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by Emilia Bonaccorsi di Patti, Cristina Demma,  
Davide Dottori and Giacinto Micucci

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# BAD LOAN CLOSURE TIMES IN ITALY

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## Abstract

We propose a procedure for calculating closure times for bad business loans in Italy using Central Credit Register data over the period 2005-2016. We find that after 2008 bad loan closure times increased, peaking in the years 2011-12; they then began to fall, returning close to their initial levels in 2016. These results suggest that the recent initiatives improving banks' non-performing loan management policies and the effectiveness and speed of recovery procedures are starting to bear fruit.

**JEL Classification:** G01, G21, G33.

**Keywords:** non-performing loans, closure times, firms' credit, banks.

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## 1. Introduction<sup>1</sup>

The significant amount of bad loans on Italian banks' balance sheets is a consequence of the double-dip recession, into which the Italian economy was plunged from 2008 to 2013, leading to a significant increase in the number of firms in financial distress. Even the lengthiness of credit recovery times contributed to the notable weight of bad loans on banks' balance sheets.<sup>2</sup>

In recent years, the Government and the supervisory authority have taken a number of steps and legislative measures to hasten the reduction of the amount of bad loans. On the one hand, the supervisory authority has asked banks to implement 'active' management policies for non-performing loans (NPL), that improve the efficiency of internal processes for the recovery and management of these assets; on the other hand, to increase the efficiency of credit recovery procedures, the Government and the Parliament approved organizational reforms of the civil justice system (Giacomelli *et al.*, 2017) and passed the 2015-16 legislative reforms of the procedural and bankruptcy laws (Brodi *et al.*, 2016; Giacomelli, Orlando and Rodano, 2018).

Evaluating the effectiveness of these measures is a difficult task above all because of the scarcity of data: information on closure times are generally drawn from surveys on a sample of banks at a single point in time (Carpinelli *et al.*, 2016) or from statistics on recovery procedures completed within a specific period of time (T.S.E.I. Organization, 2017; Cerved, 2017). Marcucci and Mistrulli (2013), using data from the Italian Central Credit Register (CCR), examine the duration of bad loans relying on sole proprietorships to assess whether gender affects bad loan closure times. Using the same source, in this paper we estimate closure times for bad loans for the universe of Italian non-financial firms. We evaluate the dynamics of each loan first classified as bad during the period 2005-16 considering, for every year in the reference period, whether a) the loan was closed by 2016, and b) how long the creditor bank reported such loan and the manner in which the loan was closed.<sup>3</sup>

This procedure allows us to calculate the closure time of each position as the amount of time that elapsed between a loan's classification as bad and it no longer being reported as such by the creditor bank; however this procedure does not give us any information about the time distribution of partial recoveries (if any) that are instead analyzed in other recent

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<sup>1</sup> We wish to thank Romina De Luca, Giorgio Gobbi, Luca Liberati, Pasquale Maddaloni, Laura Mellone, Paolo Mistrulli, Paolo Sestito and participants at the workshop held at the Directorate General for Economics, Statistics and Research of the Bank of Italy, in September 2017. The views expressed herein are those of the authors and do not necessarily reflect those of the Bank of Italy.

<sup>2</sup> For an analysis of the length of civil proceedings in Italy, see Giacomelli *et al.* (2017).

<sup>3</sup> More specifically, we analyze unsold bad loans and distinguish between write-offs and loans no longer reported by the creditor bank without recording the loan as a loss (see Section 2).

empirical contributions (Carpinelli *et al.*, 2016; Ciocchetta *et al.*, 2017; Fischetto *et al.*, 2018).<sup>4</sup>

We also estimate an econometric model that evaluates how closure times are influenced by the year of classification of the position as a bad loan (cohort) and by the characteristics of the borrowing firms, loans and banks. These estimates signal which positions are characterized by a greater expected length at the origin and provide a piece of evidence on the pattern of this variable holding equal for the bad loans' characteristics. Furthermore, in order to investigate whether potential coordination problems among lenders could increase closure times, we develop a survival analysis that controls for the extent to which firms concentrate their borrowing from banks.

The main results can be summarized as follows. From 2008 to 2012, bad loan closure times substantially increased: bad loans that were part of the 2012 cohort have an expected closure time that is 2.2 times greater than the 2006 cohort; this worsening only partially reflects the slowdown in loan sales. After 2012 bad loan closure times progressively declined, returning close to their initial levels in 2016. This result holds even controlling for multiple borrowing and is consistent with the reduction in credit recovery times observed over the last few years. This reduction was supported both by the measures taken by banks to improve the efficiency of their NPL recovery and management processes and by external elements such as the legislative reforms to make enforcement proceedings shorter and more effective.<sup>5</sup> The procedure that we propose for estimating closure times could also be used to identify the effects of these elements.

Furthermore, in our paper we find a large territorial heterogeneity in closure times: other characteristics being equal, the bad loans of firms headquartered in one of the five provinces with the shortest closure times, all in the North of Italy, are closed in about half the time it takes for firms headquartered in the five provinces with the longest closure times, all in the Centre and South. All other things being equal, these geographical differences suggest that there is still ample room to speed up bad loan closure times by reducing territorial gaps in the efficiency of civil courts.

The paper is organized as follows. Section 2 describes our dataset and the procedure that we use to estimate closure times, while Section 3 introduces some descriptive statistics. In Section 4 we describe the econometric set-up and discuss the main results. In Section 5 we perform some robustness checks, while in Section 6 we extend the analysis to control for the impact of multiple lending. Lastly, Section 7 contains some concluding remarks.

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<sup>4</sup> Ciocchetta *et al.* (2017) and Fischetto *et al.* (2018) estimate bad loan recovery rates using the same source of data (the CCR) and provide some aggregate evidence on the length of credit recovery procedures only for closed positions.

<sup>5</sup> A full evaluation of the effects of the 2015-16 legislative reforms of the procedural and bankruptcy laws is still premature both because of the short period of time these measures came into force and because very few positions are closed within the early years of their classification as bad loans.



## 2. Data

Our analysis is based on an extensive dataset at the bank-firm level that covers the universe of debts of Italian non-financial firms reported in the CCR which were first classified as bad during the period 2005-2016. . We focus on bad loans because this degree of credit deterioration is perceived to be permanent by banks. Banks could instead take several actions in order to restructure the other types of NPLs (past-due and unlikely to pay exposures) before trying to recover their credit via enforcement proceedings; furthermore, banks generally classify the position as bad before starting these types of recovery procedures.

When a firm is financed by more than one entity from the same banking group, we aggregate bad loans at banking group level (see the Methodological Appendix).<sup>6</sup> We develop our analysis at banking group level because the strategy for managing bad loans is generally defined at this level. Since the aim of our paper is to estimate bad loan closure times as the span of time spent by banks to definitively close these positions, loans transferred to other banks after mergers and acquisitions are identified and considered as having been continuously held by the acquiring banking group/bank; otherwise these positions would be recorded as a closed position by the target bank and as a new bad loan for the acquiring bank. For the same reason, even loans involved in infra-group sales are considered as having been continuously held by the originating banking group (generally infra-group sales are driven by the bank's internal procedures for managing NPLs).

For each position we calculate its closure time (defined as the amount of time that elapsed between a loan's classification as a bad loan and it no longer being reported as such by the creditor bank), examining its evolution year by year until, at the latest, the end of 2016, the last year of the reference period. Since the amount of the exposure changes over time, we refer to the value at the beginning of the quarter in which the position was first classified as a bad loan.

