Global Credit Data

by banks for banks

15 November 2017

Downturn LGD Study 2017

European Large Corporates / Commercial Real Estate and Global Banks and Financial Institutions

TABLE OF CONTENTS

ABOUT GCD

Global Credit Data (GCD) is a non-profit association owned by 53 member banks with the simple mission to help banks better understand and model their credit risks through data pooling and benchmarking activities.

GCD started collecting historical loss data in 2005, to which member banks have exclusive access. This database now totals over 150,000 non-retail defaulted loan facilities from around the world.

In 2009 GCD introduced a PD database which now covers more than 10 years of default rates and PDs. GCD also runs a name and cluster benchmarking database to help banks to calibrate and benchmark their PD, EAD and LGD 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 a GCD's data collection infrastructure place our databases as the global standard for credit risk data pooling.

CONTACT GCD

Nina Brumma
Head of Analytics and Research
nina.brumma@globalcreditdata.org

Philip Winckle
Executive Director
philip.winckle@globalcreditdata.org

www.globalcreditdata.org

SUMMARY

Does loss given default (LGD) depend on the economic cycle and if so how can it be measured? This question still concerns risk modellers and regulators as part of their comprehensive risk assessment. In 2013 GCD published a first downturn LGD study based on the GCD large-scale LGD database. This report provides an update of the analyses presented back then on a now significantly enlarged data set provided by over 50 member banks and covering over 15 years of default history.

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 and facilitates the implementation of new regulatory requirements provided by EBA and ECB in Europe.

Other requirements such as IFRS9/CECL or stress testing/CCAR create the need for more detailed default and loss modelling, especially in respect of term structure and macroeconomic dependency.

This report focusses primarily on the asset classes large corporates (LC unsecured) and commercial real estate (CRE) in Europe, as well as Financial Institutions globally. In particular, this report provides insights regarding two major questions:

- **What kind of downturn effects can be found in historical LGD data?** The data shows that the LGD varies over time. Looking at LC and CRE more in detail it seems that the connection to economic conditions cannot be analysed in a simple way and not at a single time point. Firstly, there is a relationship between the economic conditions around the time of default and the rate of quick and easy recoveries (cure rate). Secondly, for non-cured cases, the economic conditions at the later time of collecting the outstanding amount are related to the recoveries. Considered this way, the correlations are likely to be causal, with bad economic conditions around default time discouraging lenders from refinancing difficult loans and hence reducing cure rates and bad economic conditions around liquidation time depressing asset sale prices and hence reducing recoveries. Overall, this higher degree of complexity explains why it is hard to see a simple correlation of LGD outcome to economic conditions at the time of default alone.

- **Can you analyse downturn LGD for banks?** Using the comprehensive data set of GCD, we could show that loans to banks and financial institutions experience their worst recoveries at times of sovereign crises affecting the home country of the counterparty.

Member banks will be able to confirm these results and test them on sub-sets of the data, as they have the same level of data detail available. We hope that all financial institutions and regulators will consider these insights and methods when deciding on how to model downturn LGD.

INTRODUCTION

Global Credit Data – established in 2004 – manages the collection of historical LGD, EAD and default observations from its over 50 member banks. The GCD LGD data set is one of the world's largest sources of information on all aspects of LGD modelling for wholesale lending. GCD's LGD/EAD database currently comprises over 150,000 defaulted loans covering 11 asset classes.

In 2013, the downturn LGD working group of GCD published a first white paper on the analysis of downturn effects observable in the GCD LGD data sets. Due to the recent regulatory focus on the modelling of downturn effects on the LGD, e.g. in the EBA consultation paper CP/2017/02, the analyses have been updated on the most recent data sets with an extended time series. Additional analyses have been performed on commercial real estate portfolios to corroborate the earlier findings.

