Global Credit Data
by banks for banks

DOWNTURN LGD STUDY 2020

CORPORATES, BANKS AND NON-BANK FINANCIAL INSTITUTIONS

OCTOBER 2020

A STATISTICAL EXAMINATION OF THE DOWNTURN IMPACT ON CREDIT LOSSES TO INFORM COVID-19 ASSESSMENT

Downturn LGD Study 2020

This Global Credit Data (GCD) study looks into the historical effects of previous downturns on bank credit losses across various debtor types, industries and regions, with a view to helping banks understand not only the high-level impacts of a downturn, but also how credit risk drivers are impacted, including sector specific impacts across different portfolio types.

Combined with banks' independent inputs for key risk drivers – including macroeconomic forecasts, portfolio biases, and the differences between the current and previous crises – the data in this report equips banks with the fundamental tools necessary to make accurate adjustments to their credit loss estimates for the COVID-19 crisis.

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ABOUT GLOBAL CREDIT DATA

Global Credit Data (GCD) is a non-profit association owned by 50+ member banks with the simple mission to help banks better understand and measure their credit risks through data pooling and benchmarking activities. GCD's data pools support the key parameters of banks' credit risk modelling: Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD).

GCD started collecting historical loss data in 2004, offering exclusive access to its member banks. These banks receive the detailed anonymised database and can therefore confirm results and test them on customised sub-sets of data. The LGD database now totals over 230,000 non-retail defaulted loans from around the world to approximately 130,000 borrowers covering 11 Basel asset classes.

In 2009, GCD introduced a PD database which now has over 15 years of default rates and PDs. GCD also runs a name and cluster benchmarking database to help banks calibrate and benchmark their PD, LGD and EAD models.

GCD operates all databases on a "give to get" basis, meaning that members must supply high-quality data to receive data in return. The robustness of GCD's data collection infrastructure helps place GCD's databases as the global standard for credit risk data pooling.

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WHAT IS LOSS GIVEN DEFAULT?

Loss given default (LGD) reflects how much money a bank or other non-bank financial institution loses when a borrower defaults on a loan, expressed as a percentage of total exposure at the time of default. LGD is one of the key factors used to calculate expected credit losses and Advanced Internal Ratings-Based (AIRB) regulatory capital along with probability of default (PD) and exposure at default (EAD).

What's new with LGD?

Requirements for accurate credit loss and LGD modelling have been significantly increased by developments in regulation and standards over the last several years. Business usage of acute pricing information can also provide valuable insights in competitive markets. Both regulatory capital frameworks, impairment frameworks (such as IFRS 9 and CECL) and stress-testing frameworks (CCAR) created a need for detailed default and loss data. Investors, regulators and accountants require banks to be able to project expected and unexpected loss levels under different scenarios. Both banks' business as well as their capital holding strategies are significantly influenced by these calculations. Banks benefiting from GCD's consistent information exchange and wealth of data are also able to fine-tune their final estimates via benchmarking.

GCD's LGD data set

GCD's LGD data set comprises over 230,000 non-retail defaulted loan facilities from around the world, encompassing approximately 130,000 borrowers and 11 Basel asset classes. Collected since 2004, the data details the resolution of defaults from 2000 to 2017, the best part of two decades – taking in numerous sector shocks, as well two major crises, the dot-com crash and the global financial crisis.

The quality of this data set is ensured by GCD's high standards for inputs from member banks. The effectiveness of this approach is underlined by the data's consistency over time. GCD has published updated LGD reports every year for the last three years, alongside a Downturn LGD Study in 2013 and 2017, adding new data from each year gone by, as well as additional data from new member banks. The extra three years of robust data in this latest study add further depth and rigour to our time series analysis.

FOREWORD

These are turbulent times for banks and their credit risk teams. Record-high loss provisions have become headline news as institutions look to fortify their positions against the fallout from the COVID-19 pandemic, adding extra pressure to the teams responsible for calculating the likely losses on their bank's portfolios.

Global Credit Data exists to help banks get these calculations right. To this end, we recently released our LGD Report 2020 for Large Corporates, detailing the long-term average loss given default (LGD) for banks on loan portfolios to large corporates. Covering the full workout of two previous crises (the dot-com bubble of 2001-2002 and the global financial crisis of 2008-2009), this data helps shed valuable light on what banks can expect in terms of recoveries.

Now, with uncertainty still surrounding the duration and impact of the pandemic – as well as the continued provision of government support and the possible development of a vaccine – we are looking to go a step further with this, the Downturn LGD Study 2020. This study looks specifically at the historical effects of previous downturns on bank credit losses across various debtor types, industries and regions, with a view to helping banks understand not only the high-level impacts of a downturn, but also some of the sector-specific impacts across different types of portfolios.

Of course, moving from historical observed LGD rates to future losses requires further inputs and judgement calls. Building on the data in this report, banks must also factor in a range of variables, many of them unique to their business – from their macroeconomic projections to the unique exposures of their portfolios. In combination, these can help form a sensitive estimate of the impacts on their own business.

For all the uncertainty, statistical analysis of historical observed LGD is still by far our best tool for determining future estimates. With this in mind, we offer our Downturn LGD Study, in the hope that it can form part of the raw material from which banks can form their own accurate projections and help steer a course through today's challenging landscape.

Richard Crecel
Global Credit Data
Executive Director

EXECUTIVE SUMMARY

This report examines a topic that has been thrown into the spotlight in recent months by the outbreak of COVID-19 – namely, how bank credit losses are affected by economic downturns. In particular, it focuses on loss given default (LGD) – the amount a bank loses after a customer defaults – and how this is affected by downturns.

The report analyses two global reference data sets (RDSs): one for corporates comprising 86,583 defaulted loans, and another for banks and non-bank financial institutions (FIs) containing over 2,000 defaulted loans. As with the Global Credit Data (GCD) LGD Report 2020 for Large Corporates,[i] the report takes into consideration not only the time of default, but also the time of collection of recoveries. Having been collected over almost two decades, this data set includes a large bulk of mature data from the 2008 global financial crisis and the 2001-2002 dot-com bubble.

While there are multiple differences between historical crises and the one we face today, it can still be useful to run comparisons in order to inform banks' future loss estimates – though they will also need to account for the differences and align estimates with their own portfolios and macroeconomic forecasts. When banks identify an ongoing or upcoming downturn, given the lack of available data on the current situation, best practice is to use data from historical crises and potentially include a conservative add-on to loss estimates to account for uncertainty.

Analysis of the GCD LGD data set shows that economic downturns appear to drive higher LGD rates and lower recovery rates. However, the correlation is not altogether straightforward, with LGD rising on loans defaulted in the years before a crisis hits and recovering quickly afterwards. This is partly because defaults incurred before a crisis are highly unlikely to be successfully resolved during a crisis, but also because banks tend to adjust their workout strategies in a crisis – for example, they may hold on to collateral for longer in order to sell during the recovery at a better price. For this reason, the analysis shows a greater alignment between crisis years and LGD values when looking at the peak cash flow date – the centre point of recovered cash flow – rather than by the time the default was incurred.

Of course, there are many other factors that affect how a given loan or portfolio is affected by a downturn. This study explores GCD's historical data set, assessing the downturn effects on corporate debt – including a regional analysis and a case study on the manufacturing sector – the different workout scenarios used by banks in crisis periods, and the historical impact of economic downturns on banks and non-bank FIs.

In particular, this report provides insights regarding two major questions:

- **Downturn effect on historical LGD data.** LGD varies over time. Data shows that the recoveries collected during the crisis years are lower and more delayed than those collected in a non-crisis period, resulting in longer workouts.

- **Downturn LGD for Banks and Non-Bank FIs.** The comprehensive data set of GCD shows that loans to banks and non-bank FIs experience their worst recoveries at times of sovereign crises affecting the home country of the counterparty.

Once combined with banks' independent inputs for each of these variables – macroeconomic forecasts, portfolio biases, and the differences between current and previous crises – the data in this report equips banks with the fundamental tools necessary to make accurate adjustments to their credit loss estimates for the crisis period in the wake of COVID-19.

COVID-19 VS. THE GLOBAL FINANCIAL CRISIS: FACTORING IN THE VARIABLES

The COVID-19 pandemic has shaken business operations around the world, restricting activity for many sectors and grinding others to a halt. Amid this disruption, the institutions that bankroll these activities must ask themselves a critical question: as the pandemic drives more defaults, how will it impact their losses on those defaulted loans?

In its guidelines on how to calibrate the downturn loss given default (LGD) parameter for regulatory capital purposes, the European Banking Authority (EBA) suggests that the calibration of downturn LGD should be based on the observed or estimated impact of the downturn period on the relevant losses.[ii] In short, forward looking downturn estimates must be based on historical experience.

