Finance for Europe

Discussion Paper

Downturn LGDs February 2015

Summary

This paper is an industry contribution on the issue of downturn LGDs in the regulatory capital framework. It is designed to provide context to and foster further discussions on the topic.

By examining regulatory definitions, downturn drivers and downturn impacts on LGDs, the paper briefly illustrates how banks navigate through the multifaceted nature of downturn LGDs calibration. This is then summarised and organised into an illustrative analytical approach to downturn calibration. Lastly, the paper sets out possible solutions for dealing with data scarcity.

Downturn calibration is used in the regulatory framework as a way to make sure correlations between PDs and LGDs, or adverse dependencies, if any, are reflected in capital requirements.

- Given that early studies in this area focussed on market observed LGDs which appeared to be cyclical, increases in default rates in downturn periods have often been equated with increases in losses. However, experience gained by banks during past 10 years of internal modelling often confirms that work-out LGDs are less directly sensitive to macro-economical cyclicality than market LGDs.
- The regulatory framework had anticipated these types of situations, as when no adverse dependencies are observed in the portfolio or exposure history available to banks, "there is no supervisory expectation that the forward-looking forecasts of recovery rates embedded in LGD parameters will differ from those expected during more neutral conditions" (BCBS 2005 "Guidance on Paragraph 468 of the Framework Document").

Identifying a downturn and assessing its possible impact are separate steps but the choice of downturn indicator can influence the measurement of the downturn effect.

- Downturn identifiers or proxies used to capture the state of the economy are numerous, can be combined and need to be selected carefully. These identifiers include macro-economic indicators (including more or less forward looking measures such as GDP, bankruptcies, unemployment, interest rates, etc.) as well as internal measures on banks' portfolios (e.g. observed default frequencies, provisions, impairments and losses).
- These typical and well-documented risk drivers may impact on LGD levels. However, the effect of a downturn period is not necessarily always straightforward to observe. This is often due to the time lag between default events and the outcome of work-out processes.
- Downturn impacts themselves are driven by the choice and combination of downturn identifiers together with the segmentation of target portfolios. The exact relationship between downturn periods and LGD levels is dependent on the types of drivers used to capture the state of the economy, the type of client and exposure under consideration and on the firm's asset recovery strategies.
- The impact on LGD is outcome of the downturn conditions, rather than a parameter in identifying the downturn period. The LGD process starts with economic and credit related factors which precipitate the default, however the firm's recovery management and economic conditions during the recovery process may impact on the LGD outcome. Under certain downturn conditions with increased defaults, a combination of robust workout strategies and improving economy could lead to 'downturn LGDs' being lower when than compared with losses on defaults occurring outside of the downturn.

This document provides an illustration of a theoretical analytical process that a firm may use to carry out its downturn calibration to produce appropriate and prudent calibrations that are adapted to its specific situation.

Data limitations can be a challenge when estimating LGD parameters consistent with economic downturn conditions. There are however several tools that can be used to overcome such situations while at the same time **maintaining a risk-sensitive capital framework**. In particular, the use of **data pooling** should be investigated as means to overcome data scarcity when it occurs.

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1. Introduction

Loss Given Default (LGD) is a significant driver of capital. Not only because it has a direct proportional impact on capital requirements for credit risk, but also because it captures multiple dimensions of risk which include idiosyncratic factors (linked to the obligor or the facility), the context of the operation (economic environment, geography, etc.) as well as other aspects related specifically to each institution (such as the firm's organisation and recovery process or strategy to quick-sell distressed debt).

More specifically, the Basel framework requires firms to use a "downturn calibration of LGDs" in the RWA formula (see Appendix), a parameter that is based on banks' internal assessments of LGDs during adverse conditions. However, the observed potential impact of downturn economic conditions on banks' portfolios has proved to be variable.

Given LGD's important impact in the framework, the BCBS is concerned that LGD estimation could be a source of excessive variability in firms' risk weighted asset outcomes. There are several aspects to this concern, such as differences in firms' approaches to determining the downturn aspect of LGDs, but also the approach to adopt when determining LGDs in situations of limited available data, such as low default portfolios.

This document begins by recalling the basic rationale for downturn and risk weight calibration as available in regulatory documentation. It then describes the multitude of factors firms navigate when determining downturn LGDs and summarises this in an illustrative, organised approach that firms can use for downturn calibration, noting that varying LGD approaches and outcomes are justified and to be expected given the wide variety of factors at play. Lastly, it also looks at solutions that can be developed in cases of data scarcity.

