europe debt crisis elevates; 2nd half slight deterioration (GDP halt, higher unemployment).
- 2012: Most countries' GDP growth flat or low. House prices flat or decline mildly and unemployment stays high or continues to rise.
- 2013: Slow recovery from 2011 level; interest rates increase slowly but unemployment still higher than pre-crisis level.

Second stress scenario**:**
- 2011: Stimulus proves to be temporary and Europe recession develops; 2nd half deterioration (negative GDP growth, higher unemployment).
- 2012: Negative/very low GDP growth in most countries. House prices decline and unemployment continues to rise.
- 2013: Slow recovery from 2012 level; interest rates increase slowly but unemployment still higher versus pre-crisis level.

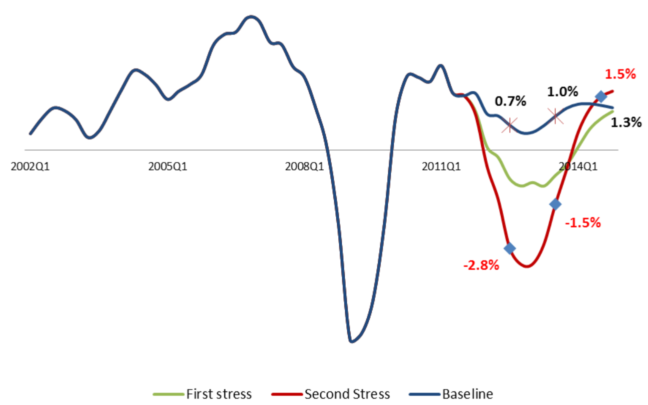

Fig. 5 Historical versus projected GDP growth percentages
Source: Data were collected from Global Insight and Moody's Analytics and were processed by the authors

First stress scenario and second stress scenario were developed from Moody's Analytics forecasts found at Economics.com.

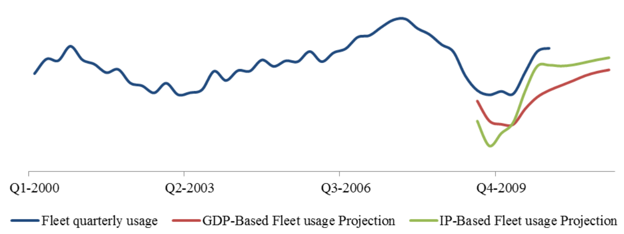

Fig. 6 Historical versus projected fleet usage against GDP and Industrial production

Source: Data were collected from Global Insight and Moody's Analytics and were processed by the authors

The historical monthly average fleet usage of the lender is presented in Fig. 6 . In the same graph we have included the results of fleet usage projections based on GDP and Industrial Production to picture out the trends.

The GDP based fleet usage projections are less extreme and show a slower recovery time than Industrial Production Index, which is a more likely future.

V. Default and Economic Loss

One distinguishes between "default" as a state (an obligor is "in default"), and "default" as an event (an obligor "defaults" on an obligation). The latter, more precisely described as a triggering event, means an event that precipitates entry into the former. That is, by "defaulting", the obligor enters into the state of being "in default" – a period we refer to as a "default episode".

By definition, a debt instrument can experience a loss only if there has been a default [21]. However, there is no standard definition of what constitutes a default. Different definitions may be used for different purposes. Typically a default occurs when any of the following conditions are met:

- A loan is placed on non-accrual;
- A charge-off has already occurred;
- The obligor is more than 90 days past due;
- The obligor has filed bankruptcy.

The Basel Accord (Basel Committee on Banking Supervision, 2004, paragraph 465) suggests using the implied historic LGD as one approach for determining the LGD for retail portfolios. This involves identifying the *realised losses* (RL) per unit amount loaned in a segment of the portfolio and estimating the default probability PD for that segment, from which one can calculate LGD, since RL = LGD*PD. One difficulty with this approach is that it is often accounting losses that are recorded rather than the actual economic losses. Also, since LGD must be estimated at the segment level of the portfolio, if not at the individual loan level, in some segments there are often insufficient data segments to obtain robust estimates. The alternative method suggested in the Basel Accord is to model the collection or work out process. Such data were used by Dermine and de Carvalho for bank loans to small and medium sized firms in Portugal [10]. They used a regression approach, albeit a log–log form of the regression, to estimate LGD [15].

In order to conform to best practices and Basel II requirements, the calculation of LGD must be based on *economic* loss as opposed to *accounting* loss [3]. The two tend to be similar on average, but there may be significant differences. The main reason for the difference is that economic loss should reflect the actual timing and amount of recovery and cost events, whereas accounting losses are driven by provisioning and charge-off policies that are partly discretionary and are based on estimates. For accounting purposes, once defaulted exposures have been charged-off, subsequent recoveries are typically not associated with any particular transaction.