Banks can close a position by following internal work-out procedures or by selling it on the market to third parties (financial institutions not belonging to the same banking group). Our dataset allows us to exactly identify the date on which a bank has sold a position on the market; the end of a standard work-out procedure is instead the date on which one of the following occurs: 1) the bank totally writes off the exposure setting aside the relative loan loss provision<sup>7</sup> (henceforth, *total write-offs with losses*); or 2) the bank no longer classifies the exposure as bad without it being recorded as a loss or having been sold (henceforth, *other closures*).<sup>8</sup> For more details, see the Methodological Appendix.

Loans closed by means of market sales include positions that have been sold to other banks not belonging to the same group or to financial intermediaries, belonging or not to the

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<sup>6</sup> For each counterpart, the CCR reports data about the overall exposure towards a bank but does not contain information on single credit lines or contracts; therefore, we consider the borrower's position towards a bank (or banking group) as closed if the firm's overall exposure towards that bank (or banking group) is closed. For more details, see the Methodological Appendix.

<sup>7</sup> A bad loan write-off requires the explicit approval of the bank's management body.

<sup>8</sup> We observe a small number of these cases.

same group. For the latter, we are not able to trace their evolution over time after the first sale.<sup>9</sup>

Overall, we analyze around 610,000 firms and 1,000,000 positions (firm/banking group pairs). Table 1 shows the number of observations for each year and their distribution according to their initial amount. During the period 2005-16, a quarter of the debts classified as bad were below €10,000. The median and the 75<sup>th</sup> percentile, equal to approximately €19,000 and €55,000 respectively in the period 2005-07, increased after the beginning of the crisis, peaking in 2013 to €30,000 and €110,000 respectively.<sup>10</sup> We find a great deal of asymmetry in the distribution of exposure values: the first quartile of the distribution represents just 0.5 per cent of the total amount of bad loans, while positions in the last quartile represent more than 90 per cent.

**Table 1**

<b>Initial loan values by year of classification as a bad loan (cohort)</b>									
COHORT	Distribution of the initial value of bad debts (euros and number of positions)				Incidence of the total amount of bad debts in each quartile of the distributions of the initial loan values (%)				
	25th percentile	50th percentile	75th percentile	Number of observations	≤ 25th percentile	25th - 50th percentile	50th - 75th percentile	≥ 75th percentile	Total
2005	5,943	18,790	57,268	51,965	0.7	3.0	8.8	87.5	100.0
2008	6,062	19,891	64,771	68,275	0.5	2.2	6.7	90.5	100.0
2012	8,974	27,203	94,564	104,704	0.5	2.2	6.8	90.4	100.0
2016	7,053	24,852	96,158	126,528	0.4	1.9	6.6	91.1	100.0
Tot. period 2005-2016	7,658	24,678	86,303	1,112,922	0.5	2.2	6.9	90.4	100.0

Source: Based on CCR data.

For every cohort, Table 2 sets out the number and the median value of the positions, distinguishing closed exposures from exposures that are still classified as bad at the end of 2016; closed exposures are distributed according to the type of closure.

For every cohort, Table A1 in the Appendix shows the distribution of the positions, distinguishing those secured by collateral (mortgages, pledges and liens) from other exposures. We identify three classes: loans totally secured by mortgages; loans partially secured by collateral (including mortgages) or totally backed by collateral other than mortgages; and unsecured loans. The presence of collateral could influence a bank's decision

<sup>9</sup> As regards positions sold to financial intermediaries, any mergers and acquisitions among these types of entities would have to be traced. Furthermore, if the acquiring financial intermediary does not participate in the CCR, it is not possible to track the loan after it has been sold. Finally, when the loan is sold to a securitization company, it would be necessary to distinguish sales that result in the derecognition of the sold asset from the seller's balance sheet and asset transfers where the seller retains the related risk and rewards; however, these distinctions cannot be made with CCR data.

<sup>10</sup> For loans other than bad debts, in 2009 the threshold for CCR reporting decreased from €75,000 to €30,000. This reduction could have partially contributed to the shift in the distribution of loans because, for firms that are financed by more than one bank in the same banking group, we classify the total exposure towards the group as a bad debt starting from the moment in which a bank in the group first classifies it as such, even if the other banks in the group do not.

to sell the loan on the market, or, in the alternative, its choice in the type of internal work-out procedure to use.

**Table 2**

<b>Number and initial median value of bad debts by cohort and type of closure</b> (number of positions and euros)									
COHORT	Number of positions				Median value				
	standard work-out procedures (1)			still classified as bad at the end of 2016	standard work-out procedures (1)			still classified as bad at the end of 2016	total
	of which: total write-offs with losses	of which: other closures	market sales		of which: total write-offs with losses	of which: other closures	market sales		
2005	18,506	8,761	18,806	5,892	18,432	12,469	19,618	29,220	18,790
2008	17,300	9,610	24,259	17,106	19,946	10,764	15,735	36,298	19,891
2012	14,091	8,057	30,572	51,984	20,529	12,050	13,646	51,062	27,203
2016	3,251	1,359	3,774	118,144	10,127	7,736	8,616	26,694	24,852
Tot. period 2005-2016	183,669	91,688	303,870	543,695	18,946	12,201	14,390	41,888	24,678

Source: Based on CCR data.

(1) Bad loans that were not sold on the market to third parties and closed by the originating bank through an internal recovery procedure.

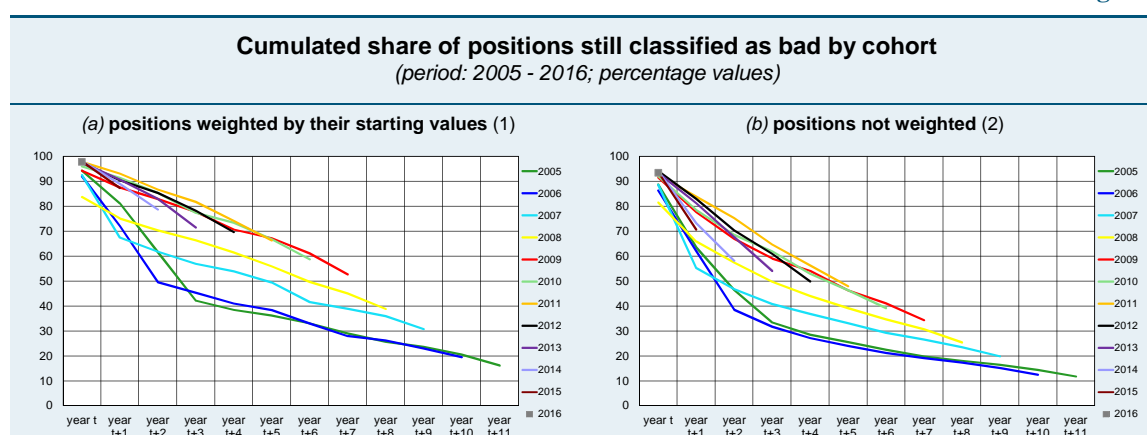
### 3. The descriptive analysis

#### 3.1 The lifetime of bad loans

For each cohort we compute the share of positions still reported to the CCR as bad at the end of each year in the period 2005-16. In Figure 1.a, this share is calculated by weighting the positions by their starting value, while Figure 1.b shows the simple frequencies.

Considering the 2005 cohort (for which we can observe a longer time horizon), after 11 years 12 per cent of the positions continued to be classified as bad by the originating banking group, while the remaining 88 per cent were closed (Figure 1.b); we get similar results even when weighting the positions by their starting amounts (Figure 1.a).

**Figure 1**



Source: Based on CCR data.