2. Going back to basics - understanding the Basel approach to LGDs

The downturn notion serves to introduce conditional LGDs consistently with conditional PDs in the RWA formula

According to the BCBS's 2005 "Explanatory Note on the Basel II IRB Risk Weight Functions", the notion of "downturn" serves to introduce the conditionality of LGDs required to be consistent with the modelling approach adopted for the regulatory risk weight function. Hence, the notion of downturn is not equivalent to a notion of margin of prudence or "automatic add-on", but is rather a way to make sure correlations between PDs and LGDs are reflected appropriately, provided that these correlations are effectively observed in data history or anticipated by expert judgment.

As a consequence, it may be perfectly feasible that banks do not observe an impact on their LGD parameters when they seek to introduce this required conditionality. If no downturn impact is observed, a conditional LGD can therefore be the same as an average LGD.

Downturn LGD calibration can equal the long term average LGD

The 2005 BCBS paper "Guidance on Paragraph 468 of the Framework Document" provides further guidance on determining downturn LGDs and confirms the understanding set out above.

Not only does it specify that the requirement to reflect economic downturns is "to ensure that LGD parameters will embed forward-looking forecasts of recovery rates on exposures that default during conditions where credit losses are expected to be substantially higher than average", it also clearly states that "*In those cases where future recovery rates are expected to be independent of future default rates there is no supervisory expectation that the forward-looking* *forecasts of recovery rates embedded in LGD parameters will differ from those expected during more neutral conditions.*" It also goes on to say that "*If no material adverse dependencies between default rates and recovery rates have been identified through analysis consistent with [the guidelines], the LGD estimates may be based on long-run default-weighted averages of observed loss rates or they may be derived from forecasts that do not involve stressing appropriate risk drivers.*"[1]

Although this guidance was published 10 years ago, there has been no other guidance or indication since that the approach to LGD calibration should be considered any differently.

Data and literature available at that time[2] was often based on datasets including both bond and loan market LGDs (or market implied LGDs). As a natural consequence, those studies established strong links between market movements, declining asset prices and rising losses derived there from. However, experience since gained by banks when performing compliant internal calibration of their (pure) loans' based work-out LGDs often illustrates that internal LGDs are less directly responsive to macro-economical cyclicality than market (observed) LGDs.

The 2008 crisis in particular has also revealed that there are potentially complex questions that firms have to deal with when making downturn assessments.

The following section therefore describes the range of different aspects that firms consider when assessing downturns and provides guidance on the different steps involved in the process, distinguishing between the identification of a downturn period and the assessment of its impact, if any.

3. Factors influencing the downturn assessment

Identifying a downturn and assessing its impact on a bank's portfolio are two different steps in the calibration process of a downturn LGD.

Choosing macro-economic proxies to capture the state of the economy and identify downturn periods requires caution

Although seemingly intuitive, it is difficult to find analysis supporting the notion that recoveries are consistently lower during periods of recession. While several authors (Schuermann, 2004; Frye, 2000; Khieu et al., 2012) comment that recoveries on bonds and loans appear to be lower during recessions, in general industry analysis does not always reveal a strong negative effect of macroeconomic variables on internal workout LGDs. Correlations between macroeconomic factors and workout LGDs might be observed in some situations, but not in others and, when they are observed, they are not always statistically significant.

As an example of this, analysis conducted by one of our member firms based on the Moody's Default and Recovery Database (DRD) from 1989 to 2014, finds positive correlation between LGDs and default rates and unemployment rates (see correlation table below). However, these correlations do not translate into statistically significant differences (see p-value table below) between average recovery rates in downturn periods (53%) versus non-downturn periods (59%).

[1] BCBS Guidance on Paragraph 468 of the Framework Document

[2] See for instance "What Do We Know About Loss Given Default", Til Schuermann, 2004

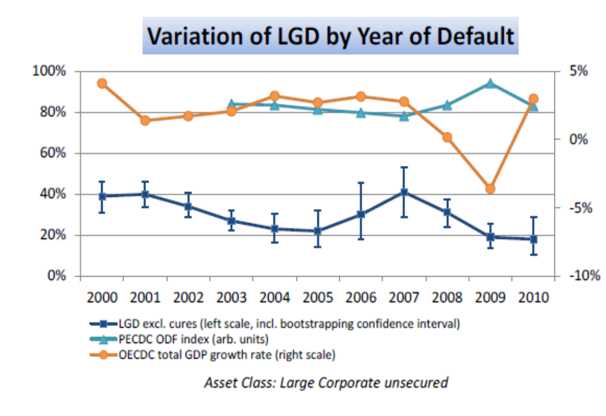
	C_N_GDP	C_R_GDP	CPI	PPI	Retail Sales	Wholesale	Unemployed Rate	R_Stock	Default Rate
Rec-CNR	0.26	0.20	0.00	0.06	0.16	0.14	-0.02	0.11	-0.46
Rec-CNRL4	0.15	0.06	0.23	0.29	0.15	0.30	-0.18	0.22	-0.22
Rec-CDR	0.25	0.20	-0.01	0.06	0.16	0.14	0.00	0.12	-0.46
Rec-CDRL4	0.13	0.06	0.20	0.28	0.14	0.29	-0.16	0.22	-0.21
Rec-NR	0.32	0.25	0.06	0.05	0.19	0.16	-0.10	0.14	-0.45
Rec-NRL4	0.18	0.09	0.23	0.23	0.17	0.26	-0.25	0.24	-0.22
Rec-DR	0.28	0.23	0.02	0.04	0.17	0.14	-0.02	0.14	-0.47
Rec-DRL4	0.15	0.07	0.20	0.24	0.15	0.28	-0.18	0.23	-0.21

