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Models for the cure rate of defaulted loans to small and medium enterprises in Italy

Table of Contents

Executive Summary

We explore the transition frequencies for Italian loans to small and medium size enterprises from non-performing to performing, i.e. the cure rate. The cure rate is of particular importance for the valuation and risk management of unlikely to pay (UtP) loans. We compare findings based on non-public data and research from the Bank of Italy using exposure level data from *Centrale dei Rischi*, the central credit register in Italy, with exposure level data from the European DataWarehouse from public SME securitisations.

The main findings are as follows. The cure rate for UtP loans is significantly different from zero even in difficult economic times like in the years 2013 to 2015 during the sovereign debt crisis. The annual probability to cure reduces with time after default with the majority of cures happening within one year. The three year probability of cure is close to the lifetime probability of cure as 90% of all cures happen within 3 years after classification to non-performing. Regional and sector effects are significant. Loans with more collateral show higher cure rates whereas the existence of one or more guarantees appears to lower the cure rate.

Our findings are consistent with those from Bank of Italy researchers for UtP loans. Using securitisation data has the disadvantage of not seeing all loans in default compared to the data from Centrale dei Rischi, but has the advantage that our analysis can be replicated for consumer loans, leases and residential mortgages and can also be performed in other countries with large SME securitisation markets like Spain or France.[1]

[1] We understand that ESMA is currently working on revising the loan-level disclosure templates for securitisation transactions. In this article, we demonstrate how such disclosures can be used for insightful analysis that could not be obtained from pool-level performance data. We hope that ESMA will maintain the scope and consistency of the data published under the securitisation regulation going forward.

The growing importance of unlikely-to-pay loans in the Italian NPL market

In 2022, the stock of non-performing loans in Italian banks reached its lowest value in the last 15 years with French and Spanish banks now holding the largest amount of NPLs in Europe. Since 2015, Italy has been the most active country in Europe by volume of NPL sales and NPL securitisations. According to Banca Ifis research, Italian banks reduced their NPL holdings from EUR 350bn in 2015 to less than 60bn at the end of 2022. During this time a total of EUR 350bn of Italian NPLs were sold of which 107bn was transferred in form of securitisations with a government guarantee on the senior tranche under the GACS scheme. The long lasting reduction in NPL ratios is now expected to have bottomed out given the macro-economic headwinds with a combination of higher inflation and interest rates and the end of the pre-amortisation period for the EUR 250bn of loans with public guarantees granted under the 2020-2021 temporary Covid-19 framework. PWC expects around EUR 60bn of new NPL in 2023 and 2024 with loans with public guarantees representing a growing share of total defaults. In our recent report on credit conditions in the UK we reported the much higher default rates on Covid-guaranteed SME loans compared to the corporate loan market overall.[2]

