

PECDC Downturn LGD Study

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ABOUT PECDC

A cross border initiative to help measure credit risk, PECDC is a non-profit association owned by the banks who share credit data anonymously.

PECDC houses the world's largest LGD/EAD database, with over 50,000 default observations totalling over €100 billion in most non-retail Basel 2 Asset Classes from 40 member banks across Europe, Africa, North America, Asia and Australia.

PECDC also has the world's largest PD database of defaults and PD estimates for large corporates, banks, SMEs and specialised lending.

Created 'by banks, for banks'

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SUMMARY

This report shows an excerpt of the analyses performed by PECDC's downturn LGD working group. This working group was initiated in 2011 in order to investigate downturn effects on loss-given default (LGD) values based on PECDC's large-scale LGD database.

For all banks applying the Basel advanced IRB approach for calculating minimum capital requirements, the modelling of the regulatory required downturn LGD calibration is of utmost importance, as capital requirements are directly proportional to the LGD values used in the calculation. Understanding the effect of economic downturns on the amounts recovered during the work-out process of defaulted loans allows estimating downturn LGD more precisely.

As a first step, PECDC's downturn LGD working group developed new analytical methods, a tool box of codes to facilitate own analysis by the member banks, and last but not least served as a platform for inter-bank discussion. In this report we focus primarily on the methods and results relevant to the asset classes Large Corporates (LC unsecured) globally, Small and Medium enterprises (SME) in the Nordic region, and Financial Institutions globally. In particular, this report provides insights regarding three major questions:

- **Do you find downturn effects in historical LGD data?** Economic downturns affect recoveries on defaulted loans in various ways, including e.g. the impact on recovery cash flows and cure rates. Using detailed PECDC cash flow data, downturn effects can be detected in historical loan data.
- **Can you link downturn effects to macro-economic developments?** LGD is given by the recovery cash flows over the full time to resolution. Taking into account the specific timing of those recovery cash flows, a co-movement of conditional LGD and GDP growth rate is observed in PECDC data.
- **Can you analyse downturn LGD for banks?** Default data for banks and financial institutions is scarce, and typically not sufficient for statistical analysis. Using the comprehensive data set of PECDC, the working group was able to derive major drivers of downturn LGD for banks, in particular its association with sovereign crises.

Member banks are welcome to apply these insights and methods for their internal efforts on modelling downturn LGD.

REGULATORY ENVIRONMENT

In the wake of the 2008 financial crisis the regulatory environment has been rapidly evolving and banks are facing new challenges, in particular with respect to their credit risk models and capital requirements.

Basel II and III require banks to “... use LGD estimates that are appropriate for an economic downturn if those are more conservative than the long-run average”. This requirement has a direct impact on minimum capital calculated under the A-IRB approach. A recent report by the European Banking Authority (EBA) has highlighted a large variation between different banks of methodological approaches and values for a downturn add-on (c.f. page 48 of the Interim results update of the EBA review of the consistency of risk-weighted assets - low default portfolio analysis, Aug 2013).

The CP4/13 paper on the IRB approach by the Prudential Regulation Authority (Bank of England) highlights the close scrutiny that is paid to downturn LGD by regulators. For example, it proposes that “where firms wish to include cures in their downturn LGD estimates, they should do this on a cautious basis with reference to both their current experience and how this is expected to change in downturn conditions.”

In summary, regulatory pressure will urge banks subject to the A-IRB approach to improve their understanding and modelling of loss given default, and in particular of downturn LGD. The downturn LGD working group aims at supporting these efforts by providing a first glance at the analyses that were enabled by the level of detail in the PECDC data.

NOTE ON TERMS USED

LGD refers to the regulatory loss given default, one component required for calculating expected loss besides exposure at default (EAD) and probability of default (PD). Expected loss is given by $EL = EAD \times PD \times LGD$, whereas LGD is given by $1 - \text{recovery rate}$. As required by Basel regulation, recovery rate, and subsequently LGD, is derived by discounting recovery cash flows to the date of default (discounted LGD). Care needs to be taken when using the term LGD as it refers to both the historical measurement of observed LGD and the forward looking estimates made for regulatory and other purposes

Conditional LGD refers to a nominal LGD (i.e. recovery cash flows are not discounted back to the date of default) conditional on not having cured. Therefore conditional LGD provides a view on the time evolution of LGD unbiased by variations in discounting periods, discount rates, and cure rates. Unbiased by cure rates, conditional LGDs tend to be higher than LGDs.