COMPOSITION OF THE DATABASE AND REFERENCE DATA SET

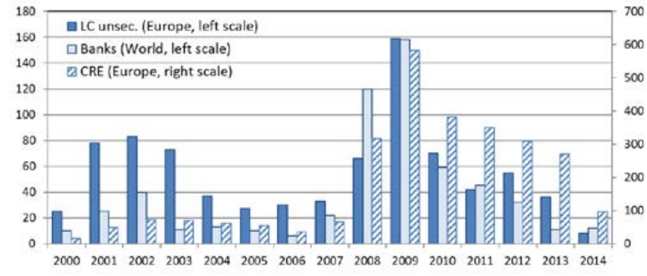
Three reference data sets (RDS) are used in this study:

- Unsecured Large Corporates (LC) which are defined according to the Basel rules as counterparties with a group turnover of €50m and above.
- Commercial Real Estate (Basel asset class specialized lending and large corporates secured by real estate).
- Banks and financial institutions

For LC and CRE, we used European data to create a more homogeneous data set. The RDS were split into cured and non-cured cases to analyse downturn effects separately and to reduce the bimodality of the LGD distribution. We analyse the $LGD_{Non\text{-}Cure}$ and the cure rate. The LGD_{Cure} is zero by definition if we ignore minor discounting effects.

The RDS used only resolved defaults, i.e. cases for which the workout is completed. For the cure rate calculation, unresolved cases are included as workouts beyond 1 year cannot cure. The data is grouped at borrower level, where all loans for each borrower are aggregated. Defaults from years 2000 to 2014 were chosen. Pre-2000 defaults can be biased towards long, difficult workouts while post 2014 default cases contain too high a mix of quick workout "cure" cases. For banks, a global data set was generated.

EXHIBIT 1
NUMBER OF DEFAULTS IN THE REFERENCE DATA SET



The standard GCD LGD calculation is made using a cap of 150% and floor of 0% per borrower using GCD's "LGD2" method, where the EAD is increased by the amount of any post default advances. The LGD is calculated by discounting the cash flows at a risk-free rate of 3 month LIBOR. The LGD levels are calculated on the raw data and do not reflect any bank specific portfolio alignment or addition of any statistical uncertainty add-ons.

> ## NOTE ON TERMS USED
>
> **LGD** refers to Loss Given Default rate which is calculated as 1 –recovery rate. The recovery rate is the net of all cash flows including external costs (using the discounted cash flows where the discount rate is equal to the risk-free rate as at the default date). This calculation is made on borrower level, capped between [0%,150%].
>
> **$LGD_{Non\text{-}Cure}$** is calculated as LGD but excluding cures from the dataset.
>
> **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.
>
> **Cure** is defined as a case having time to resolution < 1 year, no write-off and no collateral sale or guarantee call.
>
> **Resolved / unresolved cases**: Defaults are considered as 'unresolved' in case banks are still expecting further cash flows. All other cases where the lending bank has closed the recovery file 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 the so-called resolution bias which leads to unrealistically high cure rates for recent years.

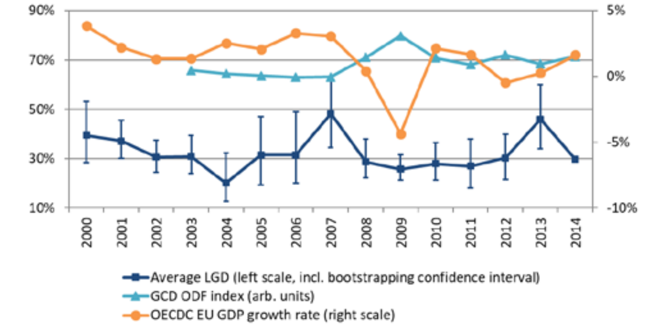
For unsecured loans to large corporates, the European RDS contains 822 non-cure defaulted borrowers. This shows the increase in available data when compared to the 843 borrowers available in 2013 globally. The asset class commercial real estate is comprised of 2735 defaulted borrowers. The number of defaulted borrowers for financial institutions available for analysis has increased significantly from 107 in 2013 compared to 576 in 2017. These effects stem from the longer time series available now as well as the increased number of GCD member banks adding data to the pool.