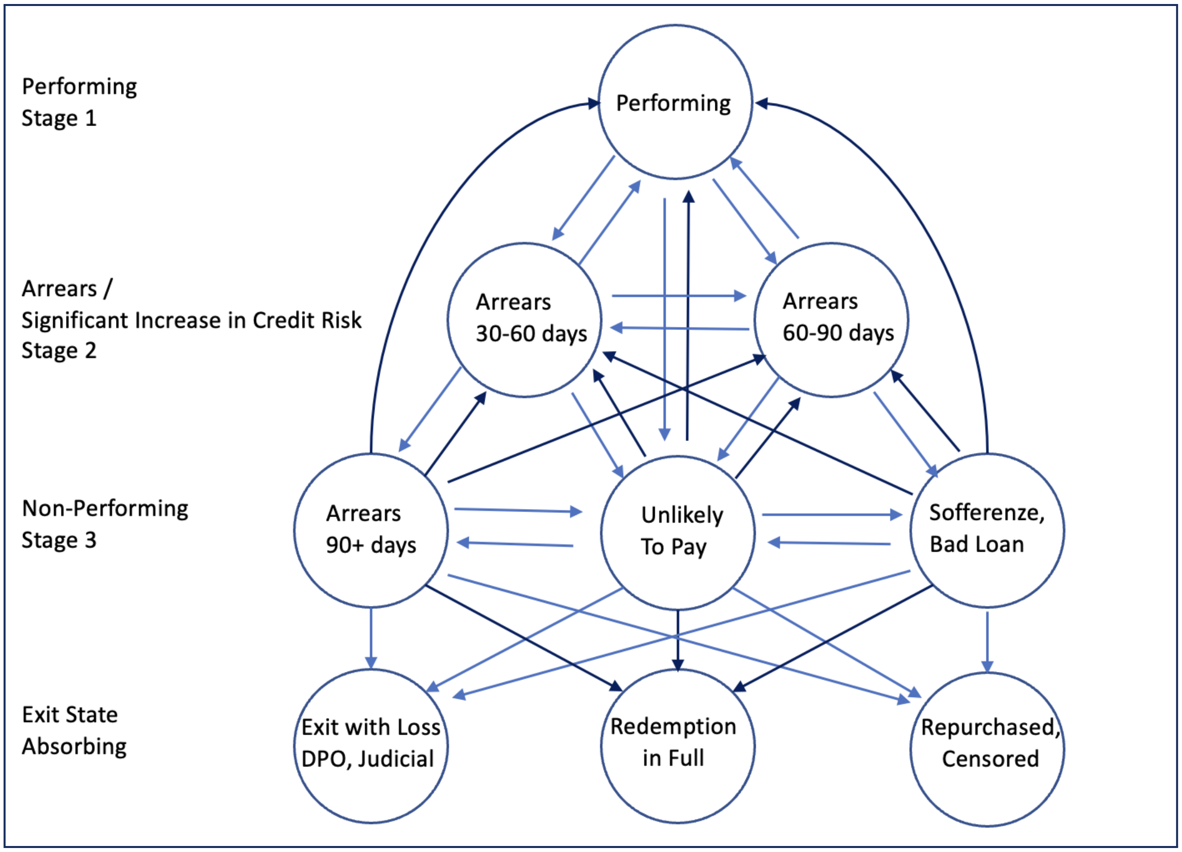


Figure 1: Transitions between different performance states. The highlighted transitions are cure transitions from a non-performing state to either performing, arrears or redeemed (in full) state, respectively.

[2] https://nplmarkets.com/en/news/article/npl-markets-credit-risk-monitor-united-kingdom

While the volume of NPLs (i.e. loans in Stage 3 under IFRS 9 accounting) has fallen in Italy and elsewhere across Europe, the amount of loans in IFRS 9 Stage 2, i.e. loans that have experienced an significant increase in credit risk, have risen to over EUR 250bn in Italy or 14% of total loans in 2022. In addition, banks have sold increasing volumes of UtP loans in Italy which in 2022 constituted around EUR 30bn of gross book value. All banks classify their non-performing exposures according to one of two reasons for default, the loan being 90 days past due or unlikely to pay (or both). In Italy, a third category of NPLs called *sofferenze* or Bad Loan is commonly used and only such Bad Loans are eligible for the GACS securitisation guarantees. Sofferenze/Bad Loans are positions that are not able to meet their payment obligations. UtP loans are positions for which it is unlikely that the borrower is able to meet their full payment obligations without the use of collateral by the bank. It is not required that a UtP position has already missed a payment to be classified in this default category. Past Due (*scaduti*) are positions not already classified as another default category, which did not meet their payments for at least 90 days.

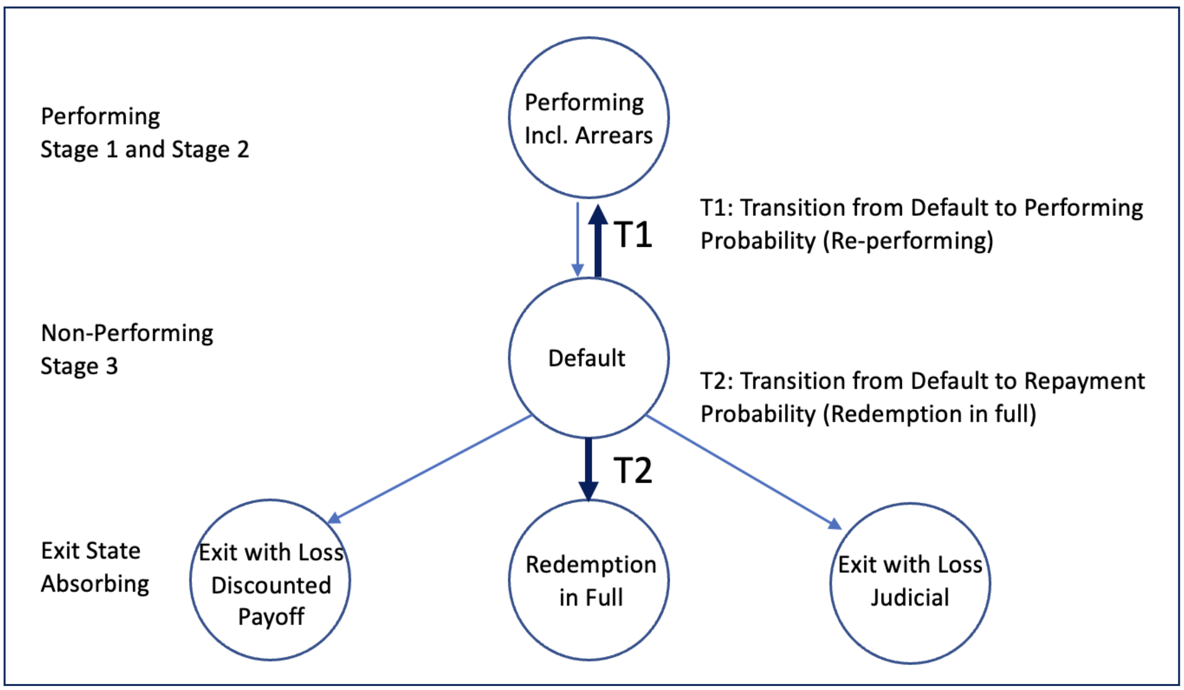


Figure 2: The simplified cure transitions considered hereunder: T1 transition from default to re-performing, T2 Transition from default to repayment in full (redemptions).