(1) Each series signals, for the positions (firm/banking group pairs) first classified as bad in any one of the quarters of the year indicated by the series, the ratio between the value of the positions still classified as bad at the end of the year  $t+1$ ,  $t+2$ , etc., and the value of these positions at the end of the quarter in which it was first classified as bad by the banking group (the values are net of loan loss provisions). – (2) Each series signals the ratio between the number of positions still classified as bad at the end of the year  $t+1$ ,  $t+2$ , etc., and the number of the positions first classified as bad in any of the quarters of the year indicated by the series.

Until 2008, the speed of the disposal process was higher during the first 3 years of a loan's classification as bad and then declined: the slope of the curve is greater for the initial years, and is flatter thereafter.

From the 2009 cohort onwards, the closure rate is considerably lower compared with the previous cohorts. For example, for the 2013 cohort, 54 per cent of bad loans remained classified as such 3 years after they were first classified as bad, while this share is equal to 33 per cent for the 2005 cohort (respectively 71 and 42 per cent weighting positions by their initial value).

In the last few years of the reference period, there was a downward shift in the curves in Figure 1, indicating an increase in the speed of the disposal process (the share of bad debts still reported to the CCR reduced over time). However, to better understand this dynamic we also take into account the changes in the composition of bad loans over time (see Section 4).

By looking at the loan size at the date on which the position was first classified as bad, we observe that closure times are longer for the largest exposures (positions belonging to the last quartile of the distribution by initial values: more than €57,000). Considering the 2005 cohort, 16 per cent of the largest positions continued to be classified as bad after 11 years, against 7 per cent for the smallest ones (those belonging to the first quartile: nearly €6,000; Table A3).

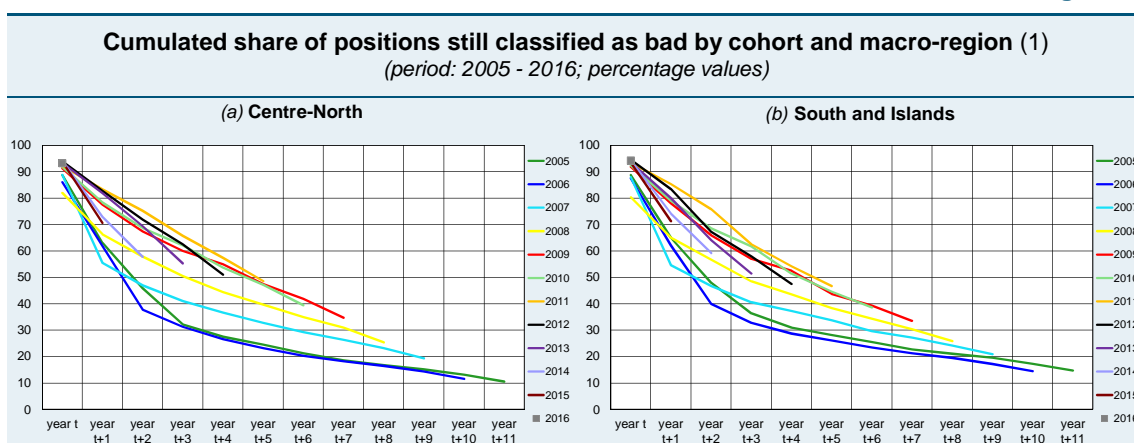
The deceleration of closure times was more pronounced for the largest positions. For the 2013 cohort, only 25 per cent of the positions in the last quartile of the size distribution were closed within 3 years of being classified as a bad debt, while this share was 60 per cent for the 2005 cohort. For the smallest positions, instead, these rates are more similar (respectively 70 and 75 per cent for the 2013 and the 2005 cohort respectively), signaling a less pronounced slowdown in the disposal process.

Furthermore, we observe significant geographical differences. In the southern regions, bad loans are closed more slowly; considering the 2005 cohort, at the end of 2016 some 15 per cent of bad loans to southern firms were still reported to the CCR, against the 10 per cent for firms headquartered in the northern and central regions (Figure 2).<sup>11</sup>

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<sup>11</sup> Shares calculated considering the number of positions not weighted by their initial values.

Figure 2



Source: Based on CCR data.

(1) Each series signals, for the positions (firm/banking group pairs) first classified as bad in any one of the quarters of the year indicated by the series, the ratio between the number of positions still classified as bad at the end of the year  $t+1$ ,  $t+2$ , etc., and the number of positions first classified as bad in any of the quarters of the year indicated by the series.

### 3.2 Types of closure

The dynamics of the curve of closure rates is the result of the temporal evolution of the different types of closure procedures used by banks to reduce the bad debts on their balance sheets. For each cohort, Table A6 shows the share of positions that banks sold on the market to third parties. This share was greater in the first few years after the loan's classification as bad, especially during the pre-crisis period. Comparing the different cohorts we can observe that, the number of years after the bad loan classification being equal, the share of positions sold on the market declined over time; this reduction was more pronounced for more recent cohorts. On average, for the 2009-11 cohorts, within 3 years of the classification as bad, banks sold 16 per cent of the positions on the market, against 31 per cent for the 2005-07 cohorts.

Closure times for standard work-out procedures became lengthier during the reference period (Table A7). For example, for the 2009-11 cohorts, within 3 years of the classification as bad, banks closed 22 per cent of the positions by means of standard work-out procedures, against 34 per cent for the 2005-07 cohorts. This decrease reflects a slowing down both in total write-offs with losses and in other closures.

Analyzing the different types of closures allow us to better understand the reasons for the more pronounced slowdown in recovery times for large positions described in Section 3.1. For these positions we observe a sharp reduction in sales on the market (Table A4); for positions between the 25<sup>th</sup> and 75<sup>th</sup> percentile of the size distribution, the slowdown in closure times (which is less pronounced with respect to larger exposures) mostly reflects the reduction in positions closed using standard work-out procedures. Finally, for smaller positions, the share of loans sold on the market rose over time but the slowdown in standard work-out procedures balanced out this increase.

To sum up, the reduction in closures reflects both the decline in sales on the market for the largest positions and the decrease in positions closed with standard work-out procedures across all size classes.

### *3.3 The positions secured by collateral*

The type of collateral can influence whether a bank decides to sell the credit on the market and, if it chooses not to the choice of internal work-out procedure. Banks are probably less inclined to sell loans backed by a real guarantee because they are given priority status in receiving a reimbursement; furthermore, if these guarantees are for large amounts, banks have no incentive to sell their exposures if sale conditions are not favorable even if closure times are long. Furthermore, given that Italian law provides for different procedures according to the type of collateral, the presence and the type of real guarantee can influence closure times. For example, in the event of a loan backed by a mortgage, a bank has an enforceable right and the recovery procedure is therefore faster with respect to unsecured loans.

We divide positions into three classes: 1) loans wholly secured by mortgages; 2) loans partially secured by real guarantees (including mortgages) or totally backed by collateral other than a mortgage; 3) unsecured loans. We consider separately those loans that are totally backed by a mortgage (case 1) in order to identify positions for which banks likely try to recover their loan via enforcement proceedings; therefore, our data provide some information on the length of this type of procedure. Instead, in the second case, the overall exposure is calculated as the sum of several loans backed by different types of collateral and different kinds of recovery procedures.