DO YOU FIND DOWNTURN EFFECTS IN HISTORICAL LARGE CORPORATES DATA?

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.

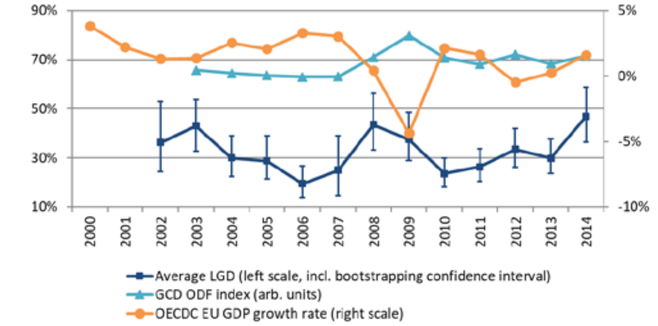
Exhibit 2 shows an overlay of GDP growth rate together with the GCD observed default rate index and the LGD for non-cured LC. We used default rates and European GDP growth rates as macroeconomic factors to identify the downturn. GDP Growth Rate was chosen because it is a standard macroeconomic factor, it shows the impact of the financial crisis which is a generally accepted downturn and it relates to the European default portfolios chosen. As expected, 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. This confirms the results from the 2013 GCD study.

EXHIBIT 2
VARIATION OF LGD$_{\text{NON-CURE}}$ BY YEAR OF DEFAULT



Asset Class: Large Corporates Unsecured, Europe

EXHIBIT 3
VARIATION OF LGD$_{\text{NON-CURE}}$ BY YEAR OF CASH FLOW



Asset Class: Large Corporates Unsecured, Europe

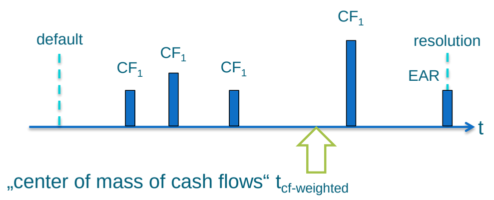
In order to assess the statistical significance of the variations over time, a bootstrapping was performed (1000 iterations) and the 2.5% and the 97.5% quantiles of the resulting distribution are plotted as bootstrapping confidence intervals. The increase in LGD between 2004 and 2007 appears to be statistically significant, despite the very low number of defaulted borrowers in these years seen in Exhibit 1.

This initial analysis suggests a variation of LGD over time in historical data, which however seems to be out of phase with the macroeconomy and in particular well ahead of the financial crisis as observed in GDP growth rates and the default rates. Such an effect is not directly plausible from an economic point of view. Possible explanations for this observation include (1) the resolution bias and (2) the effect of the economic environment during the collection / work-out phase on the recovered cash flows.

The resolution bias refers to the effect of yet unresolved cases which are not fully visible in the reference data set. For recent years the dataset might be biased towards lower LGD since generally short time to resolution leads to comparatively lower LGDs. This is the reason why we exclude defaults from 2014 onwards from the RDS. Considering the years 2010-2014 in the GCD data set, between 50-90% of all potential defaults have been resolved. Prior to 2010, the resolution rate is above 90%. Therefore, unresolved cases do have some effect, in particular for the years after 2012. However – as detailed analysis and extrapolation of unresolved cases showed – they cannot explain the drop in LGD during the severe economic downturn in 2008-2009.

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.



A second factor influencing the variation of LGD estimates is the distribution of recovery cash flows over time. Obviously, the recovery cash flows are dispersed over significant periods of time, during which economic conditions are likely to change. Work out processes typically last several years while recovery cash flows are collected, e.g. by selling off the assets of a defaulted company. The average time to resolution for non-cured LC defaults is 2.5 years. 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 borrowers results in lower recoveries and higher LGD values. Therefore, the adverse economic environment during a downturn should be expected to have a significant impact on this essential risk parameter. Looking at the timing of the underlying cash flows, it should be possible to extract a meaningful co-movement of LGD and macroeconomy from historical data.