When valuing distressed debt, the degree of distress is a critical pricing factor starting from Stage 2 loans which have shown a significant deterioration in credit risk which can be caused by a rating downgrade or a commensurate increase in the assigned probability of default or can be caused by the borrower falling into arrears on the loan payments. Loans that are more than 30 days past due are generally expected to be in IFRS 9 Stage 2 whereas corporate loans that are more than 90 days past due are classified as non-performing and Stage 3. In Italy, UtP as opposed to Bad Loans are NPL that, if properly managed, can become performing again. The goal of managing UtPs is to allow the corporate borrowers to generate cash flow from restructuring or relaunching their business and eventually return to performing. Bad Loans instead have a much lower chance to become performing again and will often end in voluntary or court ordered liquidation. The purpose of this article is to model the probability of cure, i.e. the transition from default (Stage 3) back to performing (Stage 1 or Stage 2). Figure 1 shows the large number of status changes and transitions that a loan can go through before it finally exits the pool of observed loans. When loans are observed with a quarterly frequency, as is the case here, then all the shown transitions are possible. When loans are observed with a monthly or higher frequency than a transition from performing to 60-90 days in arrears would not be possible. While the data from Bank of Italy reported below differentiate NPLs between past due, UtP and sofferenze, the data from the securitisation market do not allow us to make these distinctions accurately. Hence, we simplify the number of transitions for the empirical investigation to just two from default to performing i.e. the borrower has resumed payments on the original or a modified payment schedule or the loan is repaid in full after default (Figure 2).

For the valuation of non-performing loans other transitions are relevant like the transition to loss and the corresponding loss severity. Also, when loans start to become performing again, the new payment terms are relevant for the valuation and re-performing loans can default again at a later time. Here, we will focus on the cure transition rates T1 and T2 only.

The importance of the cure rate when valuing unlikely-to-pay loans

According to the prices observed on our transaction platform (which are consistent with average sales prices reported by to Banca Ifis[3]), Italian UtP loans achieved average sales prices of around 40% of gross book value (GBV) in 2022. This compares with prices in the low to mid 20s for bad loans which in turn price at around 8-12% of GBV for unsecured loans and 25-35% for property secured loans. Past due loans are rarely sold by banks as banks first will try to work with the borrower in house for several months before eventually reclassifying the loan to UtP or Bad Loan at which point the sale to a specialist investor may be considered. All else being equal, the difference in UtP prices to Bad Loan prices should be a direct consequence of the higher cure rate expected by investors.

In an earlier analysis we considered time after default as an important risk driver for expected remaining recovery cash flows.[4] In this note, we highlight the importance of the cure rate to value NPLs that are expected to have a probability significantly larger than zero to become performing again, i.e. past due and UtP loans. The number of days in arrears will be one of many risk factors to be considered. We study the cure rate using two data sets. We first consider the annual transition rates published by the Bank of Italy based on data from Italy's credit register *Centrale dei Rischi.* We then consider a large sample of loan-level data from the European DataWarehouse for Italian SME securitisations to study and model the cure rates in more detail.

[3] Banca IFIS February 2023. Market Watch presentation. NPL transaction market and servicing industry.
[4] https://nplmarkets.com/en/research/article/valuation-of-non-performing-loans-calibration-of-unsecured-recovery-curves-

The Bank of Italy data are published in the methodological annex of the annual report for the *private* and the *corporate* sector in Italy.[5] For each reference date, all positions are divided into four classes (*no anomalia*, *scaduti da oltre 90 giorni*, *altri prestiti deteriorati* and *sofferenza*). We will refer to these classes interchangeably as Performing, Past Due, OtherDeterioration/UtP and Sofferenze/Bad Loans, respectively. The detailed exposure level data from Centrale dei Rischi data has been analysed by researchers from the Bank of Italy with a similar intention as we discuss here, namely determining the probability of UtP loans to cure.[6]