Cure definition: Obligors can return to performing after a default, i.e. they cure. An obligor is considered cured if for all loans there is no write-off and time to resolution is less than or equal one year.

Resolved / unresolved cases: Defaults are considered as ‘unresolved’ in case banks are still expecting further cash flows. All others including cures are considered ‘resolved’. Since time to resolution for non-cure cases is typically longer than for cures, unresolved cases not yet visible in the data can lead to lead to the so-called resolution bias which leads to unrealistically high cure rates for recent years.

OVERVIEW OF DOWNTURN LGD DATA SET

The PECDC LGD data set is one of the world’s largest sources of information on all aspects of LGD modelling, providing data on 508,552 transactions resulting from 69,503 defaulted loans to 43,551 borrowers (as of June 2013). Based on transaction data contributed by its member banks, PECDC calculates own estimates of nominal and discounted recoveries and LGD values. An unbiased and consistent reference data set (RDS) is the prerequisite for understanding the variation of LGD over time. Using sophisticated filter criteria and selection rules e.g. excluding unresolved cases, cures, technical defaults (time to resolution < 14d) etc., reference data sets covering the period of 2000-2010 for three asset classes have been compiled (see Exhibit 1): Large corporates–unsecured loans, SMEs in the Nordic region, and banks.

EXHIBIT 1

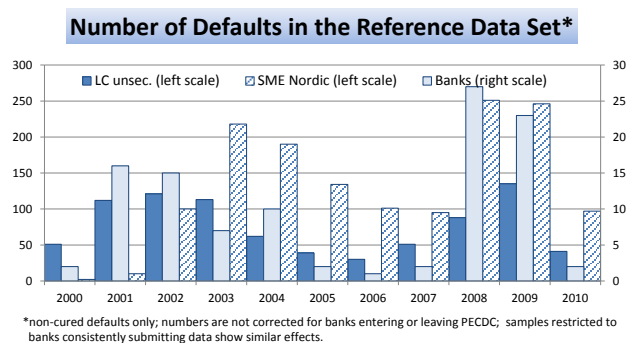


Exhibit 1 shows the number of defaults within the reference data sets: Large corporates (LC, classification according to Basel II with group turnover > 50 m€) constitute one of the most important low default asset classes where data sharing among banks leads to significant benefits, in particular by facilitating statistical analysis through creating sufficiently large samples. Globalization has led to a high degree of interconnectedness – in particular for large international companies – that allows for treating large corporates as a truly global asset class. Focussing on unsecured loans with large exposures at default (> 1 m€), the RDS contains 843 default events.

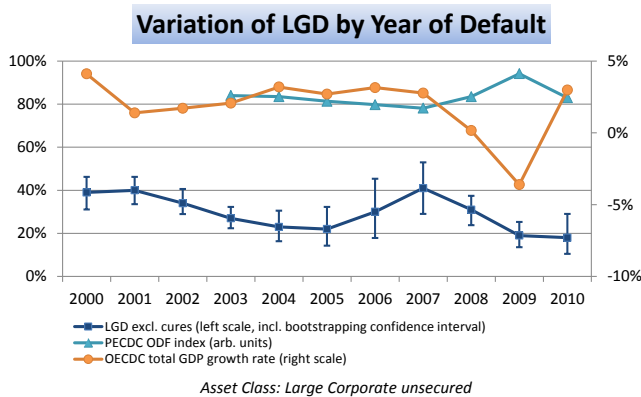
A significant number of member banks are contributing data for small and medium enterprises in the Nordic European region (Denmark, Finland, Iceland, Norway, and Sweden). Therefore, this region has been selected as test case for a less globalized asset class compared to large corporates. The SME definition includes borrower’s with annual revenues (turnover) between 1 m€ and 50 m€. After excluding small (< 10 k€) exposures at default, 1444 default events are represented in the SME RDS. The asset class “Banks” includes registered banks and investment funds according to the Basel II definition. For this asset class, 107 defaults are present in the RDS (exposure at default > 1 m€).