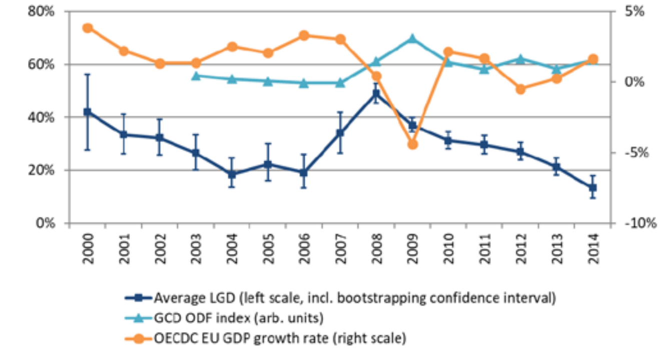
Exhibit 3 illustrates the effect of cash flow timing for large corporates. Here each LGD value (see note on terms used) is assigned to that point in time at which the average of the cash flow took place. This approach helps to isolate the downturn effect from other time related effects.

The peak LGD shifts towards the actual point in time of the crisis, i.e. from 2007 to 2008/2009, more in in-line with economic expectations. Due to the high level of detail in the GCD 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 macroeconomic indicators.

DO YOU FIND DOWNTURN EFFECTS FOR COMMERCIAL REAL ESTATE?

Commercial real estate portfolios are quite different from unsecured loan business with large corporates as they heavily depend on the value of the collateral provided. Therefore, we investigated whether the historical evolution of LGD in those portfolios deviates significantly from large corporate loan portfolios. Exhibit 4 shows the variation of LGD for the CRE asset classes over 15 years. Interestingly, the overall evolution is relatively similar to large corporates (see Exhibit 2), with a pronounced increase in LGD between 2006 and 2008 - year of default). The peak in LGD is observed one year later in 2008 for CRE compared to 2007 for large corporates.

EXHIBIT 4
VARIATON OF $LGD_{NON\text{-}CURE}$ BY YEAR OF DEFAULT

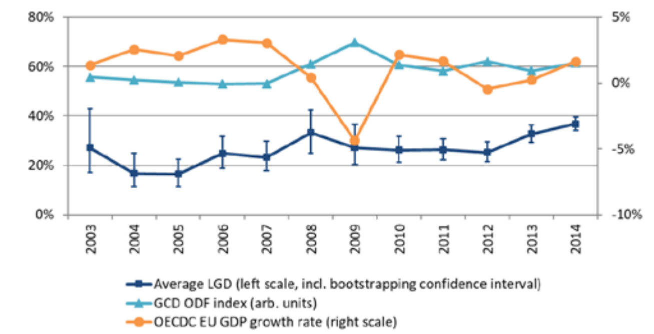


Asset Class: Commercial Real Estate, Europe

After the peak in 2008, the average LGD decreases again. From 2012 onwards, the data may be not representative any more due to low completion rates. The overall range of variation is similar for both portfolios, between 20% and 50%.

Considering the average year of the cash flows, however, the lagged co-movement of LGD and GDP growth diminishes around the crisis years 2008 and 2009, as shown in Exhibit 5. The instantaneous LGD increases again in 2012 to 2014 due to more cases with longer time to resolution and time to cash flow in this period. A similar behaviour is observed for large corporates in 2013/2014. Overall, the behaviour of LGD is similar in both European portfolios, despite the differences in loan terms and collateralization.