Correlation table showing negative correlation between recoveries/unemployment and recoveries/default rates in downturn periods. Source: AFME member firm

	CDR	CNR	DR	NR
All Industry	0.069	0.085	0.030	0.012
Capital Industries	0.325	0.242	0.236	0.073
Consumer Industries	0.285	0.236	0.413	0.481
Energy & Environment	0.025	0.024	0.022	0.018
FIRE	0.827	0.826	0.827	0.827
Media & Publishing	0.208	0.408	0.187	0.423
Retail & Distribution	0.480	0.544	0.595	0.769
Technology	0.082	0.079	0.074	0.073
Transportation	0.148	0.181	0.148	0.329

P-values for K-S test used to test the significance of the difference between recovery rates in downturn and non-downturn periods (by industry sector). The difference is significant only for one industry sector (energy and environment). Source: AFME member firm

The following chart, taken from a 2013 analysis by the Global Credit Data Consortium (former PECDC) also shows that periods of higher losses are not always correlated with periods of weaker GDP growth and higher default rates. Indeed, the trough in GDP and peak in defaults of 2009 does not correspond to the highest LGD levels over this timeframe.

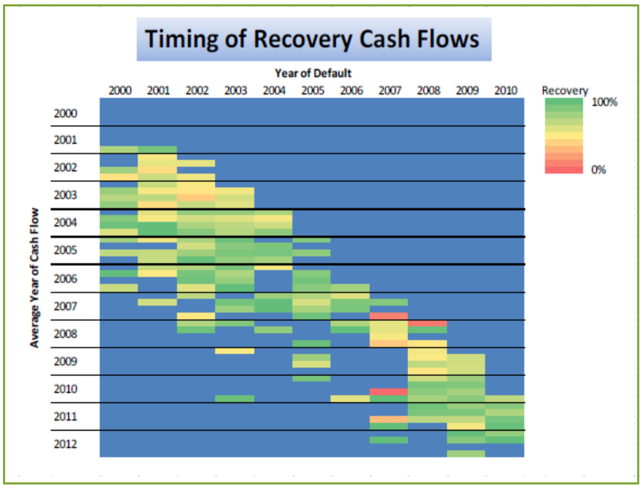


Asset Class: Large Corporate unsecured

Firms' workout strategies play an important role and need to be factored into the analysis

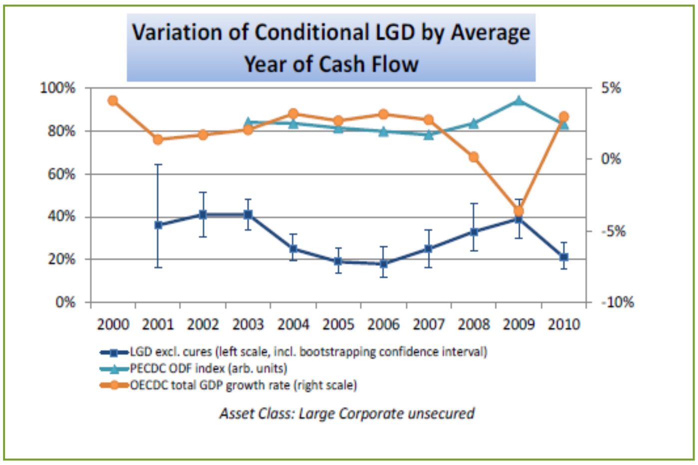
The lag identified above can be attributed to unresolved defaults which are not visible in the data set. However, it can also be due to institutions actively managing their work-out strategies in times of poor economic conditions. In such cases banks choose to delay or speed up recovery processes, depending on obligor specificities and the economic context, resulting in final default outcomes being observed at a time that is not aligned with economic cycles. The duration of work-out strategies can vary from rapid sells of distressed debt to longer work-out periods that are adapted to economic conditions and the potential improvement of obligors and collateral values.