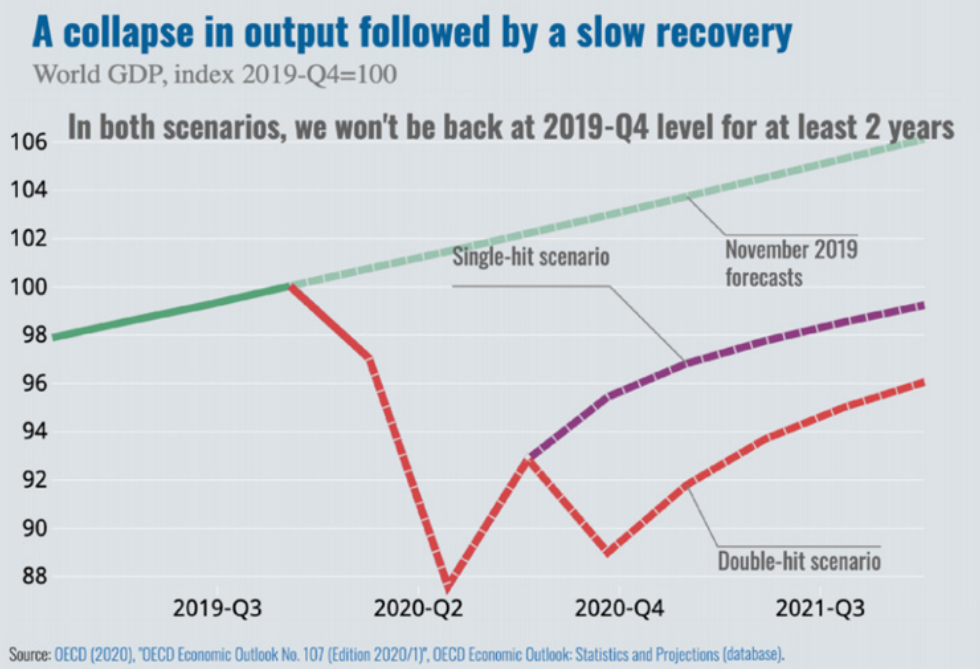
GCD's recent publication on Large Corporate LGD proves that more than 10 years after the global financial crisis of 2008 the data is now complete enough for a downturn analysis. It will take at least five years for sufficient default workout cases from the current COVID-19 crisis to be representative and therefore, in the meantime, the 2008 crisis is the most valuable source of information we have.

The relevance of the macroeconomic scenarios

Credit losses will be affected by the state of the economy during the workout period (see Exhibit 1 for two popular scenarios). A single hit and a quick "V-shape" recovery would likely promote minimal losses, while a second hit and sustained damage to the global economy could suppress prices on collateral and companies' ability to recover, making it harder for banks to recover their defaulted loans. There is no consensus on how this will play out.

EXHIBIT 1

TWO SCENARIOS FOR THE ECONOMIC RECOVERY[iii]



Crises are not born equal

COVID-19 is a global health crisis with economic consequences, bearing both similarities and differences to the global financial crisis.[iv] As the worst crisis in modern times, recovery from the current downturn is expected to take some time. Crucially, today's crisis has prompted direct government support, for both individuals and companies, that was unavailable during the previous crisis where government support was mainly in the form of liquidity through central banks. This direct support is in the form of recovery aid, deferred taxes, deferred company cash flows, and deferred rent payments – all of which serve to reduce the data set available by delaying defaults.

At the same time, there are also many similarities: low interest rates (resulting in an affordable workout), abundant liquidity put into the market, forbearance actions and suspended dividends.

Today, banks should have higher capacity to absorb non-performing loans (NPL) and losses as they are better capitalised than during the 2008 financial crisis. This means they can carefully work out cases over a longer time period, which should also result in fewer defaults by banks themselves.

Portfolio composition

Finally, banks should consider the geographical and sectoral composition of their portfolios when using historical data to estimate the impact of the current crisis.

While no region appears to be immune, some have been impacted more acutely than others. GCD data is country specific and, to isolate the downturn impact, the analysis is performed on Europe and North America separately.

When assessing by sector, hospitality and travel have been much more heavily affected by COVID-19 than they were by the global financial crisis, while we have also witnessed an unprecedented collapse in oil demand, resulting in a crash in oil prices. Meanwhile, some sectors, such as healthcare, have experienced an uptick in demand.

While predicting the severity and shape of the coming downturn period is undoubtedly complex, the detailed historical data in this study, when combined with an analysis of the above variables, provides a sound foundation for loss estimates.

REFERENCE DATA SET

Two reference data sets (RDSs) are used in this study – one covering corporates and one covering banks and non-bank financial institutions (FIs):

Corporates – defined as a class of corporate exposures that is not identified with one of the five specialised lending asset classes described in paragraphs 218 and 219 of the Basel II Accord. For the purposes of this report, Small and Medium Enterprises (SMEs) and Large Corporates (LCs) are treated together.

The Corporates RDS covers a global data set, encompassing 86,583 defaulted non-cure loans (see Table 1), from over 60 lenders worldwide. European and North American (NA) samples – representing 43,824 and 32,939 loans non-cure defaulted loans respectively – have also been chosen to investigate regional impacts, while the manufacturing sector was chosen to provide an industry perspective.

For a breakdown of corporate loans by year of default, see Exhibit 2.

Banks and Non-Bank FIs – which mainly includes Asset Management Firms, Credit Companies and Funds. This RDS was generated with a global data set, comprising 2,066 defaulted loans.

The RDS are split into cured and non-cured cases to analyse downturn effects separately and to reduce the bimodality of the LGD distribution. This report analyses the $LGD_{Non-Cure}$. The LGD_{Cure} is zero by definition if we ignore minor discounting effects.

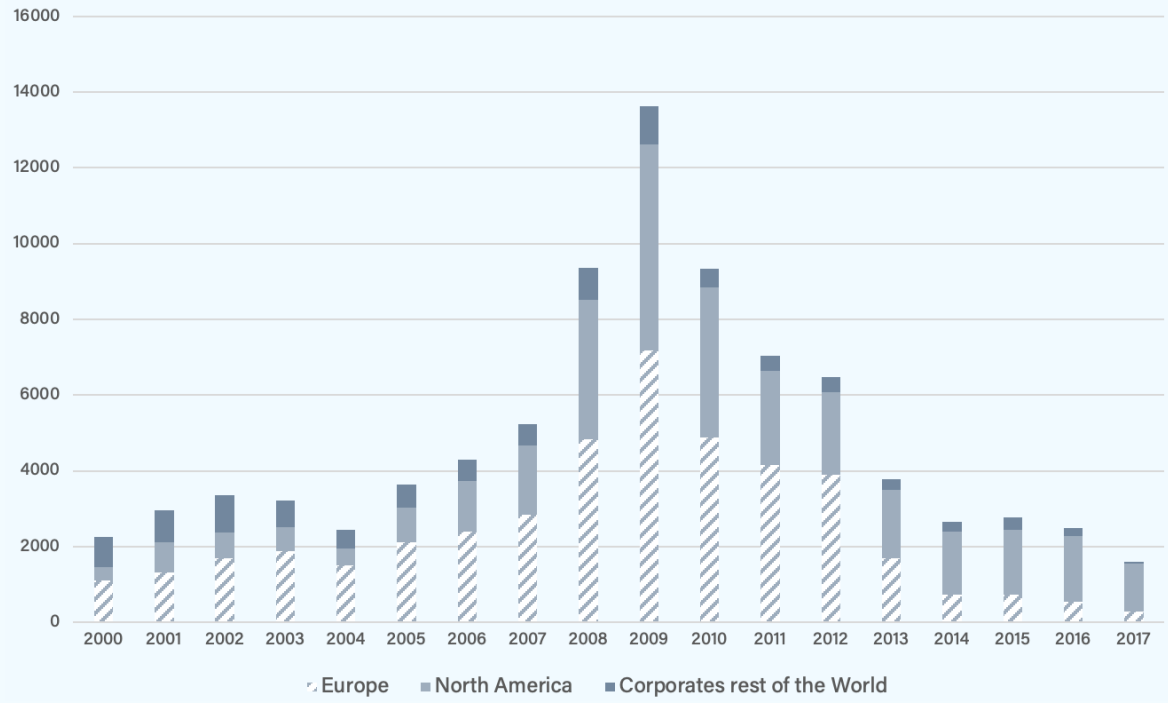
TABLE 1

NUMBER OF DEFAULTS IN THE REFERENCE DATA SET

	CORPORATES NON-CURE GLOBAL	CORPORATES NON-CURE EUROPE	CORPORATES NON-CURE NA	BANKS AND FIS NON-CURE
REFERENCE DATA SET (RDS)	86,583	43,824	32,939	2,066
EAD (bn)	263	107	120	69
NUMBER OF LENDERS	61	51	45	49

EXHIBIT 2

CORPORATE LOANS BY YEAR OF DEFAULT



DOWNTURN EFFECTS ON GCD HISTORICAL DATA - CORPORATES

The observation of downturn effects in historical LGD data is typically complicated by short time series, few data points and the multitude of input parameters for LGD estimates. Nonetheless, the data can provide useful insight.

Exhibit 3 shows an overlay of the world GDP growth rate with the GCD Observed Default Frequency (ODF) and the $LGD_{Non\text{-}Cure}$ for global corporates – using default rates and world GDP growth rates as macroeconomic factors to identify a downturn. The world GDP growth rate was chosen because it is a standard macroeconomic factor, strictly reflecting economic activity in the last 12 months compared to the previous year.