There are two valid approaches to calculate economic LGD: Market LGD and Workout LGD. If a bond or a loan is actively traded in the market, a simple way to calculate LGD is to directly observe the price in the market after the default has occurred (30 days after default is the standard). This methodology, used by rating agencies [16], relies on the trading price as the markets expected present value of eventual recovery [21], [1]. For defaulted bonds and marketable loans it is possible to obtain *market LGDs* by calculating the ratio between the current market price and the nominal value [12].

Workout LGD calculates the loss of a specific credit transaction by discounting the cash flows associated with the transaction from the time of default to the end of the recovery process. Both inflows (recoveries) and outflows (costs) must be taken into account. Favoured by banks and bank supervisors, the workout LGD approach is the focus of the remainder of this document. In the next paragraphs we present a formulaic representation of LGD, analyze how to measure the different components of the LGD formula, and discuss the main challenges for these calculations in terms of both methodology and data requirements.

Workout LGD represents the net present value of the post-default cash flows related to a given transaction. It is typically expressed as a percentage of Exposure at Default (EAD). In equation form:

$$LGD = 1 - \frac{\sum_{t}^{T} \frac{R_t}{(1+r_1)^t} - \sum_{t}^{T} \frac{C_u}{(1+r_2)^u}}{EaD} \tag{7}$$

where:

LGD = Loss Given Default

R_t = Recovery amount at time t

C_u = Cost amount at time u

t = time at which a recovery event occurs (in years from the default date, e.g. t = 0.5 means 6 mo. after default)

T = Maximum time for the recovery process (in years from the default date)

u = time at which a cost event occurs (in years from the default date)

r_1 = discount rate for recoveries

r_2 = discount rate for costs

EAD = Exposure at Default of the transaction (legal claim by the lender for credit extended, including principal and accrued interest).

VI. Stress testing expected and unexpected losses

Traditionally, bankers' training and experience meant that they thought only of expected losses, and they did so only in the short term. Both notions are obsolete, if not downright wrong in a globalized economy. The more severe losses are unexpected, and the medium to longer term should always be a banker's preoccupation. This is itself a stress test. A stress test can also be defined as a risk management tool used to evaluate the potential impact on portfolio values of unlikely, although plausible, events or movements in a set of financial variables [18]. Other themes include the role of credit rating agencies in prognostication of credit losses, risk drivers entering into counterparty models and stress testing regulatory capital requirements.

A survey of stress testing practice [32] shows that most stress tests are currently designed around a series of scenarios based either on historical events, hypothetical events, or some combination of the two. These methods have been criticised by Berkowitz [5] and Greenspan [11] for their lack of rigour. They are typically conducted without a risk model so the probability of each scenario is unknown, making its importance difficult to evaluate. There is also a distinct possibility that many extreme yet plausible scenarios are not even considered [9].

One of the key advantages of the new Capital Adequacy Framework (Basel II) is that it distinguishes between expected losses (EL) and unexpected losses (UL). This difference between EL and UL is not just a conceptual issue, but neither are we talking of two distinct populations of events. The difference is subtle, and it takes a lot of attention to appreciate it.

El and UL are two areas of the same risk distribution function, as clearly shown in Fig. 7 . Thus, expected losses tend to fall towards the body of the distribution, while unexpected losses concentrate themselves in the tail. Where they differ is in the frequency, magnitude and impact of credit risk events.

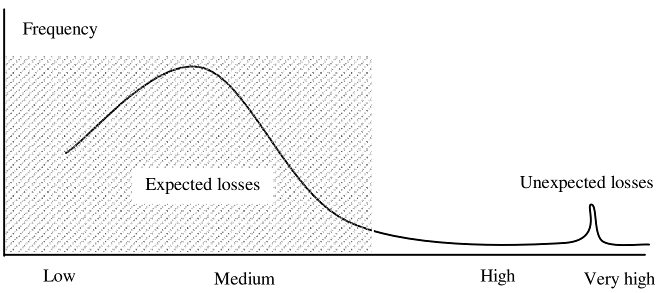

Fig. 7 Expected losses and unexpected losses come from one risk distribution, not two
Source: Adapted by authors from [7].

Expected losses and unexpected losses, and the thin line dividing them, have much to do with how a financing company manages its lending risks and its capital adequacy. One of the difficulties in making this simple fact understood is that different banks look at their EL from different viewpoints.