The following heat-map taken from the same Global Credit Data Consortium study illustrates this effect, with defaults originating from the global financial crisis years of 2007 and 2008 experiencing much later recoveries (e.g. 2012) than defaults dating from non crisis years.



The LGD by average year of recovery better captures the down-turn effect than the LGD by year of default

This indicates that another time axis than the year of default might be better suited to analysing macroeconomic effects on LGDs. The chart below shows that when LGDs are assigned to a point in time at which the average of the recovery cash flow took place, the co-movement with macro-economic conditions is more consistent with typical expectations.



Dahlin et al (2014) recall that "since bankruptcy processes can last several years (Araten, 2004), an important aspect when looking at the macroeconomic environment is the time lag between the event of default and the bankruptcy process where the firm's assets are sold. While the macroeconomic conditions at the event of default might influence the probability of default, what probably influences the LGD is the macroeconomic environment during the bankruptcy process."

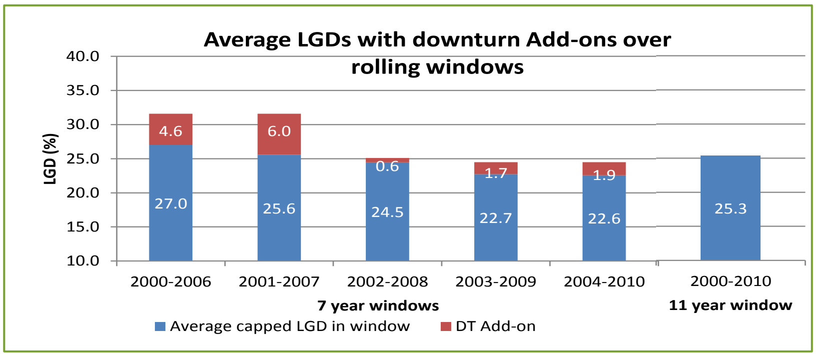
Consequently, to cope with the time lag effect and, because LGDs are not (only) impacted by economic conditions at the time of the default, downturn drivers should include forward looking elements (such as interest rates, stock indices, etc.) in addition to measures such as changes in GDP (which are more backward looking).

The choice of internal risk metrics used as downturn drivers can lead to different impact measurements

To ensure consistency with the philosophy of the capital framework and its use of conditional PDs, periods of increases in observed default frequency (ODF) appear to be the obvious starting point for identifying downturn impacts. As we saw above, depending on the data/time periods used, periods of higher defaults can be correlated with loss rates, although not always negatively.

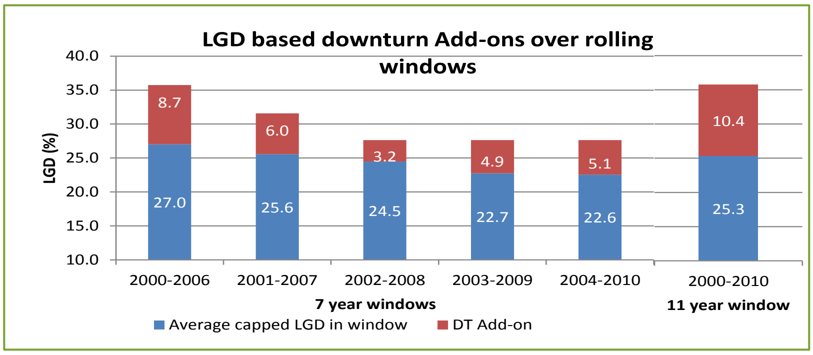
However, it has also been shown that the choice of downturn drivers itself can heavily influence the assessment of a downturn impact. For example, in a Global Credit Data Consortium (former PECDC) study carried out for the IIF in 2014, different drivers were tested on the a same data sample of real bank defaulted loans . The resulting downturn impacts were very different. When the highest default years were used to identify downturns (as shown in chart 1) the downturn impacts were up to 5 times lower than when the highest loss rate years were used as the downturn driver (as shown in chart 2)

Chart 1: Downturn driver based on significantly higher default rate periods



This study also showed that the choice of time window had an important impact on the downturn effect identified, with the downturn impact varying between 3.2% and 8.7% depending on the choice of window over a 7 year time frame and reaching 10.4% for an 11 year data window as shown below:

Chart 2: Downturn driver based on significantly higher LGD periods



Source: both charts above are taken from a joint study conducted by the Global Credit Data Consortium (former PECDC) and the IIF (IRTF project) on a reference data base of real defaults (5 362 Large Corporate resolved defaults from 2000 to 2010 at borrower level).