The ODF reflects corporate defaults occurring in the last 12 months, but with reasons for default accumulated over at least the previous year. The LGD rate in the given year reflects the real economy in the time the cases are worked out over the next one to five years.[V]

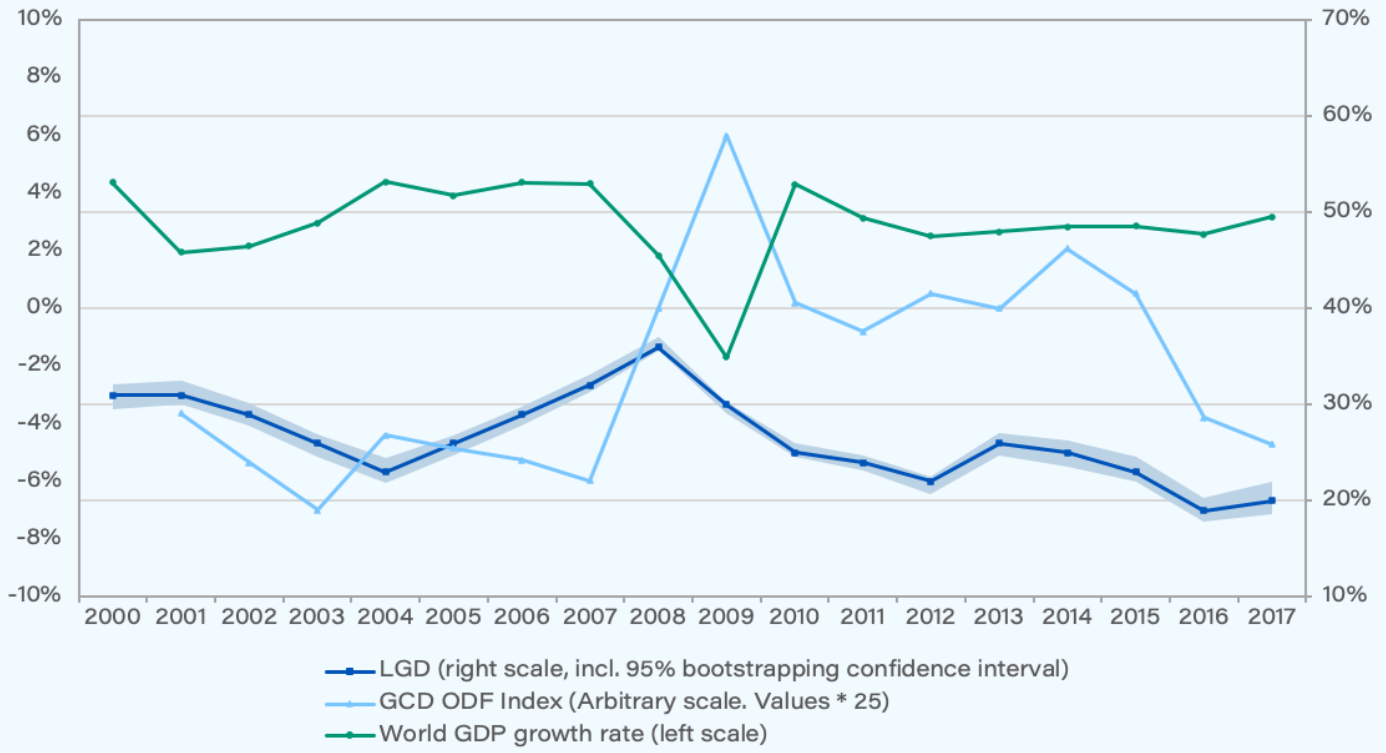
As expected, the default rate is inversely correlated with GDP growth. LGD, however, has a pronounced peak in 2008, one year before the peak of the financial crisis in 2009. This is not unusual. On the contrary, these three measures are expected to show a different pattern due to their differing time connection with the real economy.

This initial analysis suggests a variation of LGD over time in historical data, which seems to be slightly out of phase with the real economy, and noticeably ahead of the financial crisis as observed in GDP growth rates and the default rates.

EXHIBIT 3

LGD BY YEAR OF DEFAULT

CORPORATES, GLOBAL



LGD variation over time

The impact of the economic environment during the collection/workout phase on the recovered cash flows can be explored by assessing these defaults by year of peak cash flow instead of year of default, tightening the connection to the real economy.

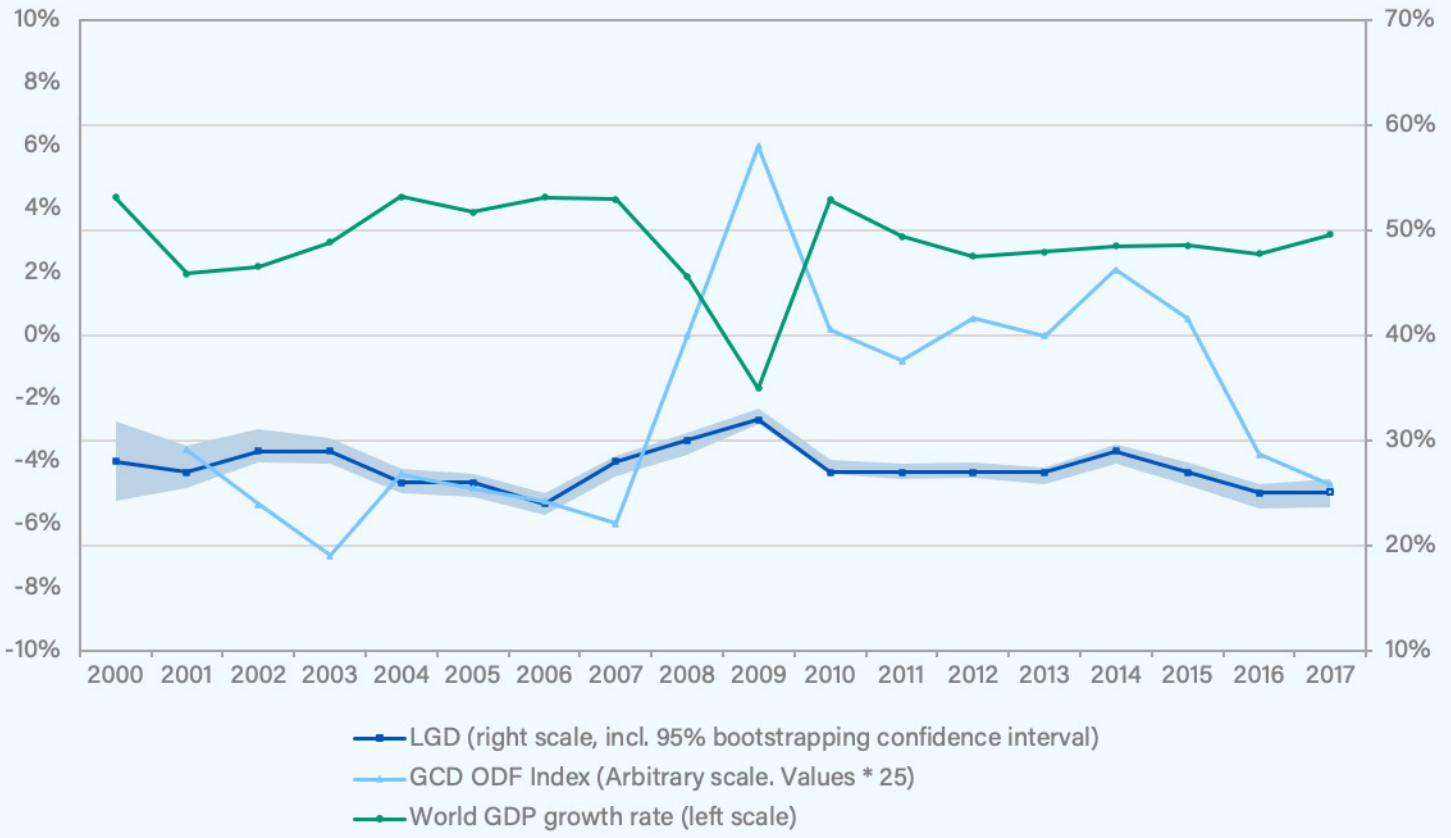
Typically, recovery cash flows are dispersed over significant periods of time, during which economic conditions are likely to change. For example, when a significant proportion of the recovery cash flows occurs during an economic downturn, e.g. in 2008-2009, the workout of those loans shows lower recoveries and higher LGD values. In turn, the average time to peak cash flow for non-cured corporate defaults in the GCD database is 2.6 years.

By taking a closer look at the timing of the underlying cash flows in historical data, it is possible to extract a meaningful co-movement of LGD and the real economy. This can be observed in Exhibit 4, which illustrates the effect of cash flow timing.

EXHIBIT 4

LGD BY YEAR OF PEAK CASH FLOW

CORPORATES, GLOBAL



When looking at cash flow timing, each LGD value is assigned to the point in time at which peak cash flow took place (see FAQs for more details). This approach helps to isolate the impact of the downturn from other time-related effects. In turn, the peak LGD shifts towards the actual point in time of the crisis, i.e. from 2008 to 2008/2009, making it more aligned with real economic activity.