For the sake of brevity, Table A8 shows the outcomes of the closure procedures for the 2005, 2009 and 2013 cohorts, but the results are very similar for the other years. Closure times are longer for positions wholly backed by a mortgage compared with those that are unsecured, mainly because the share of loans sold on the market is lower: considering the 2005 cohort, after 11 years banks sold only 21 per cent of the positions backed by mortgages, against 36 per cent of unsecured loans. Furthermore, for loans wholly secured by a mortgage, loss-free closures were reported<sup>12</sup> more frequent probably because the value of the guarantee was able to cover of large portion of the exposure.<sup>13</sup>

Comparing the different cohorts, we observe that recovery times become lengthier mainly for positions backed by real guarantees. For the 2005 cohort, within 3 years of the bad loan classification, banks closed 57 per cent of the positions wholly backed by mortgages, 60 per cent of those backed by other real guarantees, and 67 per cent of the unsecured loans.

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<sup>12</sup> The only exceptions were the 2012 and 2013 cohorts for which the share of this type of closure at the end of 2016 was very similar for positions wholly secured by mortgages and unsecured loans.

<sup>13</sup> Our dataset does not allow us to distinguish the type of mortgage (residential or commercial) or whether the owner of the asset is a firm or an individual; presumably, the debtor has a greater incentive to voluntarily repay the debt or to reach an out-of-court agreement to keep ownership of the asset.

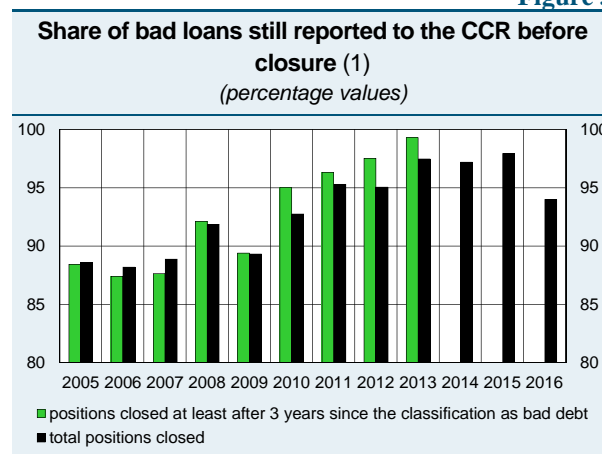
### 3.4 Handling of partial recoveries in the estimation of closure times

In order to better understand the share of closed positions described in this paper, it is worth noting that banks can partially recover their credit during the recovery procedure (partial recoveries). Closure times calculated in this paper represent the amount of time spent to definitively close the position, not the average duration weighted by the flow of recoveries over the lifetime of the position; in the latter case it would be necessary to have information about the dates of all partial recoveries (which are not included in our dataset).

According to some empirical analyses, the largest share of recoveries was obtained in the first few years following the bad loan classification. Using a sample of NPLs closed (liquidated or restructured) at the end of 2014, Carpinelli *et al.* (2016) show that within the fifth year, recovery stood at 95 and 80 per cent of the amount eventually recovered for enforcement proceedings and bankruptcies respectively (on average the recovered amount was slightly above 40 per cent of the exposure).

On the assumption that the largest recovery is obtained during the initial phase of the recovery procedure, the closure times calculated in this paper (the amount of time spent to *definitively* close a position) are likely very different with respect to the closure times weighted by the flow of recoveries over time. For positions wholly secured by mortgages, the largest share of the recovery is obtained at the end of the enforcement proceeding (by mean of an asset sale), while for unsecured loans the largest recovery is obtained in the initial years. However, our data suggest that this hypothesis is not common. In fact, we observe that for positions not backed by mortgages, the value of exposures reported to the CCR fell more slowly than their number. For example, considering the 2005 cohort, at the end of 2016 the value of positions still classified as bad was 16 per cent of their initial value, against 12 per cent in terms of the number of positions. Furthermore, considering all cohorts, the value of bad loans at the beginning of the quarter during which they were closed was 93 per cent of their initial value. This means that, on average, the last value of the position that the bank reported to the CR was only slightly lower with respect to the initial value. This percentage was nearly 90 per cent for cohorts before 2010 and more than 95 per cent for the other ones (for which, on average, the amount of time between the classification as a bad debt and the closure of the position is shorter; Figure 3). Even considering only the positions closed after 3 years of their classification as bad, for which partial recoveries could be more significant, the share still open before the closure was slightly lower (Figure 3). A caveat is that the reduction in the size of the position caused by partial recoveries could be somewhat offset by charging interest on late payments and by other fees; however our data suggest that the value of the

Figure 3



Source: Based on CCR data.

(1) Ratio between the value of the bad loan still reported by banks to the CCR at the beginning of the quarter when the position was closed and the bad loan's initial value.

position still reported to the CCR until its definitive closure was not negligible with respect to its initial amount.

Finally, the ratio between the exposure at the last reporting date and its initial value is very similar among cohorts. According to our research, any difference between closure times and the average lifetime weighted by partial recoveries remains stable over time and does not influence the main finding of the econometric analysis in Section 4.

## 4. The econometric analysis

### 4.1 The econometric set-up

In this Section we compare expected bad loans closure times across cohorts taking into account the different features of each position (banking group/firm pair, as defined in the preceding Sections). We perform a survival analysis (SA) where the survival time is the time between the loan's first classification as a bad loan and its closure (*failure event*).

We consider positions sold on the market as not observable (*censored*) after their sale. We focus therefore on the closure of bad loans still reported to the CCR by the originating bank in order to better understand the impact on the banking system of the actions taken to improve the effectiveness of closure actions. In the event of sales on the market, we cannot observe the overall length of the recovery process because our dataset does not indicate the outcome of the recovery action carried out by the acquiring entity. However, in Section 5 we run some robustness checks to address sales on the market.

SA makes it possible to better take into account the non-normal noise distribution that generally characterizes this type of data; it is also preferable with respect to a binary model because SA controls for the possibility that the increase in the wait time for the failure event can itself influence the likelihood that this event will occur. Furthermore, SA is suitable for non-negative values and allows for the possibility of right censoring, i.e. we cannot observe the actual length of those observations for which the closure event has not occurred within the end of 2016.

We conduct this analysis using an accelerated failure time model (AFT), with the following formula:

$$\ln(T) = \beta'X + \sigma u$$

where  $T$  is the (latent) length of survival of the bad loan,  $X$  is a vector of covariates or explanatory variables,  $\sigma$  is a scale parameter and  $u$  is the random disturbance term that can assume different distributions according to the functional form that we assume for the hazard rate. The hazard rate is the conditional probability that the event (the closure) will occur in a specific interval given that it has not occurred before, and it can be defined as follows:

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)}$$



where  $f(t)$  and  $F(t)$  are respectively the density function and the cumulative distribution function of the probability of changing status (closure) with respect to the initial one (first classification as a bad debt), while  $S(t)$  is the probability of remaining (or surviving) in the initial status just before time  $t$  (the survival function). The higher the hazard rate, the greater the closure rate. The hazard rate changes over time because the probability that the failure event will occur (the closure of the position) depends positively or negatively on the survival time (the waiting time already spent since the initial status).

Since *a priori* we do not know which functional form is more appropriate for the hazard rate,<sup>14</sup> we estimate the model for four distributions: Weibull, log-logistic, log-normal and generalized Gamma forms (we implicitly take into account the exponential form that is unique to the Weibull distribution). We then choose our favorite distribution comparing the values of the Akaike Information Criterion (AIC) obtained for each specification.<sup>15</sup>

In AFT models, a positive coefficient indicates that the greater the covariate, the slower the time to change status and, therefore, the longer the length of the initial status; on the contrary, a negative sign indicates the covariate's negative impact on survival time. The exponent of the coefficient can be interpreted as the ratio of the length before and after a unit increase in the covariate (time ratio). For example, for variable  $x_i$ , if  $\exp(\beta_i)$  is equal to 1.5, that means that a unit increase of  $x_i$  leads to an increase of 50 per cent in the expected duration (under the same conditions), while if  $\exp(\beta_i)$  is equal to 0.8 an unit increase of  $x_i$  is associated with a decrease of 20 per cent in the expected duration.