Traditionally, the mathematical approach to expected loss is to take it as the average loss in market value of an asset, resulting from credit-related events over the holding period of that asset [7].

*Expected loss = Probability of default * Severity loss upon default* (8)

This sensitivity of default is a function of loss given default (LGD) and exposure at default (EAD).

*Expected credit loss rate = Probability of default * (1-Recovery rate)* (9)

Credit institutions ensure that the distribution of EL is analysed both by position and on a portfolio basis. Analytics helps to address the *risk contribution* of each position, defined as the incremental risk of the exposure of a single asset's contribution to the portfolio's total risk. For management purposes, and for the whole company, a holistic EL equation for *n* positions in the loans book will be:

$$EL = PD_i(\%)*LGD_i(\%)*EAD_i(\$) \quad (10)$$

In a way similar to that of equation (6), the stress probability of default (SPD), stress loss given default (SLGD) and stress exposure at default (SEAD) should be calculated individually for each big account, reflecting obligor, transaction (and collateral), product-specific information and other deal-specific references. For the whole institution:

$$UL = SPD_i(\%)*SLGD_i(\%)*SEAD_i(\$) \quad (11)$$

The SPD and SLGD should be individually computed for all major accounts, with particular attention being paid to covenants, warranties, other add-ons and the likelihood of spikes. The same is true for EAD and SEAD. Into EAD must be mapped drawn amount, undrawn but committed (converted to cash), a factor reflecting product type (converted to capital) and other commitments that are applicable, expressed in financial terms. Estimates must include macroeconomic factors.

One of the main determinants of credit risk is macroeconomic developments that prove too adverse to the strategic plan of an enterprise, hence the need to study them ex ante. Typically, a baseline scenario of a macro stress test for the banking industry assumes that the economy will move downwards and a bank's lending, as well as its inventoried loans positions, will go through a low point.

Table 1: Stress-test for LGD under 3 different scenarios

Scenario	Year	Unstressed LGD	Stressed LGD
Baseline	2011	0.26%	0.28%
	2012	0.74%	0.78%
	2013	1.29%	1.36%
First Stress	2011	0.31%	0.42%
	2012	0.85%	0.89%
	2013	1.32%	1.39%
Second Stress	2011	0.26%	0.27%
	2012	0.76%	0.80%
	2013	1.34%	1.41%

We have calculated the LGD for each scenario using formula (5) as percentage of Exposure at Default and the results are included in the table 1. As expected the stressed loss values are higher than the unstressed losses as the considered scenarios conditions worsen.

VII. Conclusion

Stress probability of default, under adverse market conditions, SLGD, also known as downturn LGD, and SEAD are becoming basic elements in banking governance. In order to be able to calculate both expected loss and unexpected loss on a transaction level, it is crucial to be able to summarize the results of a recovery process with a single value. The ultimate recovery amount, or (1-LGD) is such a summary measure, and it must be kept in mind that it is derived from a process over time and that very different processes may lead to identical LGD values. Calculating these LGD values in a consistent manner is obviously necessary if we intend to create meaningful LGD distributions and ultimately, predictive LGD models.

In our opinion, the key role of the stress tests is to draw attention of how much capital might be needed to absorb losses in case of a financial crisis or other shocks and therefore increase the banks resistance in recession times. The importance of these tests is bigger in a stable economy because, due to the fact that there are no special risks, the banks might not be aware of the major impact of a financial crisis upon their stability. Practically, stress testing forces management to consider events that they might otherwise ignore.

In the present work we have considered non-discounted amounts. The research can be detailed and the model can be further developed by discounting the recoveries with a chosen discount factor. The LGD is calculated as of the time of default, while the cash flows associated with a recovery process typically occur over several months or years. Consequently, both recoveries and costs must be discounted back to the time of default in order to take into account the time value of money and potentially any risk borne during the workout process [28]. The impact of the choice of the appropriate discount rate may be significant, especially when the collection effort is lengthy, as is the case in large corporate bankruptcies. Because the discount rate may have a material effect on LGD calculations this can be further treated in future research.

Likewise, the research can be continued with a back testing process. This typically involves inputting actual historical macroeconomic data for a recent period into the Model, and comparing the forecast loss output to the actual losses experienced over the period. This is one of the most rigorous means to validate a Model. It may not always be possible to back-test, and some methodologies that do not involve a statistical model are generally not susceptible to validation through back testing. In such cases there are other approaches that can be taken that may provide some comfort that the model or method being employed is valid. These aspects can be continued with further in-depth research.

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