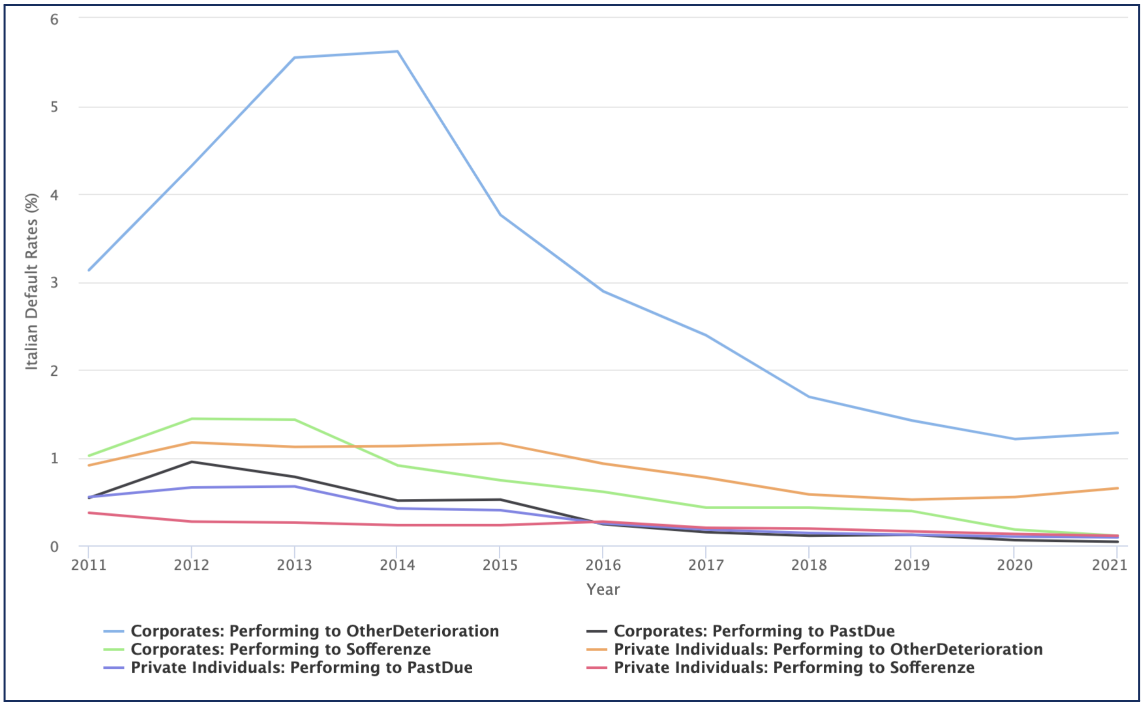


Figure 3: Annual transition rates for Italy from performing to non-performing (Default rates). Source: NPLM Data: Bank of Italy

Figure 3 shows the annual transition rates from performing to one of the non-performing statuses for households and corporates, respectively. We note that most loans enter their NPL status as UtP while a smaller fraction transitions directly from performing to past due or sofferenze. The high defaults rates during the sovereign debt crisis have subsided by 2021 and, as in other countries, the expected wave of new NPL in the Covid years 2020 and 2021 did not materialise due to state intervention measures. We note that the Bank of Italy publishes more granular and longer data sets on default rates for different loan types and geographic regions and although default rates are relevant for performing loan valuations they are not considered here.

[5] Banca d'Italia 2022. Relazione annuale - Appendice. Anno 2021 – centoventicinquesimo esercizio.
[6] M Affinito & G Meucci, 2021. "Return of the NPLs to the bright side: which Unlikely to Pay firms are more likely to pay?," Questioni di Economia e Finanza (Occasional Papers) 601, Bank of Italy

Figure 4 shows the cure rates from the different default categories to performing which are the focus of this article. The much lower annual cure rates for bad loans are shown in Figure 5. Table 1 reports the transition counts for corporate loans in Italy for the full year 2021 according to Centrale dei Rischi.

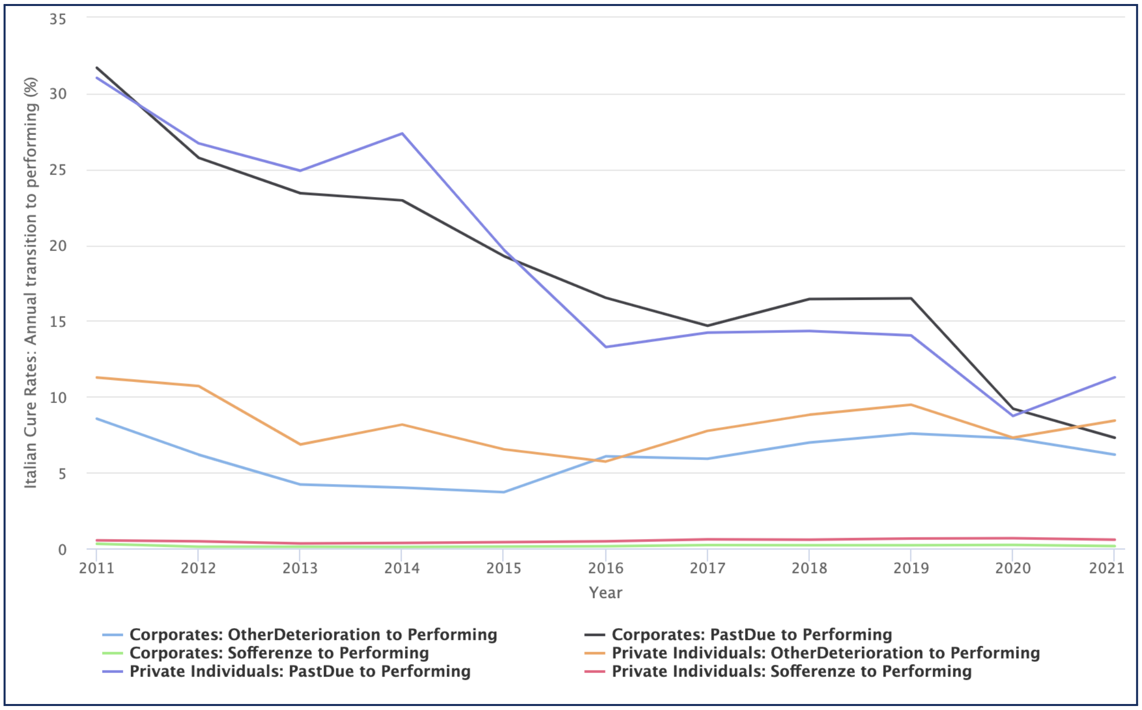


Figure 4: Annual transition rates for Italy from non-performing to performing. (Cure rates). Source: NPLM Data: Bank of Italy