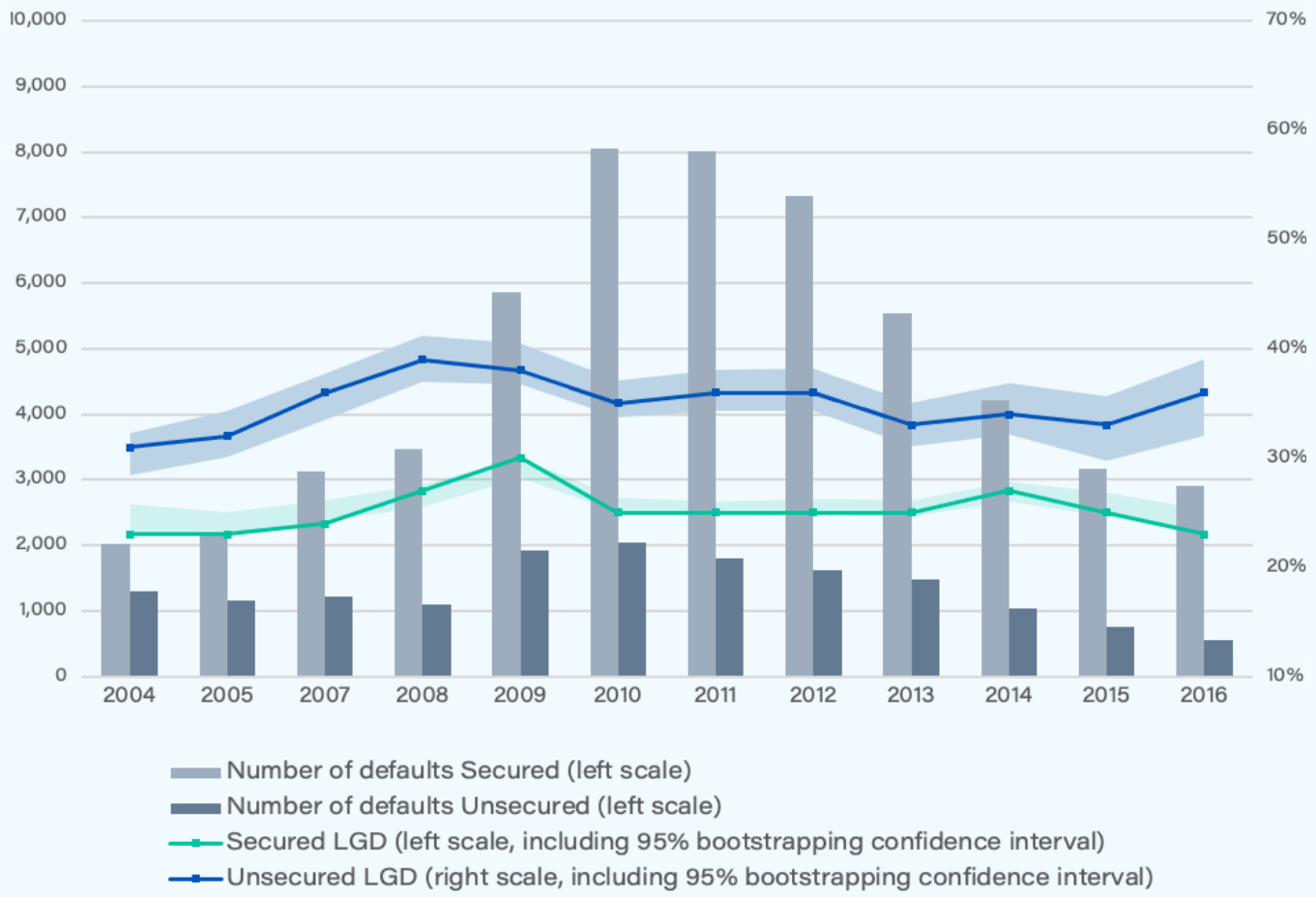
Key risk drivers observed historically are also valid during downturns. For example, GCD data confirms consistently over time that secured loans have lower LGD than unsecured loans.

Exhibit 5 illustrates this trend. While fewer data points are available for unresolved loans prior to 2004 and after 2016, the period from 2004 to 2016 (which includes a large bulk of mature data from the global financial crisis) confirms collateralisation as a key LGD driver, with secured LGD remarkably lower than unsecured LGD.

EXHIBIT 5

LGD BY YEAR OF PEAK CASH FLOW

SECURED VS UNSECURED LOANS



Due to the granularity of the GCD data set, including transaction data, these downturn effects can be directly observed not only on a global scale, but also at a regional level.

Exhibits 6 and 7 illustrate the peak LGD by year of peak cash flow in line with macroeconomic and GCD ODF trends for both Europe and North America. A breakdown of country-level data is available to GCD members.