As such, if a downturn analysis is restricted to periods of increased ODFs, there is a risk of not fully capturing downturn impacts and it may therefore be appropriate to examine periods of higher losses too.

Other risk drivers (like exposure type, collateral, country, etc.) also have an important influence on downturns and careful segmentation is therefore required

A careful segmentation of portfolios is also required to deal with the multi-faceted nature of the downturn issue. This segmentation can be based on factors linked to the environment such as geographical/economic context (global crisis, regional crisis, etc.), sectoral or market implied risks (e.g. industry default levels) and also asset class specificities (e.g. facility type, including security and seniority levels). Through segmentation, it can be shown that some portfolios are downturn immune.

European residential mortgage markets are a good example of how exposure categories can behave differently across geographies and show that downturns are not always synchronised. The EBA's "Fourth Report on the Consistency of RWA - Residential Mortgage Drill-down Analysis" shows how diverse RWAs for the residential mortgage asset class can be between European countries, with RWAs genuinely ranging from 9% to 45% for this asset class across countries as shown in the table below taken from the report. They are indeed correlated with local markets specificities in terms of risk profile and mitigation policies.

Annex 1: Country-weighted averages by country

Figure 16: Minimum, maximum and EAD-weighted average for the drill-down variables, by country

<table>
<tr><th></th><th>RW</th><th>LTVO
Min | Mean | Max</th><th>ILTV
Min | Mean | Max</th><th>DTSO
Min | Mean | Max</th><th>LTIO
Min | Mean | Max</th><th>CRMO
Min | Mean | Max</th></tr>
<tr><td>AT</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>BE</td><td>10%</td><td>73% | 80% | 86%</td><td>62% | 68% | 73%</td><td>31% | 37% | 45%</td><td>3.9 | 4.1 | 5.4</td><td>24% | 40% | 58%</td></tr>
<tr><td>CZ</td><td>26%</td><td>71% | 76% | 86%</td><td>70% | 73% | 76%</td><td>29% | 35% | 38%</td><td>4.3 | 4.5 | 5.6</td><td>0% | 2% | 7%</td></tr>
<tr><td>DE</td><td>16%</td><td></td><td>73% | 79% | 85%</td><td></td><td></td><td>0% | 22% | 38%</td></tr>
<tr><td>DK</td><td>12%</td><td>70% | 71% | 82%</td><td>72% | 75% | 90%</td><td></td><td>3.2 | 3.2 | 5.7</td><td>0% | 0% | 14%</td></tr>
<tr><td>ES</td><td>17%</td><td>66% | 73% | 75%</td><td>59% | 65% | 70%</td><td>27% | 32% | 45%</td><td>4.7 | 5 | 7</td><td>0% | 1% | 16%</td></tr>
<tr><td>FI</td><td>10%</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>FR</td><td>16%</td><td>77% | 85% | 91%</td><td>71% | 72% | 84%</td><td>21% | 30% | 36%</td><td>3 | 3.3 | 4.8</td><td>4% | 62% | 75%</td></tr>
<tr><td>IE</td><td>45%</td><td>73% | 75% | 78%</td><td>103% | 109% | 117%</td><td>16% | 25% | 36%</td><td>3.5 | 4 | 5.9</td><td>0% | 0% | 0%</td></tr>
<tr><td>IT</td><td>15%</td><td>63% | 67% | 68%</td><td>59% | 61% | 65%</td><td>29% | 37% | 45%</td><td>4.4 | 5 | 6.2</td><td>0% | 0% | 7%</td></tr>
<tr><td>LU</td><td>16%</td><td>54% | 75% | 87%</td><td>51% | 68% | 76%</td><td></td><td></td><td>5% | 87% | 100%</td></tr>
<tr><td>NL</td><td>10%</td><td>86.6% | 87.1% | 89%</td><td>83% | 87% | 94%</td><td>23% | 26% | 29%</td><td>4.6 | 4.8 | 6</td><td>17% | 41% | 67%</td></tr>
<tr><td>NO</td><td>9%</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>PL</td><td>18%</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>PT</td><td>22%</td><td>76% | 77% | 80%</td><td>66% | 70% | 77%</td><td>17% | 31% | 62%</td><td>4.3 | 4.9 | 6</td><td>0% | 4% | 55%</td></tr>
<tr><td>SE</td><td>5%</td><td>69% | 72% | 75%</td><td>59% | 68% | 72%</td><td></td><td></td><td>0% | 1% | 4%</td></tr>
<tr><td>SK</td><td>30%</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>UK</td><td>11%</td><td>65% | 71% | 79%</td><td>64% | 70% | 89%</td><td>16% | 23% | 30%</td><td>3.1 | 3.6 | 4.8</td><td>0% | 0% | 0%</td></tr>
<tr><td>Total</td><td>15%</td><td>54% | 76% | 95%</td><td>51% | 74% | 117%</td><td>13% | 27% | 62%</td><td>2.4 | 3.9 | 7.2</td><td>0% | 18% | 100%</td></tr>
</table>