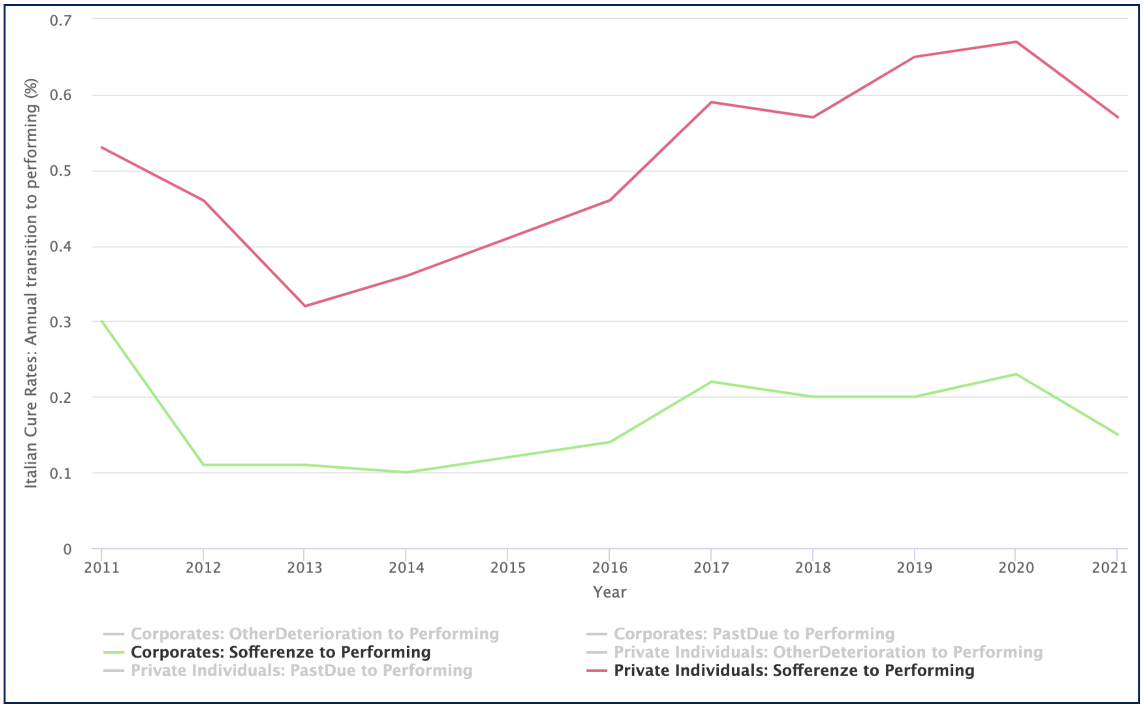


Figure 5: Annual transition rates for Italy from sofferenze to non-performing. (Cure rates for bad loans). Source: NPLM Data: Bank of Italy

Account status BOP	Performing	Past Due	Unlikely to Pay	Sofferenze	Exit with loss
Performing	699178	311	9279	806	8
Past Due	100	899	171	81	1
Unlikely to Pay	3382	136	44088	4893	96
Sofferenze	187	43	1231	117261	2014
Total	702847	1389	54769	123041	2119

Table 1: Transition matrix for loans to Italian corporates for the year 2021. Source: Bank of Italy

Annual cure rates for bad loans are consistently below 1% and in our experience are largely ignored i.e. assumed zero when pricing Bad Loans. The long term decline in the cure rates for past due loans in Figure 4 and their apparent conversion with the cure rates of UtP loans is curious and we cannot offer an explanation. The cure rates for UtP has been more stable and for corporates seem to be negatively correlated with the default rate i.e. low cure rates in the difficult years 2013 to 2015 when defaults peaked with increasing cure rates in subsequent years.

Average probability of UTP firms returning to the performing state		CR sample	CR-Cerved sample
		14.1	12.2
By year of classification as a UTP (cohort)	*2008*	*21.6*	*18.0*
	2009	*17.6*	*15.5*
	2010	*16.3*	*13.5*
	2011	*12.9*	*10.3*
	2012	*11.8*	*9.4*
	2013	*10.6*	*8.7*
	2014	*10.8*	*9.7*
	2015	*14.5*	*13.5*
	2016	*16.5*	*17.5*
By sector of economic activity	Agriculture	*20.7*	*17.4*
	Manufacturing	*15.0*	*13.6*
	Construction	*11.2*	*9.8*
	Services	*14.4*	*12.7*

Figure 6. 3-year transition rates from UtP to performing by cohort and sector. Source: Affinito and Meucci (2021)

The aggregated data from Bank of Italy does not allow the direct estimation of multi-year transition probabilities or lifetime cure rates. Affinito and Meucci (2021) based on exposure level data were able to track UtP borrowers over many reporting quarters and decided to model the three year probability of UtP loans to transition back to performing.

They observed that 90% of cures happen within 3 years. Of the cured loans 50-70% re-performed in year one, 20% in year two and 10% in year three. They found significant heterogeneity by region and industry sector with northern provinces showing higher cure rates and construction loans showing lower than average cure rates (Figure 6). For 105,000 UtP exposures they were able to match the borrower with financial balance sheet data from Cerved and found that firm size is negatively correlated with the cure probability but firm capital is positively correlated. Loans with more collateral were positively correlated to the cure rate (Figure 7).