Exhibit 1 additionally shows that generally the development of the number of defaults registered in the PECDC database reflects the overall economic development with a larger number of defaults in times of economic downturn (2001-2002 and 2008-2009). This is also in line with the recent PECDC study on observed defaults frequencies.

DO YOU FIND DOWNTURN LGD EFFECTS IN HISTORICAL DATA?

The observation of downturn effects in historical data is typically complicated by short time series, few data points and the multitude of input parameters for LGD estimates. Clearly, such analysis is likely to benefit from data sharing among banks. Exhibit 2 shows an overlay of GDP growth rate for all OECD countries together with the PECDC observed default rate and the standard PECDC borrower LGD for unsecured loans to large corporates. Clearly, the default rate is inversely correlated with GDP growth. LGD, however, does not follow this trend: a pronounced peak in LGD can be observed in 2007 well before the peak of the financial crisis in 2008-2009.

EXHIBIT 2

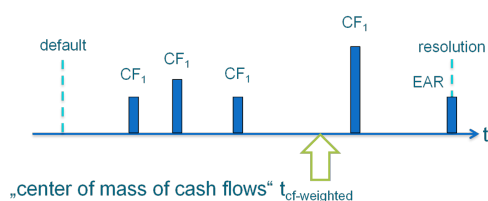


In order to assess the statistical significance of the variations over time, a bootstrapping was performed (1000 iterations) and the 2.5% and the 97.5% quantiles of the resulting distribution are plotted as bootstrapping confidence intervals. Clearly, the increase in LGD between 2005 and 2007 is statistically significant.

This initial analysis confirms a variation of LGD over time in historical data, which however seems to be out of phase with the macro-economy and in particular well ahead of GDP growth rates. Such an effect would not be plausible from an economic point of view. Possible explanations for this counter-intuitive observation include the resolution bias and the effect of the economic environment during the collection / work-out phase on the recovered cash flows.

NOTE ON CASH FLOW TIMING

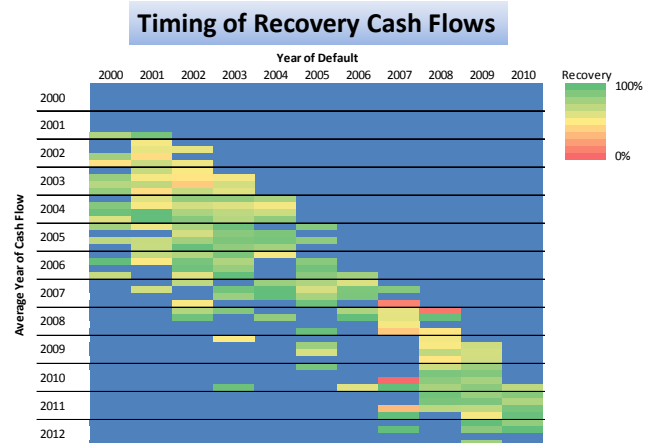
The average year of cash flow refers to a concept similar to the Macaulay duration of bonds. The cash flow weighted time or average year of cash flow represents the weighted average of all relevant points in time between default and resolution where cash flows took place.



The resolution bias refers to the effect of yet unresolved cases which are not fully visible in the reference data set. For example, defaults that occurred in 2008 and later might give rise to higher LGD values after their resolution. Since a fast resolution of default cases is typically assumed to be associated with low LGD values, a downward bias in the time series might occur for the most recent time slices. Additionally, loans may cure from default, typically on a short time scale of less than one year depending on the cure definition. Since cures count as resolved cases, more recent time slices in the data set are more populated with cures than it would be expected on the long run. Considering the years 2005-2010 in the PECDC data set, at least 66-80% of all potential defaults have been resolved. Prior to 2005, the resolution rate is basically 100%. Therefore, unresolved cases do have some effect, e.g. for the year 2010. However – as detailed analysis and extrapolation of unresolved cases showed – they cannot fully explain the drop in LGD during the severe economic downturn in 2008-2009.