Note: Country-weighted averages are based on bucket medians, but the upper bound is used for the lowest bucket. For exposures above the latest bucket, 160% is taken for LTVO and ILTV, 80% for DTSO and 9 for LTIO. Exposures reported as non-available are excluded. Only countries with at least four observations are represented. CRMO statistics are calculated on the percentages of exposures with credit risk mitigant (other than mortgages) over the total amount of residential mortgages.

Source: EBA data collection (reference date: December 2012), EBA calculation

Different products also have different implications in terms of recovery estimates. A downturn analysis conducted on the basis of data covering a non homogenous variety of asset types can lead to confusing signals. For instance, within the corporate exposure class, it is necessary to segment portfolios by facility type, differentiating between bonds, where recovery rates are market implied (market value of resale), and loans, where recovery rates are determined by the individual institution's work-out strategy. As different types of recovery can lead to different downturn results, it is necessary to assess whether there is a downturn effect on the basis of homogenous asset classes.

Lastly, an institution's individual approach to calculating recoveries will also have an impact, e.g. depending on whether recovery flows are discounted or undiscounted, include proxies for unresolved defaults, etc.

In conclusion…

When considering downturn LGD calibration, it is necessary to separate the issues of identifying the downturn period and then assessing the downturn impact.

Losses are also the result of a process. This process has a duration, beginning with the default date and ending with default resolution. Events occurring during that process which impact the level of losses (e.g. recoveries, sales, etc.) are themselves impacted by conditions that occur during that process and not only by conditions present at the time of default. LGDs used for modelling are "output parameters" resulting from this process. In other words, they are a variable depending economic conditions and credit related factors which include a firm's recovery management and considering losses only at the beginning of the recovery period (i.e. the point of default) fails to capture any cyclical effect that occurs during the recovery period.

In order to determine downturn LGD calibration, firms could therefore test the relationship between the dependent variable (the LGD) and its independent predictors/risk drivers such as macro economic conditions, credit factors specific to exposure and the nature and duration of the workout process. The following section provides an illustrative process for doing so.

4. A theoretical analytical process for downturn calibration

The factors examined above can be summarised in a series of steps that may be involved in determining downturn LGD calibration.

These steps are provided for illustrative purposes only to help guide the reader through the multifaceted nature of the downturn calibration issue and should be read with care.

They are not intended to provide a comprehensive methodology for determining downturn LGDs, as this will necessarily have to be firm specific and will depend on the types of portfolios being analysed and the level of data availability in each case.

Instead, the illustrative process below may be used as a tool to understand and guide a firm's downturn analysis and calibration. Importantly, the steps would by no means necessarily be sequential (i.e. steps A →B → C →D → E→ F) or identical in each situation and the list below should therefore not be construed as a box ticking exercise. The process ultimately adopted will rather depend on the outcome of an individual firm's analysis at each step, which will have to be statistically robust, and could give rise to range of various steps being used (e.g. **A** →B → C → A →B → C → A →B → C → D → E→ or A →B → C → D →B → D → E→ F; etc.) and therefore different outcomes being reached in each case.

Regulation could help enhance the consistency and comparability of downturn assessment methods by promoting this type of analytical process.

Indicative LGD downturn calibration steps

A. *Define the downturn scope*
   a. Is it global / regional / sectoral?
   b. What time periods are under consideration?
   c. What are the available downturn drivers and metrics?
      i. Are they macro-economic, market observed, market implied?
      ii. Are they forward-looking or point in time?
      iii. Are they contextual (macro-economic) or internal and specific to the bank's portfolios or sub-segments (bank's internal risk metrics)
      iv. What is the magnitude of the downturn according to the selected drivers or metrics?
   d. Choose and document the appropriate combination of downturn drivers

B. *Define the portfolio or asset segmentation that is appropriate for risk calibration*
   a. By client type, geography, industry, size, behavior, jurisdiction, etc.

b. By exposure type, seniority, collaterals, guarantees
c. According to internal processes, if relevant: collateral/guarantee management, client monitoring, collection and recovery strategy
d. Confirm whether segment envisaged is consistent with business experts' views
    i. Examine representativeness, time stability, tendencies
    ii. Determine which quantitative risk measurements are available to support the proposed segmentation
    iii. Explain the qualitative rationale for sensitivity, if any, to downturn drivers and to downturn magnitude

C. Define target risk metric under study for downturn calibration
a. Consider EADs, recovery events and amounts, recovery history,etc.
b. Consider type of LGD: work-out LGDs, observed market LGDs, implied market LGDs, observed losses, provisions, impairments, etc.