Covariate		Variable distributions and probability of returning to a performing state computed at different percentiles						
		Average	SD	P10	P25	P50	P75	P90
Firm Size (total assets)	variable distribution - natual logarithm	7,04	1,45	5,27	6,06	6,97	7,96	8,95
	variable distribution - thousands of euros	3.507	7.783	194	429	1.067	2.873	7.713
	probability of returning to a performing state			***15,2***	***13,8***	***12,4***	***11,0***	***9,8***
Firm Capital	variable distribution - ratio	-0,04	0,55	-0,33	0,00	0,05	0,15	0,31
	probability of returning to a performing state			***9,5***	***11,8***	***12,2***	***13,0***	***14,4***
Firm ROA	variable distribution - ratio	-0,04	0,24	-0,22	-0,04	0,01	0,06	0,12
	probability of returning to a performing state			***10,2***	***11,8***	***12,3***	***12,8***	***13,4***
Number of Creditor Banks	variable distribution - natual logarithm	1,17	0,48	0,69	0,69	1,10	1,39	1,79
	variable distribution - numbers	2,69	2,28	1	1	2	3	5
	probability of returning to a performing state			***13,0***	***13,0***	***12,3***	***11,8***	***11,1***
Collateral	variable distribution - ratio	0,29	0,38	0,00	0,00	0,00	0,63	0,98
	probability of returning to a performing state			***11,4***	***11,4***	***11,4***	***13,2***	***14,2***
Firm (actual) Age	variable distribution - natual logarithm	2,30	0,85	1,39	1,79	2,30	2,89	3,37
	variable distribution - numbers	12,67	11,18	3	5	9	17	28
	probability of returning to a performing state			***10,2***	***11,0***	***12,1***	***13,5***	***14,7***
Impairment Length	variable distribution - natual logarithm	0,74	0,14	0,69	0,69	0,69	0,69	1,10
	variable distribution - numbers	1,12	0,36	1	1	1	1	2
	probability of returning to a performing state			***12,5***	***12,5***	***12,5***	***12,5***	***10,0***
Debt Size	variable distribution - natual logarithm	6,06	1,62	4,02	4,86	5,95	7,13	8,20
	variable distribution - thousands of euros	2.030	6.533	55	128	382	1.248	3.652
	probability of returning to a performing state			***16,1***	***14,3***	***12,3***	***10,5***	***9,0***

Figure 7: Cure rates for UtP loans by risk factor at different percentiles. Source: Affinito and Meucci (2021)

Cure rate models derived from securitisation data

We download data from public securitisation transactions from the European DataWarehouse which has collected securitisation data under the ECB loan-level initiative since 2013 and under the ESMA templates which came into force for use under the European securitisation regulation in September

2020. We select all 67 available Italian securitisation transactions of SME loans. The total database contains 10.2m quarterly observations for a total of 1.64m unique loans to 1.30m borrowers. Data before 2013 have been deleted due to data quality issues in the data deliveries. There are 136,000 unique defaulted loans in the database (Table 1). We align the data published under the ECB data template with those under the more recent ESMA templates and keep only those observations where loans have an account status of default and where we can observe a transition in the next following quarter. We identify a cure event as a transition from account status default to performing or redeemed or prepaid where redeemed/prepaid loans must not report a loss allocation. A few securitization deals show very high cure rates in certain quarters which is the result of incorrectly reporting all loans as redeemed at the last reporting date. We remove the loans from those transactions with extreme cure rates. The data waterfall is shown in Table 2. The total observed transition counts are reported in Table 3 which does not show the number of repurchased and censored observations which, however, are counted at the total observation count at the beginning of period (BOP).

Step	Rows	Loans	Borrowers	Loan_Defaults
Full data set	10222303	1644777	1300691	136848
Default data only	344412	125666	106798	125666
Clean up extreme cure rates	340427	123445	104942	123445

Table 2: Data waterfall after initial data preparation and cleansing for Italian SME securitisation data. Source: NPLM, Data: EDW.

Account Status BOP	Total Number BOP	Performing	Arrears	Default	Prepaid	Redeemed
Performing	8407464	6795509	90124	31415	125896	187091
Arrears	165157	51012	50693	35907	2784	3504
Default	431817	16192	5296	320620	4517	2304

Table 3: Total number of transitions in Italian SME securitisation data. Source: NPLM, Data: EDW.

After data preprocessing we estimate quarterly cure probabilities with a discrete time hazard model using a logistic regression. The model approach is a standard method for modelling the probability of default i.e. the transition from performing to default. Models for quarterly cure rates are rare in the academic literature as most published models for the dynamics after default focus on loss given default as defined in the Basel bank capital regulations. Some LGD models have been proposed that model loss as a two stage process where in a first step the probability of a non-zero loss to occur is estimated by logistic regression and in a second stage, the size of the loss is estimated. The probability of a zero loss to occur after default is related to our study as it is an estimate for the lifetime cure rate. We model the quarterly transition to cure for two reasons. The first reason is related to the data available to us from EDW. Estimating a lifetime cure rate is made more difficult as many default events are censored in the data partially caused by changes in the loan identifiers between the two datasets reported under the ECB and ESMA data sets, respectively. The second reason is our interest in seeing short term impacts on the cure rate from the macroeconomic environment. It is reasonable to expect macroeconomic effects to change the cure hazard more directly than the lifetime cure rate which in Italy only materialises over a period of several years.