We consider the following covariates: dummies capturing the presence and the type of collateral (unsecured loan, loan partially backed by a real guarantee, loan wholly backed by a real guarantee other than a mortgage, loan wholly backed by a mortgage), the loan amount (its log or squared value or dummies based on the quartiles of its initial value), bank size dummies (top 5 banking groups, other large and medium banks, small banks and foreign intermediaries), sector dummies (Ateco 2-digit code), province dummies, dummies for the firm's legal form and cohort dummies.

Our econometric set-up makes it possible to evaluate the impact on the expected bad debt closure time of each characteristic of the position at the date on which it was first classified as a bad debt (other things being equal). Particularly, for each cohort we are able to evaluate how the expected closure time differs from the reference cohort.

## 4.2 The results

Table A9 reports our estimates for every distribution. The size and the sign of the coefficients are very similar regardless of the distribution; although the functional forms for

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<sup>14</sup> The Weibull model assumes a two-parameter extreme-value distribution for  $u$ , the log-logistic a logistic one, the log-normal a normal one and the generalized Gamma a three-parameter log-Gamma.

<sup>15</sup> The Weibull model (and, therefore, also the exponential one) assumes that the hazard functions are parallel (as in the non-parametric approach), i.e. the ratio between the hazard rate values of the positions with different features is not time-varying. The log-logistic, the log-normal and the generalized Gamma distributions do not impose this restriction.

the hazard ratio are different, the size of the coefficients is very informative in terms of time ratios, i.e. the relative times with respect to the reference class.

The AIC criterion suggests that the more appropriate distribution is the generalized Gamma, followed by the log-normal. This reveals that the hazard ratio is non-monotonic: other things being equal, the hazard ratio initially increases and then decreases. Given that the difference between the AIC values for the generalized Gamma and the log-normal distribution is small, for computational reasons we choose to consider the log-normal one.<sup>16</sup>

Results show that the sector dummies coefficients, not reported in table for the sake of space, are jointly significant in all the specifications and generally indicate longer times for the reference sector (construction).<sup>17</sup> The same holds for province dummies and for those related to the borrower's legal form.<sup>18</sup>

Moreover, the results confirm that closure times are longer for bad loans of larger initial amounts, though the marginal effect of loan size on closure time decreases as the estimated coefficient for the squared log amount is negative.<sup>19</sup>

Duration is shorter for positions wholly covered by mortgages and longer for those only partially collateralized, everything else being equal.<sup>20</sup> The coefficients on the bank-size classes show that, *ceteris paribus*, closure times are longer for the largest banks compared with the others.

The evolution of closure times is described by the estimated coefficients for the cohort dummies. In all considered specifications, the cohort effect on closure times is inversely U-shaped: everything else being equal, the expected bad loan duration increased year on year, peaking in the two cohorts 2011 and 2012, and then progressively declined.

Figure 4 shows how cohorts differ in terms of time ratios (i.e. the ratio between the closure time for each cohort and the closure time of the reference cohort, 2005). For bad loans entered in 2011, the time ratio is at around 2.2; this means that a bad loan entered in 2011, *ceteris paribus*, would have a closure time that is more than double that of a bad loan entered in 2005. In contrast, loans first classified as bad after 2012 have a declining closure time, even more so since 2014. The difference with respect to the 2005 cohort seems to basically vanish for the 2016 cohort, but this estimation has to be interpreted with care since the observations for the 2016 cohort are only available for one year and the estimation is hence based on the

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<sup>16</sup> The Log-Normal can be nested into the Generalized Gamma when the parameter  $k$  is equal to zero (while the Weibull distribution corresponds to the case  $k = 1$ ). The parametric test  $k=0$  is however rejected partly because of the very narrow confidence interval caused by the large number of observations.

<sup>17</sup> Only the mining sector turns out to have a longer closure time than the construction sector.

<sup>18</sup> With respect to the reference class (sole proprietorships), closure times are shorter for the other legal forms.

<sup>19</sup> Because of the concavity of the estimated duration, the rise in the time ratios caused by a change in the size of the position weakens for higher amounts. A position with an amount equal to the median of the distribution has, *ceteris paribus*, a duration that is 34.7 per cent higher than a position with an amount equal to the first quartile; a position with an amount equal to the third quartile has a duration that is 33.2 per cent higher than a position with the median amount.

<sup>20</sup> *Ceteris paribus*, positions that are wholly covered by mortgages have a duration that is 11 per cent shorter than non-collateralized positions, while the duration of positions covered by other forms of collateral is about 6 per cent longer.

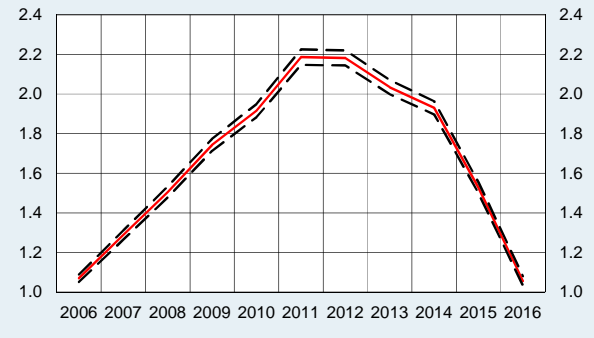
comparison with other cohorts with respect to positions closed within just one year of their classification as bad.

In Figure 5 we show the estimated hazard rates (panel a) and the survival functions (panel b) for some cohorts (showing all cohorts would have made the figure more difficult to read). The hazard ratio points out how the closure rate (failure rate) varies with the position's age: for any given cohort, after a loan is classified as bad, the estimated closure rate initially increases, reaching a maximum at around the two-year mark, and then declines.

Comparing the hazard functions across cohorts, it can be observed that, at any given time since the loan's classification as bad, the closure rate has moved downward (Figure 5.a) and the hazard rate curve has gradually flattened from the initial cohorts to the 2011 and 2012 cohorts for which the hazard rate maxima have significantly lower values.

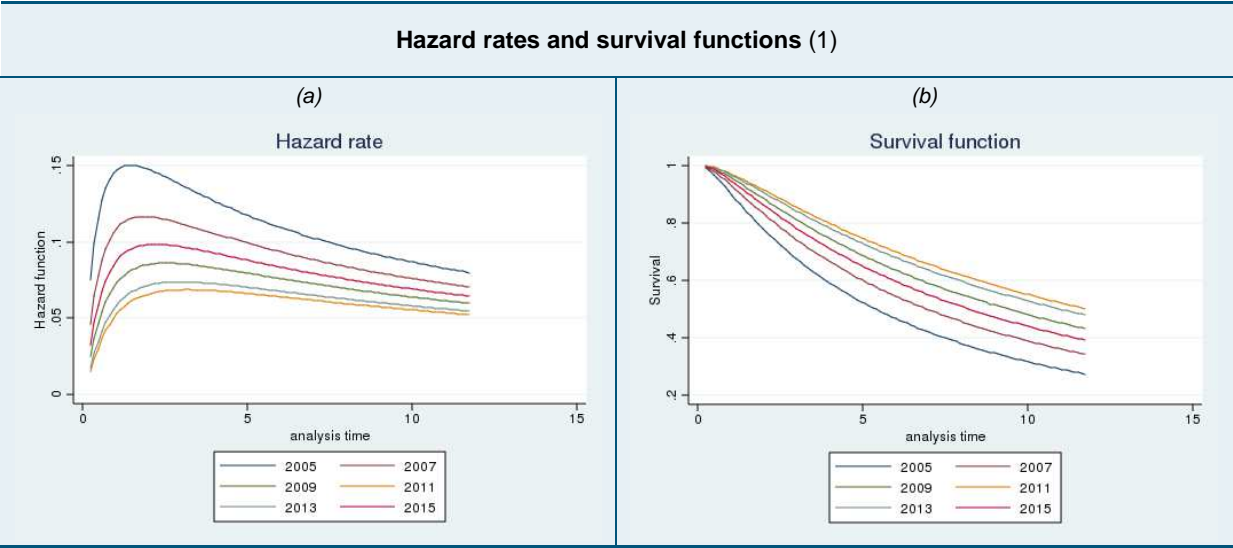
Figure 4

Closure times for bad business loans by cohort (1) (as a ratio to the closure time of loans classified as bad in 2005)



Source: Based on CCR data. (1) Estimated by a log-normal model of duration (column 3 in Table A9). The dotted lines represent the 95 per cent confidence intervals.