A second factor influencing the variation of LGD estimates is the distribution of recovery cash flows over time. Exhibit 3 shows the recovery heat map for unsecured loans to large corporates which provides an indication of when recovery cash flows (vertical axis) are realized in relation to a default in a particular year (horizontal axis). The recovery rate shown for each quarter reflects the average value for those default cases where the average cash flow occurred in that particular quarter (for an explanation, see note on cash flow timing).

EXHIBIT 3



Obviously, the recovery cash flows are dispersed over significant periods of time, during which economic conditions are likely to change. Work out processes may last several years while recovery cash flows are collected, e.g. by selling off the assets of a defaulted company. The time of the average cash flow shown here also provides an indication about the variation in time to resolution which seems to be dependent on the economic cycle as well. Even more interestingly, the achieved recovery rate, i.e. the sum of the collected cash flows in relation to the exposure at default of the loan, is not distributed uniformly over time. For loans that defaulted after the burst of the dotcom bubble in 2001 and 2002, medium recovery rates of ca. 50% can be observed in the subsequent years 2002 and 2003. Relatively high recovery rates – leading to high recovery rates – can be observed for those cash

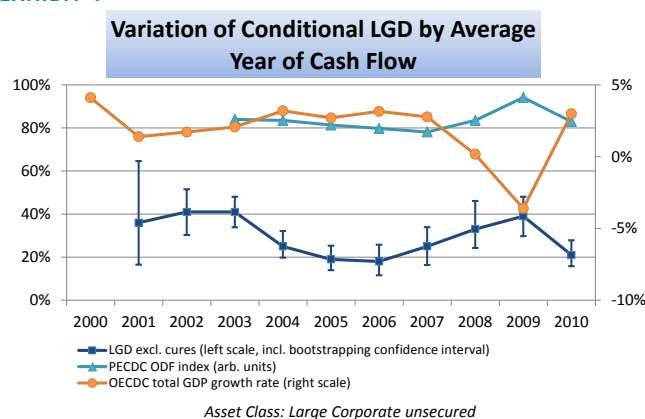
flows taking place in the period from 2005 to 2007, exactly in those years when only a few new defaults occur due to economic growth. Starting with 2008, decreasing recovery rates can be observed which extend well into 2009 and 2010, in line with increasing default rates during the financial crisis.

Exhibit 3 is a first indication that another time axis than the year of default might be better suited for analysing the macro-economic impact on LGD. In particular, this picture highlights the well-known fact that not only the year of default but additionally the period of time subsequent to the default is relevant for extracting appropriate LGD estimates from loan data. Due to the high level of detail in the PECDC data set, including transaction data, those effects can be directly observed. Based on this fundamental assessment, the evolution of loss given default values over time can be analysed with respect to their co-movement with macro-economic indicators.

CAN YOU LINK DOWNTURN EFFECTS TO MACRO-ECONOMIC DEVELOPMENTS?

Exhibit 4 illustrates the effect of cash flow timing for large corporates. Here each conditional LGD value (see note on terms used) is assigned to that point in time at which the average of the cash flow took place. Obviously, when a significant proportion of the recovery cash flows occurs during an economic downturn, e.g. in 2008-2009, the workout of those borrowers results in lower recoveries and higher LGD values. Therefore, the adverse economic environment during a downturn seems to have a significant impact on this essential risk parameter. Looking at the timing of the underlying cash flows, it is indeed possible to extract a meaningful co-movement of LGD and macro-economy from historical data (significant on 5% level, p-value 1.2%, adj. R² 55%).

EXHIBIT 4



Is this effect a specific feature of the asset class large corporates or is it possible to find it in other asset classes as well? For example, small and medium enterprises are typically more severely affected by their local economic and legal environment compared to globally operating large corporates.