EXHIBIT 6

LGD BY YEAR OF PEAK CASH FLOW

CORPORATES, EUROPE

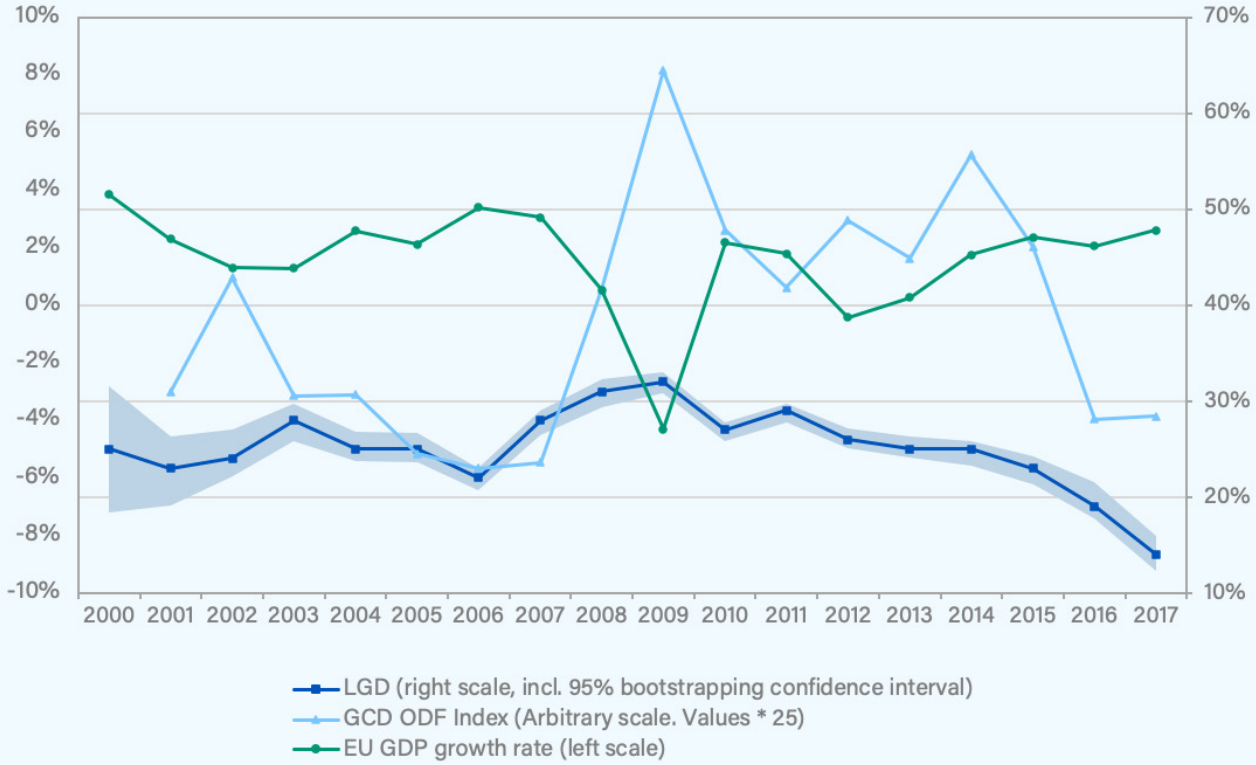


EXHIBIT 7

LGD BY YEAR OF PEAK CASH FLOW

CORPORATES, NORTH AMERICA

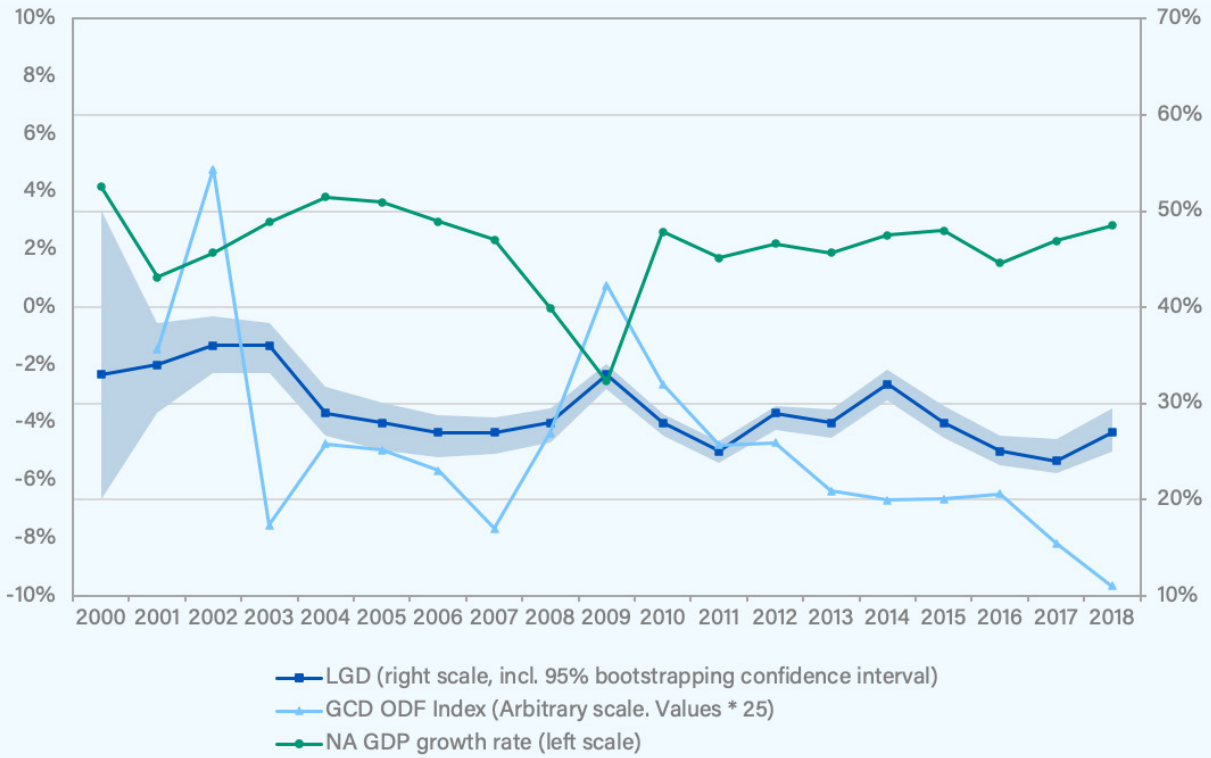
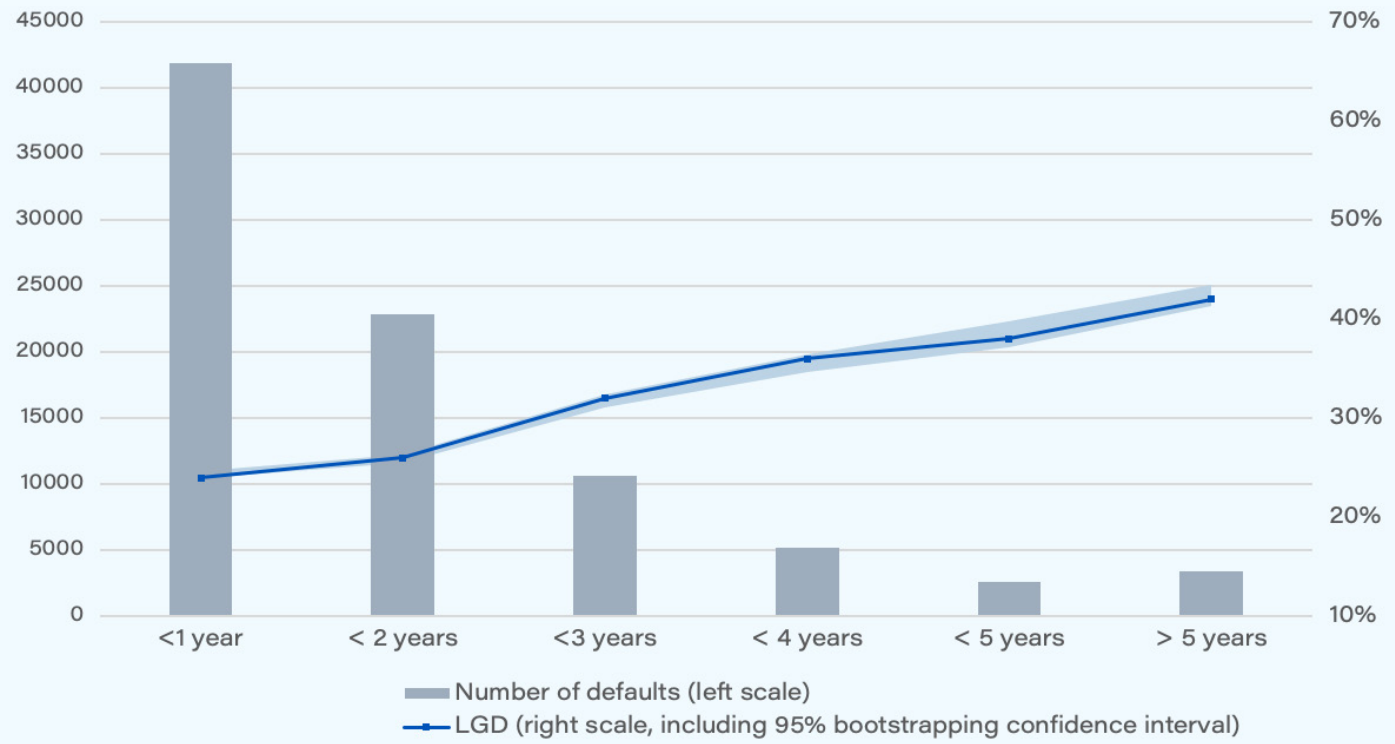


EXHIBIT 8

LGD BY TIME TO PEAK RECOVERY

CORPORATES, GLOBAL



Workout processes may last several years as recovery cash flows are collected, such as by selling off the assets of a defaulted company. The correlation between the workout period and the LGD outcome can be seen in Exhibit 8, where average LGD levels based on Time to Peak Recovery (TTRec) buckets are displayed. The longer the TTRec the higher the LGD.

Almost 50% of recoveries happen in the first year after default, achieved through quick debt reduction activities and in most cases a return to performance. Meanwhile, the sale of collateral usually takes longer than a year and, therefore, many cases take two years or more to workout. More complex workouts can take up to 6 years or longer, although cases that take longer are expected to have worse outcomes, without attributing causality.

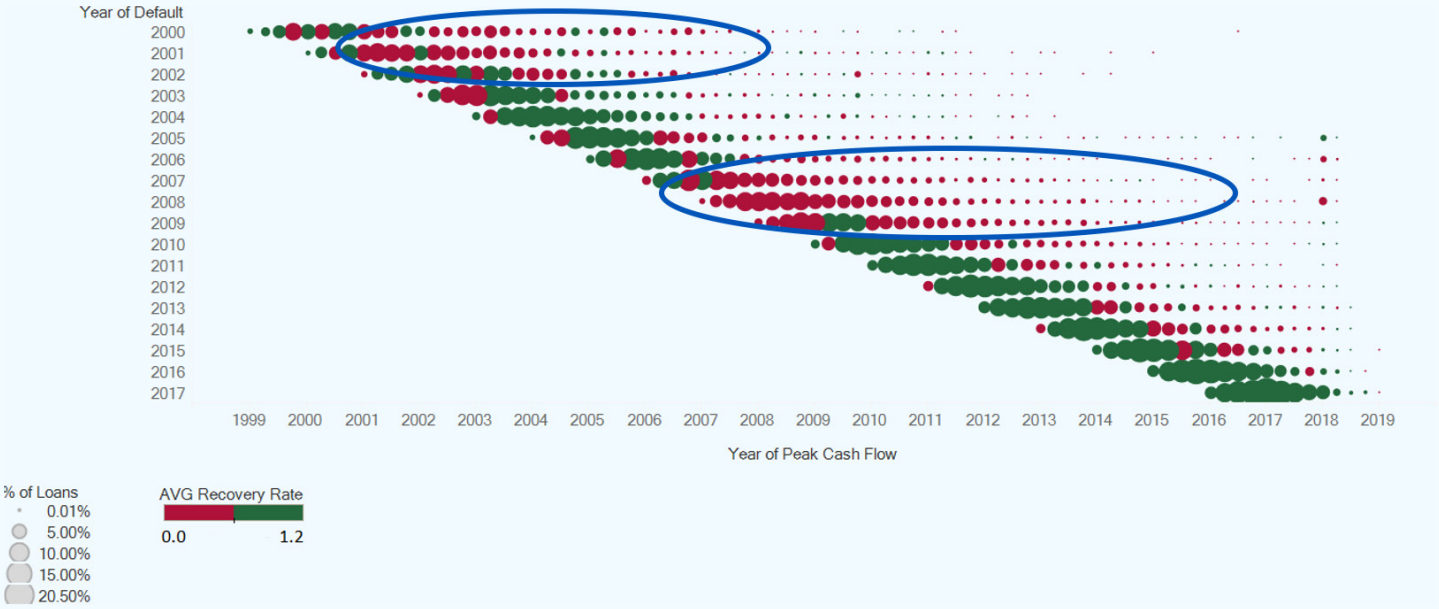
Exhibit 9 shows the recovery heat map for corporate loans. The heat map is a tool used to examine the profile of crises while capturing the impact on recoveries. Areas of red dot concentration illustrate the magnitude and duration of the impact of both the 2001-2002 and 2008-2009 downturns. This provides an indication of when recovery cash flows (horizontal axis) are realised in relation to a default in a particular year (vertical axis). The recovery rate shown for each quarter reflects the average value for those default cases where the peak cash flow occurred in that particular quarter. The colour indicates if the recovery rates were below the average of 72% (red) or above (green). The size of each dot represents the percentage of all defaults in a given year reaching the peak recovery in that quarter.

Two effects can be observed from this: First, recoveries collected during the crisis years are lower than normal. Looking at cash flows occurring from Q3 2000 to Q1 2003 and from Q2 2008 to Q1 2010, only