Figure 5



Source: Based on CCR data. (1) Estimated by a log-normal parametric model of duration with dummies for provinces, sectors and firm legal forms (col. 3 in Table A9). The failure event is represented by closure with standard work-out procedures, while exits because of sales on the market are considered a censoring event.

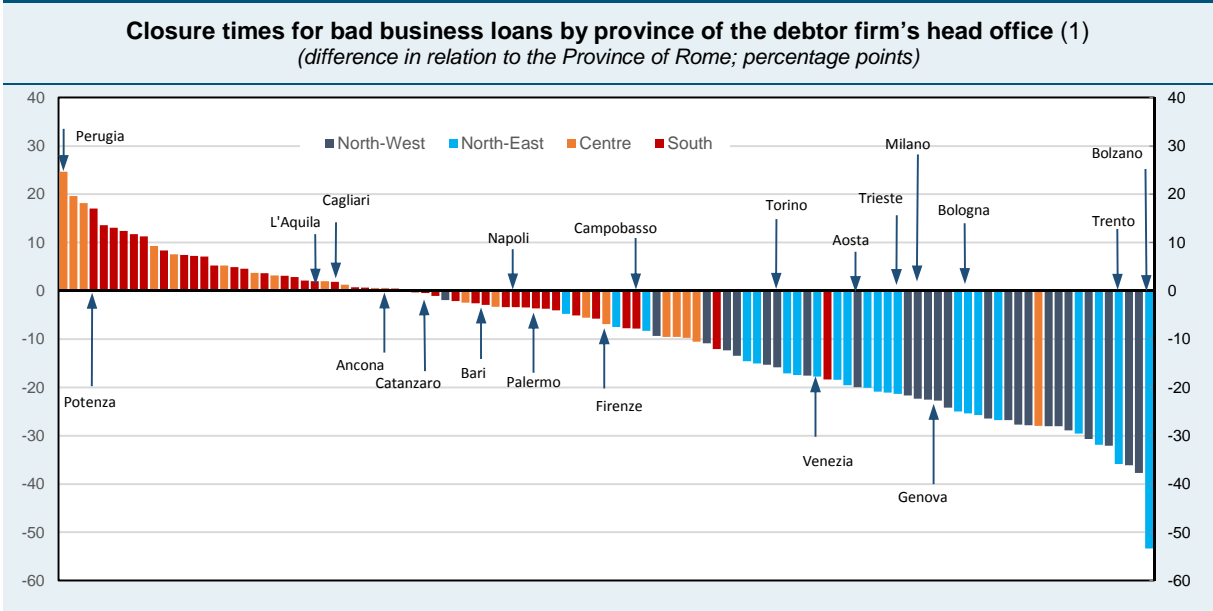
The survival function, which shows the probability of remaining in bad loan status, increased until the 2011 and 2012 cohorts and then declined, suggesting that closure times actually increased till then and then decreased (Figure 5.b.) For positions first classified as bad in 2015, the hazard rate and the survival function appear closer to those of positions entered as bad between 2007 and 2009.

The model also makes it possible to compute the median time to failure (MTF), a measure of the expected survival time before failure. For each position, the MTF is the period

of time that corresponds to a 50 per cent probability that a bad loan is closed before or after that length of time. Intuitively, for a sufficiently large sample of positions with the same covariates, it can be expected that half of them are closed before the MTF and the other half are closed after it. In this sense, the MTF is a synthetic measure of the expected closure time. The estimated median closure times are 5.4 years for the 2005 cohort, 11.9 for the two years 2011 and 2012, and 5.7 years for 2016.<sup>21</sup> It is worth underlining that such values are obtained from parameters of the estimated survival function in a time span whose longest duration is 11 years for the 2005 cohort and shorter for the subsequent cohorts.

Moreover, the model makes it possible to quantify the wide heterogeneity in bad loan closure times among Italian provinces, controlling for the positions' other features. The expected duration is much shorter in the autonomous province of Bolzano, followed by the Lombard provinces of Como and Brescia, and the autonomous province of Trento: for Bolzano, the duration is less than half that of the reference province (Rome), while it is around 35 per cent shorter for the other provinces mentioned above. Longer closure times are found for some central and southern provinces (with Perugia, Terni, Arezzo, Potenza, Caltanissetta, Chieti and Carbonia having the longest closure times), where the closure times are about 15 per cent more than Rome (Figure 6). Overall, other characteristics being equal, the bad loans of firms headquartered in the five provinces with the shortest closure times, all in the North of Italy, are closed in about half the time it takes for firms headquartered in the five provinces with the longest closure times, all in the Centre and South. Differences in efficiency or in the amount of procedures handled by the courts could be among the factors explaining such variations between provinces (Giacomelli et al., 2017).

Figure 6



Source: Based on CCR data.  
 (1) Estimated by a log-normal model of duration (column 3 in Table A9).

<sup>21</sup> Since the model is non-linear, each position's survival function depends on the whole of its features. Hence, each position in the model has its own median time to failure. In order to have a synthetic measure for every cohort, we refer to the cohort-wise sample average of the predicted median times to failure.

The results emerging from this analysis are consistent with the indicators published by Cerved (2016 and 2017) based on data from the Corporate Registry, which show a wide variation in the lengths of bankruptcy and foreclosure proceedings among the various provinces.

Closure times are generally lower in the northern regions, even if there are significant differences within the same macro-area. In Table A10 results are shown from the full model with province dummies (column 1) and from a more aggregate and easy-to-read model with macro-area and macro-sector dummies (column 2).<sup>22</sup>

In the North-West, the expected closure time is lower with respect to the other macro-areas; the discrepancy is limited in comparison with the North-East but it widens greatly (up to about 28 per cent) with respect to the Centre and South of Italy. Among the different sectors, closure times are longer for loans to construction firms (by more than 10 per cent compared with manufacturing and service firms). With respect to the firm's legal form, closure times are shorter for limited liabilities companies (for instance, limited liability companies and public limited companies), by around 17 per cent in comparison with unlimited liability companies (for instance, sole proprietorships and general partnerships).