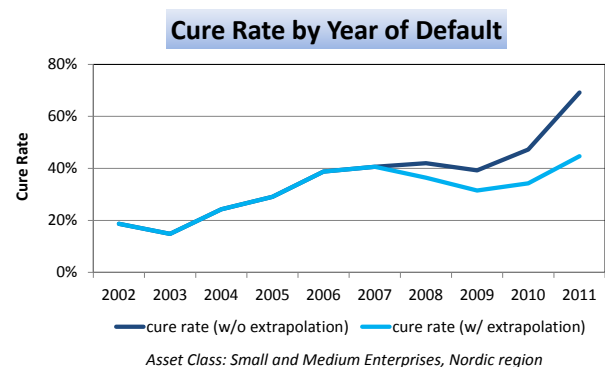
It turned out that the observation of a meaningful co-movement between LGD and macro-economic parameters depends on the possibility to isolate the economic effects. For example, in the Nordic European region (Denmark, Finland,

Iceland, Norway, and Sweden) the effect cannot be observed on a regional level. For the analysis of LGD resulting from SME defaults, the level of granularity is essential. For example, the LGDs for the Nordic region can be decomposed into country-specific LGDs. This analysis showed that – even within the Nordic region – significant differences in economic development as well as in LGD development over time can be observed. When analysing individual countries, similar patterns like the one for large corporates can be observed.

Therefore, an analysis on a country basis is highly recommended for SME in order to account for national differences e.g. in the legal framework and in collection processes. For aggregating individual country LGDs to regional LGD values, a weighting scheme e.g. by GDP should be applied in order to avoid imbalances with respect to the number of defaults contributed by each country.

Another effect of economic downturn can be observed for cure rates. For example, the relationship between cure rates and macro-economic development has been analysed for SMEs in the Nordic region and for large corporates globally. These analyses additionally highlight the importance of appropriately extrapolating unresolved cases in order to remove the resolution bias (see note on terms used). Exhibit 5 shows the cure rate for Nordic SMEs with and without considering the extrapolated number of cases yet to be resolved. The steep increase in recent years is caused by more timely resolution of cured cases (less than one year according to PECDC definition) which leads to an over-representation of cures compared to non-cure cases.

EXHIBIT 5



Applying an extrapolation based on past experience with respect to time to resolution allows for correcting this effect. Now, a drop in the cure rate can be observed for the years 2008-2010, in line with the economic downturn during the financial crisis. Overall, unrealistically high cure rates are often an indicator of data missing due to yet unresolved defaults.

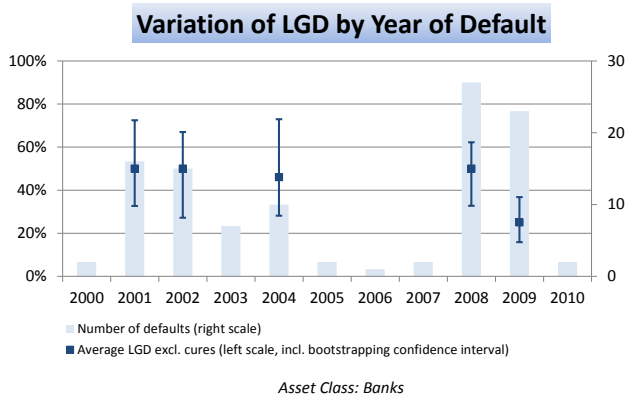
CAN YOU ANALYSE DOWNTURN LGD FOR BANKS AND FINANCIAL INSTITUTIONS?

Data on losses associated with defaults of banks and financial institutions is scarce, and typically not sufficient for statistical modelling. Using the comprehensive data set of PECDC, the working group was able to analyse some of the most important drivers of downturn LGD associated with bank defaults.