EXHIBIT 9

TIMING OF RECOVERY CASH FLOWS

CORPORATES, GLOBAL

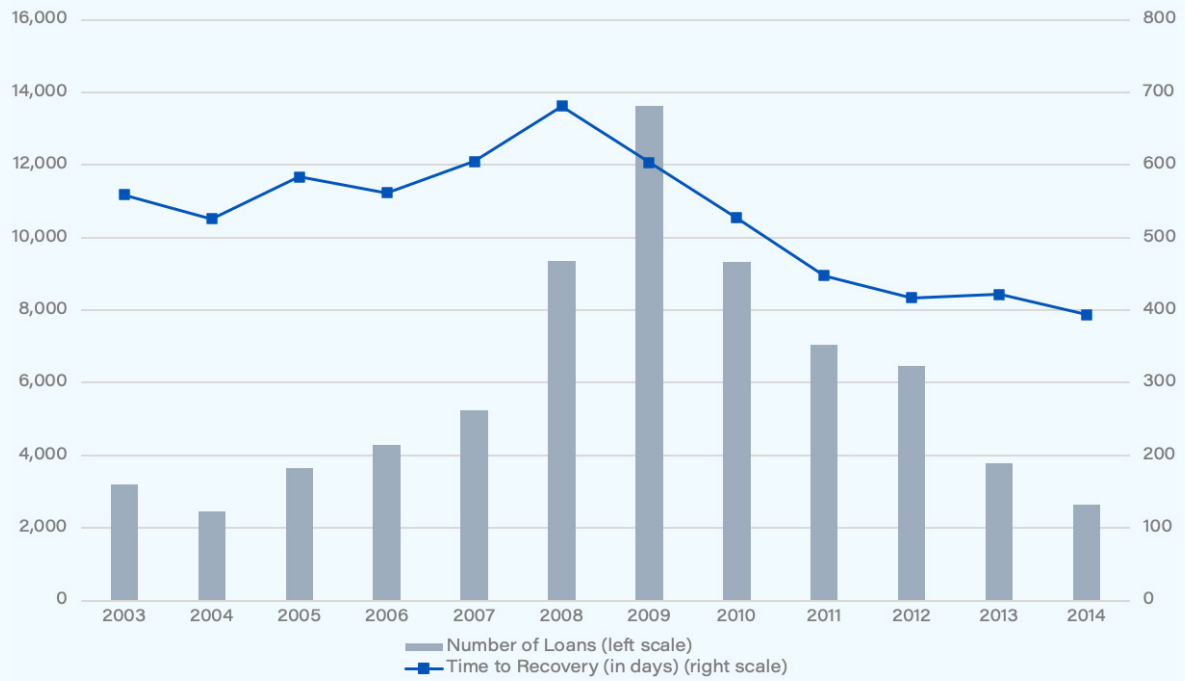


red dots are visible – indicating below-average recovery rates, in line with the 2001-2002 tech stock crisis, and 2008-2009 global financial crisis. Second, the recoveries for defaults occurring during a crisis year tend to be collected later in time. The default years 2007-2009 show longer tails than non-crisis years, suggesting that recoveries are delayed in times of crisis. This is examined further in Exhibit 10.

EXHIBIT 10

TIME TO PEAK RECOVERY BY YEAR OF DEFAULT

CORPORATES, GLOBAL



On average, a loan reaches its peak cash flow recovery after 546 days (1.5 years). The large number of cases defaulting in 2008 and 2009 were slower to recover, averaging 642 days (1.8 years). However, by 2010 and 2011, recoveries were realised much quicker, in line with the improved macroeconomy.

Exhibits 9 and 10 are a further indication that the year of peak recovery is a better time reference for analysing the macroeconomic impact on LGD than the year of default. In particular, these graphs highlight 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. Based on this assessment, the evolution of LGD values over time can be analysed with respect to their co-movement with macroeconomic indicators.

Workout scenarios in crisis period

The impact of an economic downturn can also be observed in cure rates. For the purposes of GCD's analyses, a cure is defined as a case having a time to resolution of one year or less, with no write-off and no collateral sale or guarantee call.

As seen in Exhibit 11, the relationship between cure rates and macroeconomic development has been analysed according to this definition, which explains the one year lag in the relationship between cure rates and world GDP growth.

EXHIBIT 11

CURE RATE BY YEAR OF DEFAULT

CORPORATES, GLOBAL

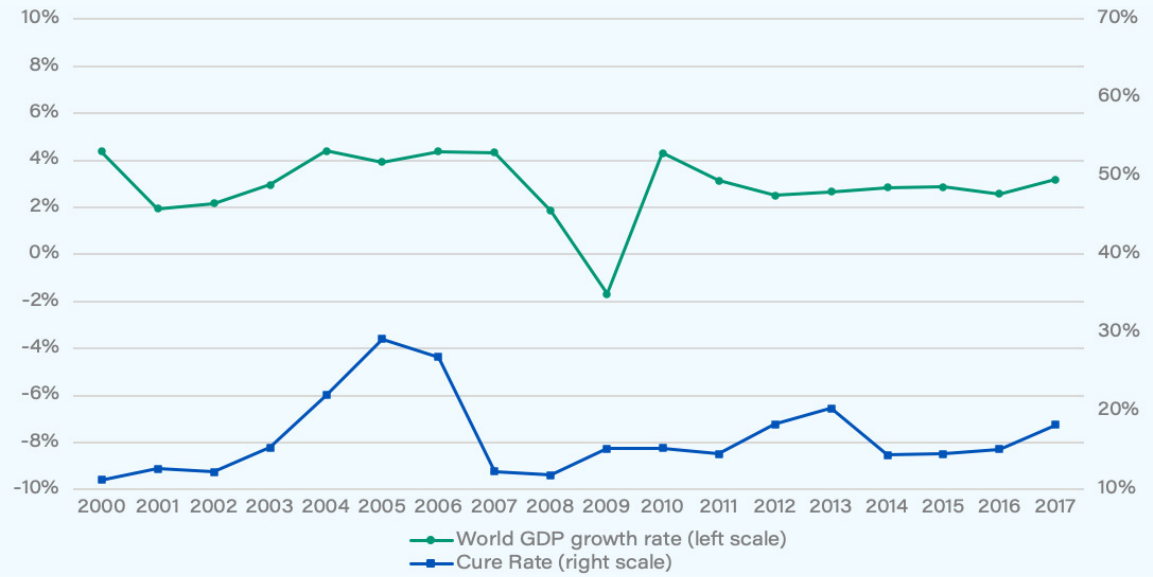


Exhibit 12 provides further details regarding the activities occurring during the time to recovery period, and how a downturn can affect these different workout scenarios.

The outcome reflects not only restructuring efforts by the bank but also the capacity of the company to overcome its problems as well as general market conditions.

EXHIBIT 12

WORKOUT SCENARIOS BY YEAR OF PEAK CASH FLOW

CORPORATES, GLOBAL

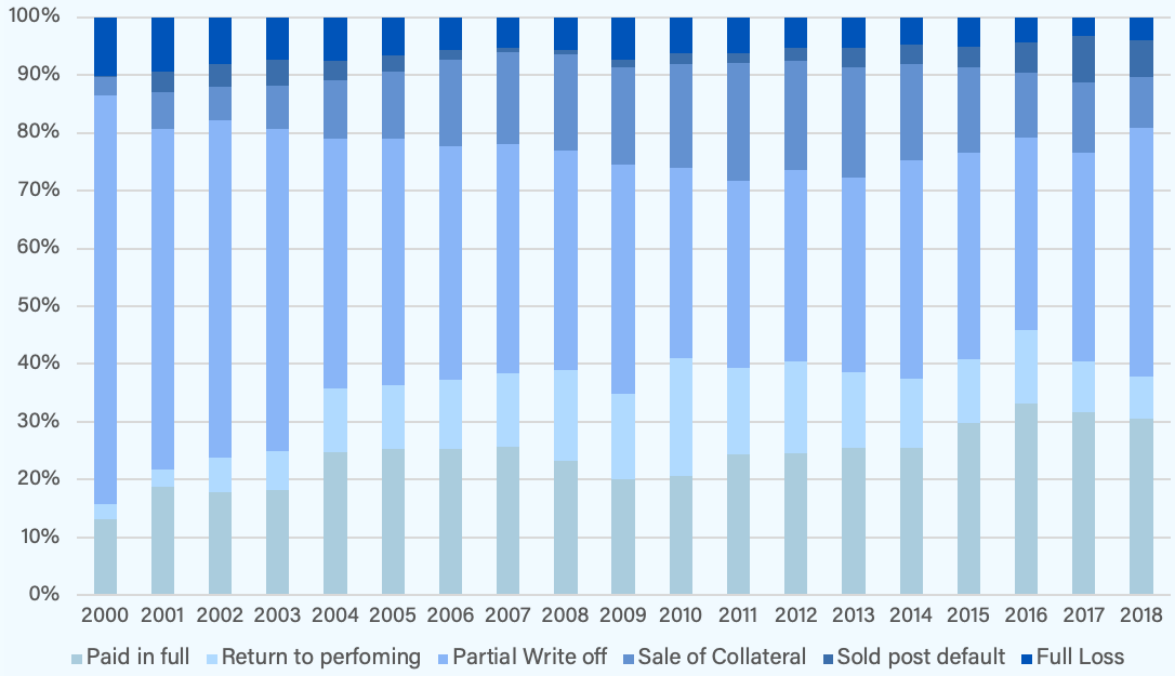


Exhibit 12 illustrates the variety of workout paths ending in distinctly different economic results for the lender. It is interesting to note the increasing use of the "Sale of Collateral" scenario after 2009, with a peak in 2011.

Banks generally have the power to choose when to start the liquidation process for collaterals. Especially in times of crisis, banks may prefer to wait for improved economic conditions before starting liquidation. The longer time to resolution under the sale of collateral scenario is a good indicator for time lag assumption in macroeconomic time series analysis.