Indicative LGD downturn calibration steps (cnt'd)

D. Assess downturn impact
a. For the risk metric defined in step C, measure the variations associated with the downturn period defined in step A over the segments defined in step B.

E. Conclude on calibration adjustments for downturn effects
a. With appropriately defined downturn period (step A) and target portfolios (step B)?
    i. Yes: an impact is observed and is material (see steps C and D)
    ii. No: downturn impact is not observed

F. Next step: develop predictive model if relevant.

The illustrative approach set out above appears to be largely aligned with an example of regulatory guidance recently published by the US FED[3]. In the FED's view, the selection of reference data periods should cover a reasonable mix of economic conditions and they definine adverse economic conditions as periods of "high unemployment or falling home prices". The FED also specifically asks banks to test, for each exposure segment, "the extent to which variation in default rates is tied to changes in economic conditions and not to other sources such as changes in business strategy, underwriting practices, or the legal environment". The guidance however does refer to the "significantly higher than average default rate" criteria, although, as we have seen in the previous section, this can have unexpected consequences in terms of downturn impacts.

5. Data limitations and LGD floors

Data limitations can pose an important challenge to the estimation of LGD parameters in general, and of LGD parameters consistent with economic downturn conditions in particular. We are aware that there is currently an on-going discussion within the BCBS as to whether firms should be allowed to model such parameters, particularly for certain portfolios known as low default portfolios (LDPs) where a given institution may possess relatively little data on an individual basis or whether minimum supervisory LGD levels, or LGD floors, should be used in relation to such portfolios.

[3] Guidance on Selection of Reference Data Periods and Approaches to data Deficiencies – BCC 14-3, 23 October 2014

As the sections above demonstrate, LGDs are an essential component in correctly assessing risk and risk sensitivity. A risk sensitive capital framework cannot solely be focused on PDs. However, the replacement of firms' LGD estimates with minimum supervisory LGD parameters that become binding constraints would i) misrepresent and disguise actual risk and ii) incentivise misguided origination for banks. Indeed, with actual levels of risk not being recognised, firms may instead be incentivised to favour products or counterparties with lower recovery prospects and higher risk but potentially generating higher returns. Moreover, under such circumstances, they will have less incentive to take on collateral (as its mitigative effect will not be reflected in their LGDs) and will favour unsecured lending instead, resulting in a distorted view of their actual risks. Ultimately, this will lead to an increase in risk as well as less diversification across a firm's portfolios. This is contrary to supervisory objectives and will instead lead to herd behaviour that will ultimately make the financial system more unstable.

It is also misleading to think that calibration risk can be addressed this way. Supervisory LGDs are not immune to model or calibration risk, nor are they necessarily a better reflection of what the appropriate level of own funds should be for such portfolios.

Additionally, the imposition of LGD floors will reduce incentives for firms to put improved systems in place to capture loss data and invest in further building up their understanding of losses and recoveries. Instead of resolving data issues, the introduction of floors is more likely to perpetuate data scarcity and will discourage the risk management of "data poor" portfolios

Lastly, unless fully coordinated, far from improving the current situation, different floors, introduced at varying speeds by regulators in different jurisdictions for different portfolios will reduce comparability between RWA outcomes and potentially create level playing field issues.

We also consider that there are other routes to be pursued to address issues associated with a perceived lack of data. These are described in the following section.

6. Alternative solutions to imposing LGD floors

Expert judgement

Regardless of data quantity and quality, risk calibration is not and can never be a purely statistical exercise. While expert judgment should never be relied upon solely either, it is important to recognise and allow business expertise to fulfil its important role and in particular to accept that it can be a robust supplement in cases of data scarcity.

Collateral management

In order to improve both data quality and quantity, a greater focus on incentives should be exercised by regulators to encourage data capture on all asset classes. This should be directed towards collateral management, including collateral registration, improved data collection, market valuations and documentation requirements. As pointed out above, we are concerned that collateral taking will be disincentivised under supervisory imposed LGDs. However, not only does improved collateral management lead to improved data quality and LGD modelling, collateral is crucial in the survival of a firm in crisis.

Data pooling

Data pooling is a powerful tool that can be used to overcome data scarcity issues occurring at the level of individual firms. The introduction of the risk sensitive Basel 2 framework has seen the development and promotion of data pooling exercises, with pools now being widely available from commercial, public and non–profit organisations such as well-established rating agencies, industry groups and public sector delinquency registers. They should be encouraged both in capture and in use. Examples of such initiatives are provided below.