Exhibit 6 shows the number of defaulted banks and financial institutions in the PECDC sample data set in the period from 2000-2010. The defaults are centred on the well-known

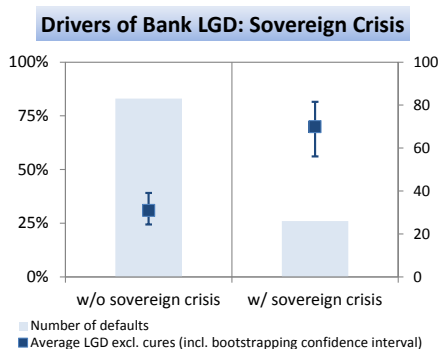
banking crises: first, the Argentinian crisis is visible in 2001-2002. Second, the financial crisis of 2008-2009 is well reflected in the data, including the Icelandic bank defaults in 2008. Obviously, the vast majority of bank defaults are associated either with a local or a global downturn in the financial markets. Therefore, those years where LGD values can be sensibly observed for bank defaults (error estimation not possible for years with less than 10 defaults) are already invariably associated with a downturn in the relevant financial market, giving rise to the question whether any additional downturn add-on is required.

EXHIBIT 6



Understanding the drivers of LGD is an essential input for further modelling efforts in the Basel context. Therefore several potential parameters were analysed for identifying the major drivers. For example, when a bank default is linked to a sovereign crisis (e.g. in Argentina and Iceland), LGD values (dark blue spots with confidence intervals derived from bootstrapping) tend to be significantly higher compared to other bank defaults as shown in Exhibit 7.

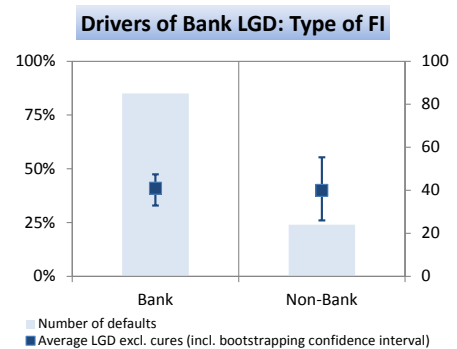
EXHIBIT 7



Clearly, the crisis in Argentina in 2001-2002 and the crisis in Iceland in 2008 were not only accompanied by severe distortions of the local financial markets, but additionally the ability of the government to provide support to these markets was undermined. The significance of the difference between LGD values realised during the Argentinian and Icelandic banking crisis in contrast to all other bank defaults holds also from a statistical point of view (assessment of estimation uncertainty by bootstrapping). Given the increasing amount of empirical evidence on the linkage between banking and sovereign crises, this effect could be recognized in downturn LGD models for financial institutions. Regarding other drivers,

e.g. the necessity of a further sub-segmentation of the asset class into banks and non-bank financial institutions, the LGD distributions were analysed separately. Exhibit 8 shows the LGD values realised for banks and non-bank financial institutions, pointing out to almost identical LGD values for both sub-segments.

EXHIBIT 8



A similar result was obtained for the potential relationship between the size of a bank (value of assets) and LGD. Given the amount of data in the sample, no relationship could be detected so far.

In summary, the PECDC data set for bank defaults provides a highly valuable source of information, in particular for supporting discussions with regulatory authorities.

CONCLUSIONS

In summary, the following conclusions can be drawn from the analyses presented here:

- The effect of economic downturn on LGD can be observed in historical data sets provided that the timing of recovery cash flows is taken into account
- Using the average year of cash flow, a clear comovement of GDP growth rates and conditional LGD can be observed provided that homogenous asset classes can be defined.
- Cure rates seem to be depressed during economic downturns.
- Observed bank LGD value are – in most cases – associated with local or global banking crisis.
- In case a sovereign crisis coincides with a bank default, LGD values tend to be significantly higher

The results created in the downturn LGD working group can be applied by PECDC member banks for improving and further sharpening their modelling efforts. For example, elaborate filter criteria for effectively utilizing PECDC data have been developed and tested. Additionally, all pieces of methodology have been implemented in a ready-to-use toolbox – providing a blueprint and a starting point for banks’ own analyses.

ATTRIBUTION

This document is based on a voluntary inter-bank working group composed of PECDC member banks chaired by Nina Brumma of KfW.

Working group support and analytics were performed by