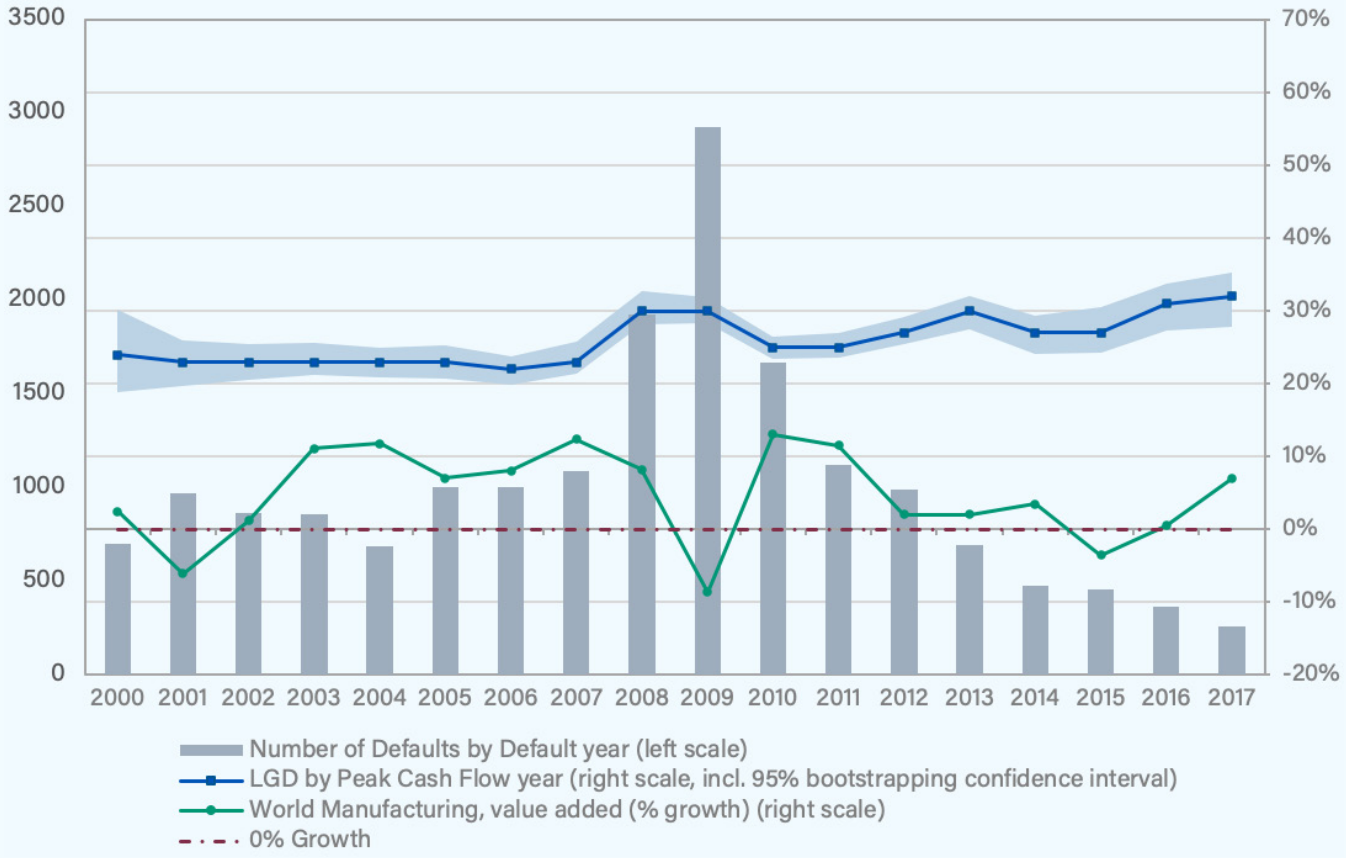
Downturn impact on industry

The trends identified above can also be seen in the data for specific sectors. Exhibit 13 uses the same technique employed for the wider corporate data set, applying it to a subset of corporate defaults from the manufacturing industry. This is contrasted with an appropriate macroeconomic indicator, in the form of world manufacturing value added growth.

EXHIBIT 13

LGD BY YEAR OF PEAK CASH FLOW

CORPORATES, MANUFACTURING, GLOBAL



The graph shows the same distinct relationship between downturn (strong negative macroeconomic growth) and the number of defaults. What's more, LGD by year of peak cash flow also aligns with the wider corporate data set as higher during 2008-2009.

DOWNTURN EFFECTS ON LGD FOR BANKS AND NON-BANK FINANCIAL INSTITUTIONS

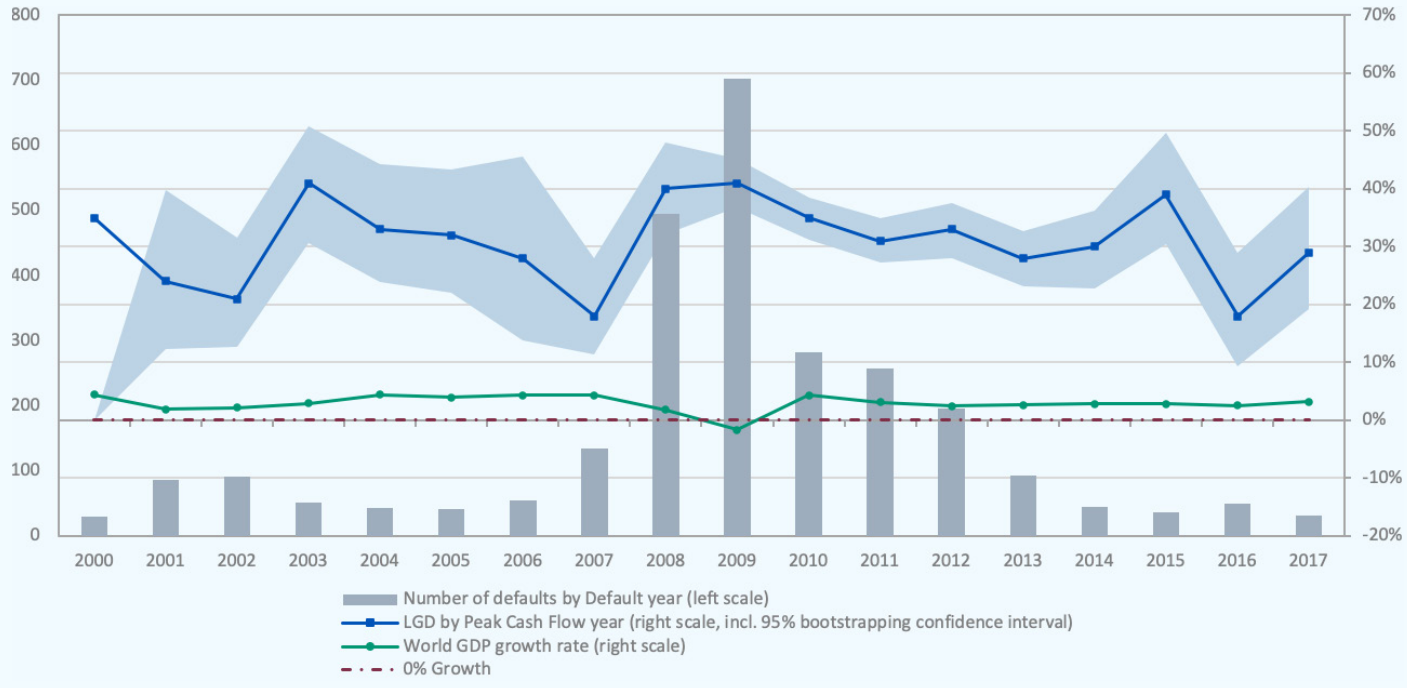
While data on losses associated with bank and non-bank financial institution (FI) defaults is generally assumed to be scarce (and therefore only of limited use for statistical time series analysis), GCD's comprehensive LGD data set is large enough to allow for statistical exploration of some of the important drivers of downturn LGD associated with financial industry defaults.

This can be seen in Exhibit 14, which shows the number of defaulted banks and FIs in the GCD sample data set in the period from 2000-2017. The distribution of defaults reflects the global financial crisis of 2008-2009. The majority of bank defaults are associated either with a local or a global downturn in the financial markets. The LGD values show a variation of around 35%, although the error bars remain relatively large due to the low number of defaults per year. During the global financial crisis years, the defaults that had peak cash flow at the time suffered LGDs of around 40%, in line with the macroeconomic data for those years.

EXHIBIT 14

VARIATION OF LGD BY YEAR OF PEAK CASH FLOW

BANKS AND NON-BANK FIs



LGD and the impact of sovereign crises

As already shown in previous sections, however, the relationship between LGD and downturns is not as straightforward as that between defaults and downturns. Bank and FI defaults are unique, in that they have both international and local causes, while their recovery is often affected by the ability and willingness of the sovereign to recapitalise or restructure the industry.