After data preprocessing the variable selection process starts with a univariate analysis of all available risk drivers. We do not describe all available potential risk drivers in the EDW here. Table 4 shows the univariate discriminatory power of the individual risk drivers selected for a simplified cure model, where Cat stands for categorical and Num stands for numerical. We sacrifice a few percentage points in the area under the ROC curve in favour of a simple model that is easier to interpret and implement.

Risk.Driver	Type	#NAs	AUC
PastArrearsFlag	Cat	0	0.680
NumberOfDaysInArrears.bin	Cat	0	0.644
Amortisation Type	Cat	0	0.637
NumberUniqueCollaterals	Num	0	0.560
LoanAgeMonth.bin	Cat	0	0.548
InterestRateTypeSimple	Cat	0	0.530
NumberUniqueGuarantees	Num	0	0.506

Table 4: Univariate analysis of the risk drivers in the simplified cure model. Source: NPLM

The risk drivers in Table 4 are as follows. The past arrears flag indicates that a borrower had payment difficulties in the past prior to the current loan default. As mentioned above we do not observe the Basel III default category for many loans i.e. we cannot easily distinguish past due from UtP loans in the EDW data. As such this flag can be seen as an imperfect indicator for the past due status. Loans with prior arrears have a much higher cure rate than loans without past arrears. Number of days in arrears is a binned variable capturing the effect that the longer a loan is in arrears the lower the cure rate becomes. Number of unique collaterals and number of unique guarantees count the available collaterals in the collateral section of the EDW data split by guarantees and other collateral. Loan age is the time since origination measured in months. Amortisation type helps identify annuities from interest only loans or loans on a bespoke repayment schedule (such a schedule is not reported in the more recent ESMA data) and interest type is a simplified categorisation of fixed vs floating loans compared to the data field actually reported in the securitisation data.

Category	N.Obs	Probability	Log-Odds
[0,120]	186256	0.0479	-2.99
(120,180]	33499	0.1322	-1.88
(180,270]	36129	0.0864	-2.36
(270,360]	30849	0.0344	-3.33
(360,720]	42253	0.0227	-3.76
(720,Inf]	12801	0.0109	-4.51

Table 5: Cross table for the variable Number of days in arrears. Source: NPLM

Table 5 shows the cross table of the observed cure rates for different times in arrears. The relationship is nonlinear which can be expected. The cure rate is only defined for loans after default which for most loans means more than 90 days past due. Hence, loans with short term arrears of less than 120 days are less likely to cure compared to loans with more than 120 days in arrears. However, for a longer time after default the observed cure rates drop significantly.

Figure 8 shows the calibration plot indicating an adequate model fit of the wide range of different cure rates observed for different clusters. A perfect fit would align all cluster points on the diagonal.

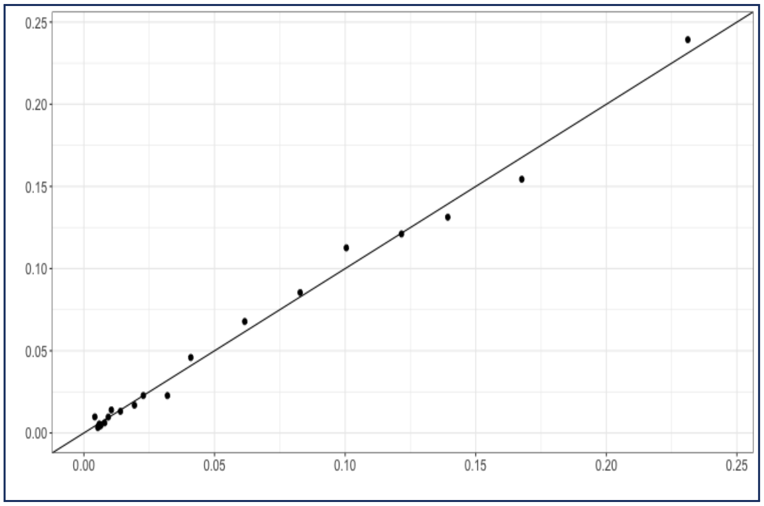


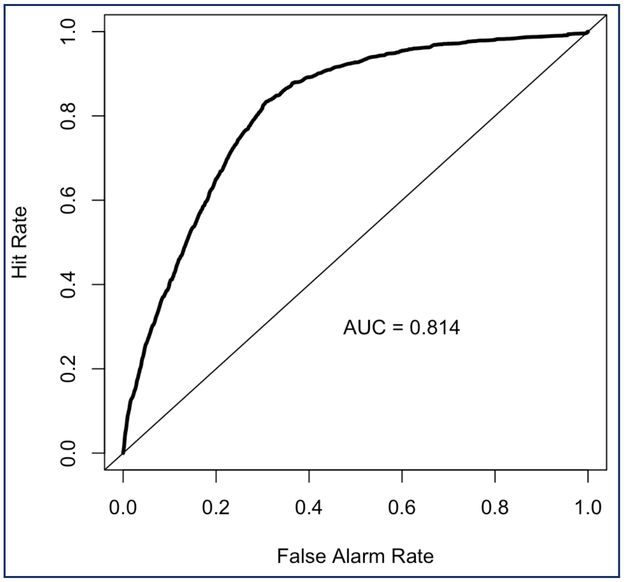
Figure 8: Calibration plot of the simplified cure model. Source: NPLM

Table 6 shows the simplified logistic regression model estimated for the quarterly cure rate. All variables show the expected sign. Loans secured with a larger number of collaterals have a higher cure rate. Loans with more guarantees, however, show a lower cure rate, an effect that is not immediately obvious. Younger loans show a lower cure rate than loans older than 5 years. Floating rate loans and loans with an interest rate type of “Other” have a higher cure rate than fixed rate loans and interest only loans have a lower cure rate than those with an annuity or fixed repayment schedule (FRXX or FIXE, respectively).