EXHIBIT 5
VARIATION OF $LGD_{NON\text{-}CURE}$ BY YEAR OF CASH FLOW

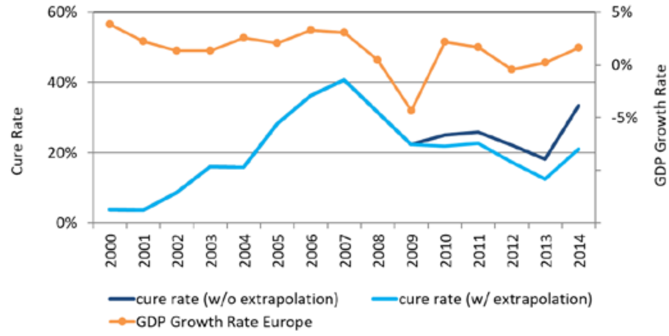


Asset Class: Commercial Real Estate, Europe

CAN YOU ANALYSE DOWNTURN EFFECTS ON CURE RATES?

Another effect of economic downturn can be observed for cure rates. Here, the relationship between cure rates and macro-economic development has been analysed for large corporate and commercial real estate loans in Europe. This analysis highlights the importance of appropriately incorporating unresolved cases in order to remove the resolution bias. Exhibit 6 shows the cure rate for European large corporates with and without considering the extrapolated number of cases yet to be resolved. The notable increase in recent years is caused by more timely resolution of cured cases (less than one year according to the GCD definition) which leads to an over-representation of cures compared to non-cure cases.

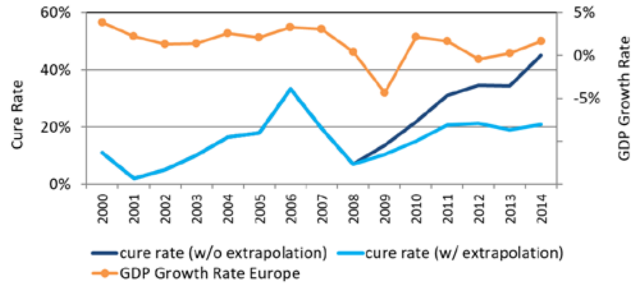
EXHIBIT 6
CURE RATE BY YEAR OF DEFAULT



Asset Class: Large Corporate unsecured, Europe

Applying an extrapolation based on the fact that unresolved cases after one year are per definition non-cures allows for correcting this effect. Now, an increase in the cure rate can be observed before 2007 combined with a significant reduction in cure rate during the financial crisis in 2008-2009, in line with the economic downturn during the financial crisis. A similar analysis has been performed for the CRE portfolio. Here, cure rates show an all-time high in 2006, then dropping off rapidly until they reach a minimum for borrowers defaulting in 2008. Although the variation of the cure rate is approximately in line with economic expectations, one can nevertheless observe that cure rate as well as non-cure LGD rates are not fully in sync with the macroeconomic indicators like GDP growth.

EXHIBIT 7
CURE RATE BY YEAR OF DEFAULT



Asset Class: Commercial Real Estate, Europe

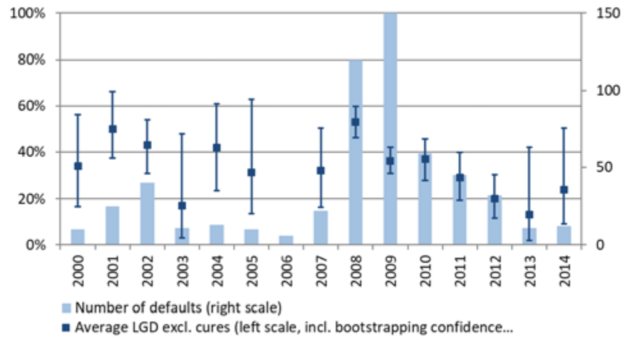
This leads to one important consequence: simple model component approaches like $LGD(t) = p_{cure}(t) \times LGD_{cure}(t) + \left(1 - p_{cure}(t)\right) \times LGD_{non-cure}(t)$ could only reflect the full behaviour of LGD rates in economic downturns when all intricacies of the temporal behaviour of these components are modelled appropriately. Currently, there is no standard yet on sensibly modelling point-in-time LGD.