#### 4.3 Heterogeneity of expected bad loan closure times over time

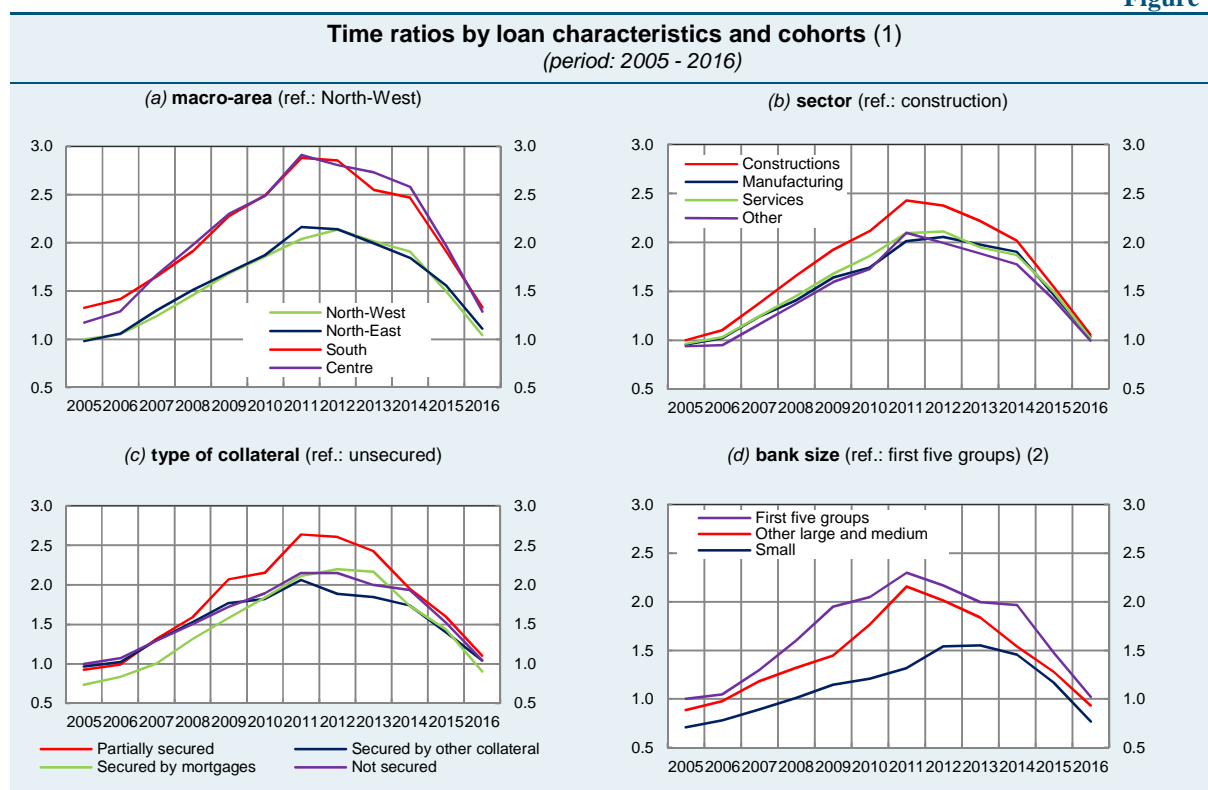
In the baseline model, loan characteristics may affect the expected closure times but they do not affect the differences among cohorts measured by the cohort dummies. In this subsection we extend the baseline model to allow for the possibility that differences among cohorts may depend on differences in some loan characteristics. In particular, we consider the interactions between cohorts and the following features:<sup>23</sup> (i) the geographical area; (ii) the macro-sector; (iii) the presence and type of collateral; and (iv) the size class of the bank. Results are reported in Table A12, while a graphical comparison based on the point coefficient estimation is shown in Figure 7.

The analysis by geographical area suggests that, not only are closure times longer in the Centre and, even more so, in the South, but in these areas the increase in closure times during the recession was steeper than in the northern areas. The expected bad loan closure time for firms headquartered in the Centre was similar to that for southern firms, even exceeding it for bad loans entered in 2013 and 2014 (Figure 7.a). For the two most recent cohorts, however, there was a significant reduction in the geographical differences, mostly because of the large decline in closure times in areas with longer durations.

In the construction sector, the increase in closure times was greater: while other sectors saw their closure times double between 2005 and 2011, in the same period the construction sector saw its closure times increase by 150 per cent (Figure 7.b). Again, a clear improvement can be observed in the most recent years for all sectors.

<sup>22</sup> In the more disaggregate model, province dummies are generally significant, thus showing that there are important territorial differences also among the provinces, as well as among the macro-areas.

<sup>23</sup> If  $x_j$  is the categorical control variable to be interacted with cohort dummies, for each cohort  $s$  it is possible to obtain the time ratio between any given value  $p$  of  $x_j$  and its reference value  $q$  at the first cohort. This time ratio is equal to:  $\exp(\beta_{1q} + \delta_s + \gamma_{1qs})$ , where  $\beta_{1q}$ ,  $\delta_s$  and  $\gamma_{1qs}$  are respectively coefficients of: variable  $x_j$  at category  $q$ , cohort dummy  $d_s$  and the interactions between them.



Source: Based on CCR data.

(1) Estimations based on a log-normal parametric model of duration (Table A12). In each panel, time ratios are calculated as the ratio of closure times with respect to the reference category specified in the panel subtitle and the 2005 cohort. – (2) The category 'foreign banks' is not reported because for this category, the estimated time ratio is highly erratic due to the limited number of observations in the sample.

Taking into account the type of collateral, in the older cohorts bad debts that were wholly secured by a mortgage had a significantly lower duration (by around one fourth) than positions covered by other collateral, but closure times increased for the cohorts that followed. For the most recent cohorts, however, these times progressively declined.

This result is consistent with an improvement in the efficiency of real estate enforcement proceedings, an improvement which began even before the enactment of the 2015-16 reforms. The greater use of ICT technologies and a more streamlined procedure for foreclosure auctions may have also played a role. Cerved (2016, 2017) recently reported that the duration of bankruptcy proceedings has declined since 2013, falling, in the two years 2015-16, to the levels that prevailed in 2007, well below those recorded in 2010 and 2011 when proceedings lasted nearly 9 years. Cerved also reported that while this trend began before the 2015-16 reforms, it intensified once they were enacted.<sup>24</sup> Regarding these reforms, available preliminary evidence shows that the new regulations have contributed to the reduction in the length of the pre-sale and sale stages (Giacomelli, Orlando and Rodano, 2018).

<sup>24</sup> Such an acceleration may reflect the effects of Decree Law 83/2015, which has imposed on insolvency administrators a 24-month deadline for the liquidation of assets. In general, the ongoing time reduction may have been spurred by more efficient management practices on the part of courts, favored in turn by greater use of ICT. These changes may have increased the efficacy of previous reforms; for instance, the 2005-07 reforms changed insolvency thresholds by excluding smaller firms (mainly partnerships) from the proceedings and by limiting admission to a narrower range of firms (generally limited companies).

Closure times are shorter for smaller banks, especially in comparison with the top five groups (Figure 7.d). The inverse U shaped pattern can be observed for all classes, but with different dynamics. For the top five groups, the worsening in closure times occurred earlier than for smaller banks.

All in all, the analysis of an extended model that takes into account the interaction between loan characteristics and cohort dummies suggests that, if on the one hand, the initial increase and then decrease of the expected closure time was a widespread trait, on the other, the initial levels and the extent to which they rose were not always uniform.

## 5. Robustness checks

We perform some robustness checks. The first check is a back testing of the goodness of the estimates, carried out by comparing the estimated survival probability with its sample counterpart by cohort and age. For any given cohort, the deviation is small on average, standing at less than 1 per cent. For any given age, the deviation is generally limited to less than 2 per cent on average, while the model tends to slightly overestimate the survival probability in the early and late years and slightly underestimate it in the intermediary stage. Also, the comparison between predicted and actual hazard rates shows that the error is on the order of 1 per cent on average.