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.981	0.2228	-13.38	< 1.0e-10
‘Amortisation Type‘FIXE	-2.464	0.1900	-12.97	< 1.0e-10
‘Amortisation Type‘FRXX	-1.895	0.1883	-10.07	< 1.0e-10
‘Amortisation Type‘OTHR	-2.987	0.2050	-14.57	< 1.0e-10
InterestRateTypeSimpleFloating	0.272	0.0362	7.53	< 1.0e-10
InterestRateTypeSimpleOther	0.313	0.0778	4.03	5.70e-05
LoanAgeMonth.bin(12,24]	-0.010	0.1118	-0.09	9.31e-01
LoanAgeMonth.bin(24,60]	-0.050	0.1061	-0.47	6.39e-01
LoanAgeMonth.bin(60,Inf]	0.375	0.1068	3.52	4.37e-04
NumberOfDaysInArrears.bin(120,180]	-0.275	0.0346	-7.93	< 1.0e-10
NumberOfDaysInArrears.bin(180,270]	-0.773	0.0382	-20.25	< 1.0e-10
NumberOfDaysInArrears.bin(270,360]	-1.653	0.0569	-29.06	< 1.0e-10
NumberOfDaysInArrears.bin(360,720]	-2.198	0.0589	-37.33	< 1.0e-10
NumberOfDaysInArrears.bin(720,Inf]	-2.958	0.1438	-20.58	< 1.0e-10
NumberUniqueCollaterals	0.154	0.0138	11.13	< 1.0e-10
NumberUniqueGuarantees	-0.110	0.0202	-5.43	5.69e-08
PastArrearsFlagY	2.998	0.0580	51.73	< 1.0e-10

Table 6: Summary of the quarterly cure model estimated with a logistic regression.
Source: NPLM

We analyse the discriminatory power with the area under the receiver operating curve (AUC) and the simplified models show an AUC of 81.4%. Models with 50% AUC are no better than random and the discriminatory power of our model can be considered satisfactory. Table 7 shows the marginal AUC for reduced models with one of the risk drivers excluded.



	AUC	z value	Pr(>|z|)
Full Model	0.8143		
'Amortisation Type'	0.8057	16.55	< 1.0e-10
InterestRateTypeSimple	0.8135	4.60	4.30e-06
LoanAgeMonth.bin	0.8117	8.12	< 1.0e-10
NumberOfDaysInArrears.bin	0.7446	59.72	< 1.0e-10
NumberUniqueCollaterals	0.8121	11.91	< 1.0e-10
NumberUniqueGuarantees	0.8138	4.72	2.40e-06
PastArrearsFlag	0.7313	54.42	< 1.0e-10

Table 7: AUC, the area under the receiver operating curve, for the simplified cure model for the full model and models reduced by one of the variables. Source: NPLM

Figure 9: Receiver operating curve for the simplified cure model. Source: NPLM

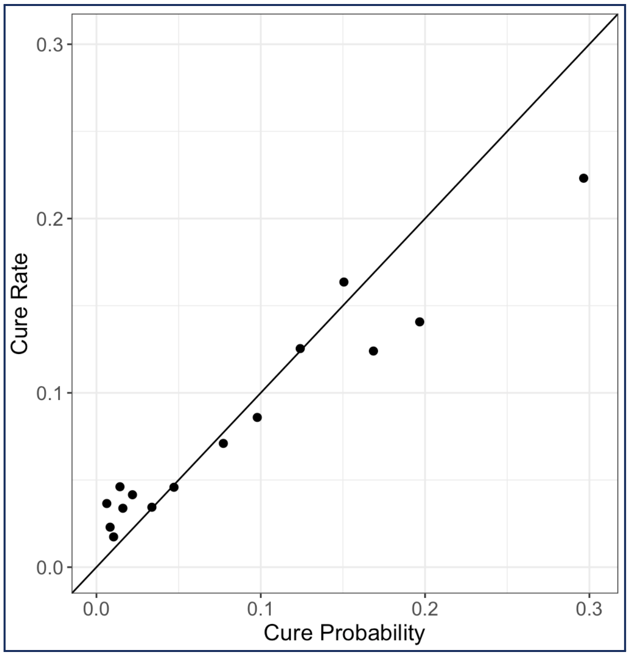


Figure 10: Calibration plot on the out of sample test data set. The training sample uses data until 2019 and test data from 2019 onwards. Source: NPLM

Figure 10 shows the predicted cure rates vs. observed cure rates out of sample for multiple clusters for a revised model fitted to data up until 2019 (training data) and tested on the remaining data from 2019 onwards (test data).

To conclude, we estimate a simplified model for the cure rate hazard, i.e. the probability that a loan cures from one quarter to the next for a sample of Italian SME loans observed in public securitisation transactions. The cure rate model is a critical input to value UtP loans in Italy and observed cure rates vary widely by cluster depending on a number of risk drivers.

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