DOWNTURN EFFECTS ON LGD FOR BANKS AND FINANCIAL INSTITUTIONS

Data on losses associated with defaults of banks and financial institutions is assumed to be scarce, and typically deemed as not sufficient for statistical modelling. Using the comprehensive data set of GCD, some of the important drivers of downturn LGD associated with financial industry defaults can be analysed statistically.

Exhibit 8 shows the number of defaulted banks and financial institutions in the GCD sample data set in the period from 2000-2014. 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. The majority of bank defaults are associated either with a local or a global downturn in the financial markets. When considering the number of borrowers, please note that each defaulting counterparty in a group is counted, e.g. in the Lehman Bros Group there were hundreds of borrowers of which some were reported to GCD by its members. The LGD values show a variation around 40%, although the error bars remain significant due to low numbers of defaults per year. During the financial crisis however, they stabilize around 50% for 2009 and approx. 40% for 2009 and 2010. From 2010 onwards the LGD drops to ca. 20%. This drop cannot be fully attributed to unresolved cases as for banks the percentage of resolved cases is around 80-90% in basically all years except 2015 (not shown here).

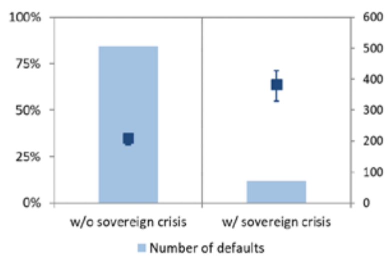
EXHIBIT 8
VARIATION OF LGD BY YEAR OF DEFAULT



Asset Class: Banks (World)

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, Iceland and Cyprus), 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 9.

EXHIBIT 9
DRIVERS OF BANK LGD: SOVEREIGN CRISIS

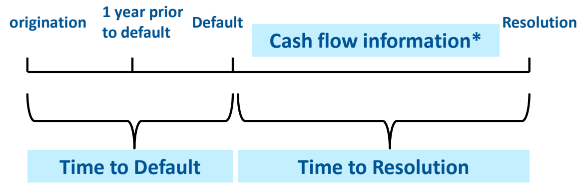


Asset Class: Banks (World)

Clearly, the crisis in Argentina in 2001-2002, in Iceland in 2008, and in Cyprus in 2013 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, Icelandic and Cypriot banking crisis in contrast to all other bank defaults holds also from a statistical point of view (assessment of estimation uncertainty by bootstrapping).

GCD DATA STRUCTURE

Five event dates allow analysis of LGD term structure from origination to resolution. Time to default influence on LGD can be analyzed as a potential driver and included in lifetime LGD modelling.



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

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. business models of banks or others, the GCD data provides information-rich data to analyse these.

CONCLUSIONS

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

- The steady increase of the amount of data in the GCD database allows for new statistical analyses as time series become longer and new members add data, allowing for more granular and homogeneous reference data sets.
- The link between macroeconomic factors and the default rate can be clearly observed in the GCD data.
- The variation of cure rate and non-cured LGD in different macroeconomic scenarios is indeed visible in the data for the three analysed portfolios large corporates, commercial real estate, and banks.
- However, the attribution of the observed LGD variations to common systematic factors is complicated by the rather complex timing encountered for the different components like LGD and cure rate.
- For bank and financial company LGDs our previous results were confirmed: In case a sovereign crisis coincides with a bank default, LGD values tend to be significantly higher.

Further efforts to collect data including the timing of e.g. cash flows is crucial to resolving the downturn LGD puzzle. Time sensitive approaches to modelling downturn – or more generally speaking point-in-time LGD – can be more detailed and comprehensive if based on granular data collections.

For this study, European data was used. A comparative analysis of European versus other regions (e.g. Northern American defaults) and their particularities in the macroeconomic context might be interesting for future analysis.

ATTRIBUTION

Analytics were supported by d-fine
Contact: markus.seifert@d-fine.de