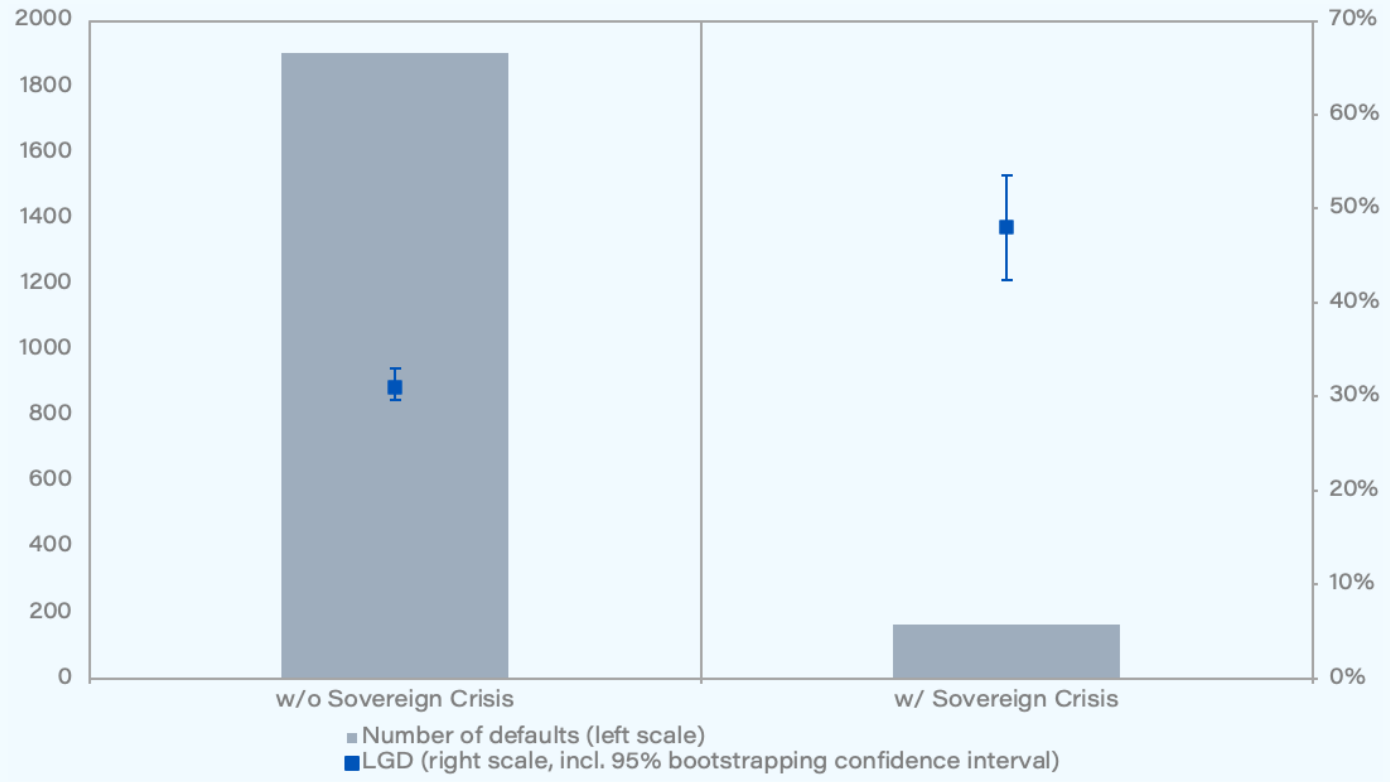
Understanding the drivers of LGD is nevertheless essential for further modelling efforts. Therefore, several potential parameters were analysed for identifying the major drivers. Most notably, LGD values when a bank default is linked to a sovereign crisis (e.g. in Argentina in 2001-2002, Iceland in 2008 and Cyprus in 2013) tend to be significantly higher compared to other bank defaults as shown in Exhibit 14.

This could perhaps be explained by the fact that the crises in Argentina, Iceland and Cyprus were not only accompanied by severe distortions of the local financial markets, but also characterised by a rare reduction in the relevant governments' abilities to provide support to these markets. The significance of the difference between LGD values realised during the Argentinian, Icelandic and Cypriot banking crisis in contrast to all other bank defaults also holds from a statistical point of view (assessment of estimation uncertainty by bootstrapping), as shown in Exhibit 15.

EXHIBIT 15

DRIVERS OF BANK LGD:

SOVEREIGN CRISIS



Given the increasing amount of empirical evidence on the linkage between banking and sovereign crises, this effect could be recognised in downturn LGD models for banks and FIs. Regarding other drivers, such as bank or FI business models, information-rich data is available exclusively to GCD member banks.

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CONCLUSION

In summary, the following conclusions can be drawn from the analyses presented in this report:

- The GCD data clearly highlights the link between macroeconomic factors and the default rate. Default cases always visibly increase in downturn years.
- The variation of cure rates and non-cured LGDs in different macroeconomic scenarios is visible in the data. In downturn years, fewer loan defaults solve themselves (cure).
- Recovery rates during downturns are lower (and therefore LGD is higher). However, defaulted loans can take several years to recover, so it is important to look at the economic conditions at the time the recovery is happening.
- The peak cash flow date aligns well with the macroeconomic conditions. Tough economic conditions (downturn) at the time the bank recovers the money results in a higher LGD.
- For bank and non-bank financial institution LGDs, GCD's previous conclusions have been confirmed: in the case of a sovereign crisis coinciding with a bank default, LGD values tend to be significantly higher.
- Banks can use GCD data to estimate LGD for future downturns by using the links established between downturn periods and cure, non-cure recovery, and time to peak cash flow recovery.

FAQS

What reference data set has been used for this study?

The reference data set (RDS) for this study contains only resolved defaults (i.e. cases for which the workout has been completed), submitted up to June 2020. A default is considered as 'unresolved' in the instance that the lending bank is still expecting further cash flows. All other cases where the lending bank has closed the recovery file are considered 'resolved.'

Cases with year of default from 2000 to 2017 were chosen due to completeness. Pre-2000 defaults can be biased towards long, difficult workouts, while post-2017 defaults contain too high a mix of quick workout (cure) cases. A cure is defined as a case having a time to resolution of less than one year, no write-off, and no collateral sale or guarantee call.

Results are shown on loan level. 'Facility,' 'loan,' and 'deal' are considered the same for the purposes of this report, with the term 'loan' used for consistency throughout. Most of the loans in the GCD data sets are loans of some type, such as term loans or overdrafts. However, the data also includes significant numbers of contingent loans, including letters of credit or derivatives, as well as some bonds and equity.

How is LGD and its variation over time calculated?

LGD refers to the Loss Given Default rate, which is calculated as 1 – recovery rate. The recovery rate is the net of all cash flows as a fraction of the EAD, including external costs (using the discounted cash flows where the discount rate is equal to the risk-free rate of three months' EURIBOR as at the default date). This calculation is made at the loan level.

The LGD calculation is made using a cap of 150% and floor of 0%, where the exposure at default (EAD) is increased by the amount of any post-default advances. The $LGD_{Non-Cure}$ is calculated as LGD, but excluding cures from the data set.

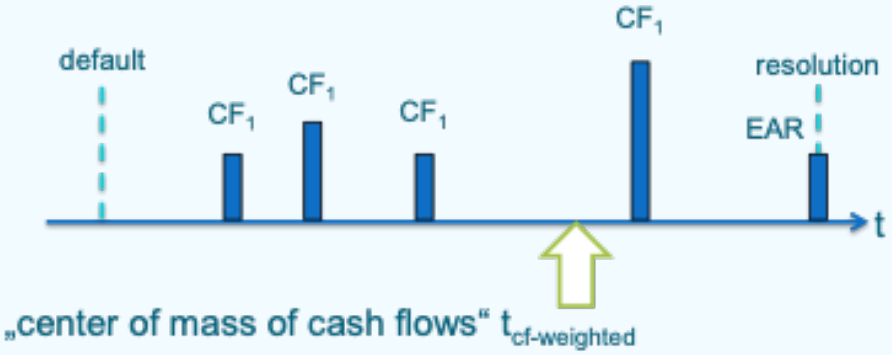
The LGD levels are calculated based on raw data and do not reflect any bank-specific portfolio alignment or addition of any statistical uncertainty add-ons. Variations could include using a different discount rate based on a combination of the risk-free rate and a risk premium for systematic risk at the time of default.

To assess the statistical significance of the variations over time, a bootstrapping was performed. A simple standard deviation calculation produces extreme values and larger amounts of data are required to stabilise the central tendency. The variation of the mean is shown here by bootstrap confidence intervals, a simple non-parametric method for constructing confidence intervals.

What is the difference between time to resolution and time to peak cash flow?

Time to resolution (TTR) is calculated as the period between the default and the resolution of a borrower workout (i.e. repayment, write-off, return to performing, etc.)

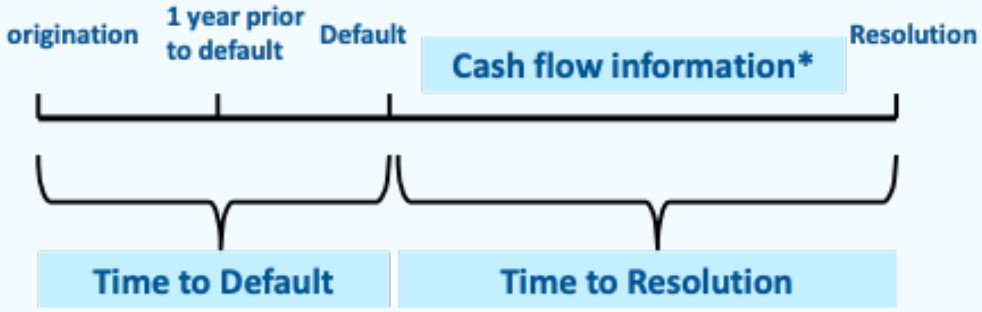
The year of peak cash flow refers to a concept similar to the Macaulay duration of bonds. The cash flow weighted time or average year of peak cash flow represents the weighted average of all relevant points in time between default and resolution where cash flows took place.



For cases without a clear repayment cash flow, the best approximation has been chosen:

- For full loss cases, the middle point between default and resolution
- For return to performing and sold post default, the resolution date

For reference, the full lifecycle of a defaulted loan, from origination to resolution can be seen below.



**Cash flow information includes amount, date, currency, cash flow type, source of cash flow, and liquidated collateral ID.*

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[i] https://www.globalcreditdata.org/library/lgd-report-large-corporates-2020

[ii] https://eba.europa.eu/eba-publishes-final-guidelines-on-the-estimation-of-lgd-under-an-economic-downturn

[iii] https://www.oecd.org/economic-outlook/

[iv] https://www.worldbank.org/en/news/press-release/2020/06/08/covid-19-to-plunge-global-economy-into-worst-recession-since-world-war-ii

[v] ODF is the ratio between the count of defaulted loans over total loans for the period of one year. ODF is based on data available in the GCD Probability of Default (PD) & Rating Platform, a unique data source which allows banks to anonymously compare their PDs and observed default rates with peers for different types of credit loan portfolio.


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