By drawing on data from data pools, firms can build up models that are tailored to their businesses and portfolios even when data is scarce at the individual firm level. In this respect, data pools are a tool similar to internal databases, providing information that firms can harness to build representative, firm-specific samples by restructuring the pooled information according to drivers that are relevant to the firm in question. Even in cases where the pooled data may be deemed not to be sufficiently representative or comparable to a specific firm's internal portfolio, a firm can still compare its internal calibrations with the multibank average from the pool and explain any differences.

The industry would be keen to discuss in more detail with the regulatory community how firms can harness and adapt pooled data to their specific portfolios.

Floors should be a last resort, and if they are necessary, calibrated collectively using pooled data

Supervisory LGD floors should only be established as a last resort solution, and even then, as temporary measures. If they are needed at all, they should be set at different levels for different portfolios (instead of a single overall floor), taking into account the different risk characteristics of various portfolios. In order to make them less of a blunt instrument, they should also be based a collective assessment using data pools from different sources.

7. Examples of data pooling initiatives

- S&P Capital IQ, including its PF consortium for project finance.
- S&P LossStats
- Global Credit Data Consortium (former PECDC), brings together LGD modelling data for over 90 000 defaulted loans, of which 700 are from the financial institution asset class.
- Club de Paris: sovereigns
- Moody's Analytics Losscalc: sovereigns and municipals
- Bank of Italy data pooling initiative: the contribution to data pooling is mandatory for Italian banks. It covers the closed default cases of Italian counterparties (i.e. resident in Italy), for all kinds of portfolios and on balance as well as off balance exposures. It also includes incomplete work-outs with more than 10 years of default history. The contribution is on yearly basis, and it regards the default cases closed during the year, plus incomplete work-outs. The information collected includes EAD, recovery information with cash flow details, direct and indirect costs as well as information such as product details, collateral and guarantees etc. March 2015 will be the first contribution time, based on default cases closed in 2014.

8. Reference material on LGD modelling

- Altman (2006), 'Default Recovery Rates and LGD in Credit Risk Modeling and Practice'
- Brumma, Urlichs and Schmidt (2014), 'Modelling downturn LGD in a Basel framework'
- Dahlin and Storkitt (2014), 'Estimation of Loss Given Default for Low Default Portfolios', Master's Thesis in Mathematical Statistics, Royal Institute of Technology, Stockholm
- Frye, Jon (2000), 'Depressing Recoveries' Risk Magazine
- Global Credit Data Consortium (former PECDC) (2013), 'PECDC Downturn LGD Study'
- Khieu, Mullineaux and Ha-Chin Yi, (2014), 'The Determinants of Bank Loan Recovery Rates', Journal of Banking & Finance, Vol. 36, No. 4,
- Laurent & Schmit, (2005), 'Estimating distressed LGD on defaulted exposures: a portfolio model applied to leasing contracts', in Recovery Risk, edited by Edward Altman, Andrea Resti and Andrea Sironi.
- Moody's Special Comment, 'Adjusting Moody's LGD Assessments to Meet Basel II Downturn Requirements'
- Schuermann, Til (2004), Federal Reserve Bank of New York, 'What Do We Know about Loss Given Default', Wharton Financial Institutions Center Working Paper No. 04-01

Appendix

Downturn LGDs in the Basel framework

$$\text{Capital requirement (K)} = [\overbrace{LGD}^{\text{LGD (as part of the ASRF model)}} * N[(1 - R)^{\wedge}\text{-}0.5 * G(PD) + (R / (1 - R))^{\wedge}0.5 * G(0.999)]$$

$$- PD * \underbrace{LGD}_{\text{LGD (as part of the Expected Loss)}}] * (1 - 1.5 \times b(PD))^{\wedge} \text{-}1 \times (1 + (M - 2.5) * b(PD))$$

Source: BCBS, An Explanatory Note on the Basel II IRB Risk Weight Functions

The model underlying the Basel AIRB-approach to capital requirements is the Asymptotic Single Risk Factor (ASRF) model where the sum of expected and unexpected loss is estimated by calculating the expected conditional loss for an exposure given an appropriately conservative value of the single systematic risk exposure provided by the BCBS. This can be expressed as the product of PD and LGD.

Banks estimate *average* PDs and these are transformed into *conditional* PDs using a supervisory mapping function. To be consistent, the LGD parameter should also be conditional and the framework therefore requires banks to reflect this conditionality, or "downturns", in their LGD calibration. Given the evolving nature of practices in this area at the time of its development, and in contrast to PDs, the BCBS did not provide an explicit supervisory function to transform average LGDs into conditional LGDs