Then, some checks are performed concerning the choice of a sale on the market as a censoring event rather than a failure event. If sold positions are systematically different from those managed through standard work-out procedures and these differences cannot be accounted for by the control variables included in the regressions, then the estimated coefficient may be biased. Though such an issue cannot be excluded *a priori*, it seems fairly reasonable to exclude the possibility that banks choose to systematically sell better or worse positions from a closure-time viewpoint on the basis of a detailed position-by-position analysis, especially when small loans are concerned. Loan portfolios are usually sold and it seems plausible that the choice refers to observable features or categories (such as the amount of the loan, its age, the debtor type, etc.) and not to the single position's specific characteristics.

In order to investigate whether the results are affected by the different ways of handling a bad loan sale, we perform the following robustness checks: (i) we estimate a model where the failure event's definition is broadened to include those sales; (ii) we estimate a competing risk model, where the failure event is only the closure through standard work-out procedures as in the baseline model, but the sales of bad loans on the market are considered a different kind of exit, as an alternative ('in competition') to the standard failure event.

It is worth noting that these two models are not only different with respect to the baseline, but also between them. In model (i), indeed, when a bad loan is sold on the market we record a failure event that – as such – enters into the analysis; hence the estimated survival probability also embodies factors that affect the likelihood that a bad loan is sold on the market. In model (ii), conversely, when a bad loan is sold on the market, the failure event being analysed *does not* occur, as it is an alternative way to end the survival of the bad loan;

hence, in this model estimates refer to the effects of variables on standard work-out procedures but not on the likelihood of market sales.

The results from model (i) are shown in Table A11 (columns 3 and 4). They are generally consistent with the findings obtained from the baseline specification; in particular, they confirm both the positive effect of the bad loan amount on duration and the inverse U-shaped relationship with cohorts.

Model (i), where sold bad loans are included in the definition of “failure event”, diverges from the baseline specifications in the following ways: (a) the expected closure time is longer for debts secured by mortgages, thus suggesting that banks tend to keep positions secured by mortgages; (b) the expected closure time is longer for the other large and medium-sized banks than for the top five groups, mirroring the greater likelihood shown by the latter class in the period under analysis to sell bad loans on the market. All these results are consistent with those that we find by estimating a multinomial logit model where the dependent variable is represented by four different possible statuses for a position (remaining a bad loan; being sold on the market; being closed through standard work-out procedures and recording a loss; being closed through standard work-out procedure without it being recorded as a loss).<sup>25</sup>

The competing risk model (ii) provides estimates in terms of ‘sub-hazard ratio’, a different metric than the AFT one in the baseline model; therefore, coefficients from the two models are not readily comparable. However, the direction of the effects of the variables, as well as their relative magnitude within each specification, are consistent with the results from the baseline model.

Hence, it can be summed up that, even considering bad loan sales on the market as an alternative source of extinction, results appear to be robust and the main conclusions of the duration analysis are not substantially affected by the way bad loan sales are handled.

## 6. Multi-bank borrowing and closure times

The theoretical literature points out that in case of distress, for firms borrowing from more than one bank (multi-lender borrowers, MLB), lenders’ free riding behaviors make it difficult for banks to reach a restructuring agreement (Bolton and Scharfstein, 1996; Gertner and Scharfstein, 1991). This result is consistent with the existing empirical evidence in Baglioni, Colombo and Rossi (2018), who show that the restructuring probability decreases when the number of lenders is above three because of coordination problems.

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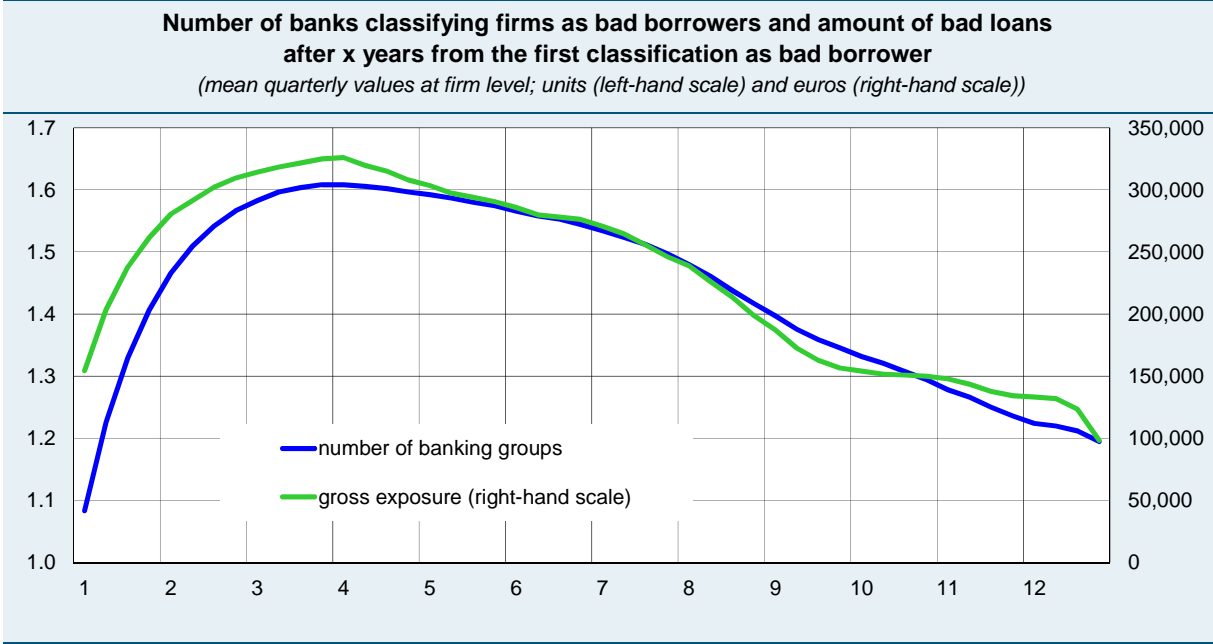
<sup>25</sup> Results from the multinomial logit show that, if a position is fully secured by a mortgage, both the likelihood of it being sold and the likelihood of it being closed at a loss are lower, while the likelihood of remaining classified as a bad loan and the likelihood of no longer being reported to the CCR for other reasons increases. Computing those effects with respect to an unsecured position at the average values of other covariates, the likelihood of being sold on the market is 4.5 percentage points lower, while the likelihood of no longer being reported to the CCR without it being recorded as a loss is 2.7 points higher. The other types of collateral – partial or total but without mortgages – have smaller effects. With respect to the top five groups, the likelihood of selling bad loans on the market is 2.9 percentage points lower for the other large and medium-sized banks.



Coordination failures could also emerge in credit recovery procedures undertaken by banks. Therefore, we extend the baseline model to explore whether the extent to which firms concentrate their borrowing from banks affects bad loan closure times. Namely, we investigate whether bad loan closure times are longer in the event of multi-bank borrowing (multi-borrowing effect) by considering specific variables on the number of relationships that firms maintain with banks.<sup>26</sup>

For each firm, we define the number of lending banks as the maximum number of banks reporting bad loans from 2005 to 2016. Figure 8 shows the mean value, at firm level, of the number of banks classifying the firm as a bad borrower. In the event of multi-borrowing, banks tend to classify as bad their loans towards the same firm in different points of time. It follows that the number of banks classifying the firm as a bad borrower increases, reaching its maximum value after around three years from the first classification; this number then decreases following the end of the recovery procedures. We observe the same trend for the average value of gross exposures, signaling that banks first classify as bad smaller loans.

**Figure 8**



Source: Based on CCR data.

About 62 percent of the firms in our database borrow from only one bank (single-lender borrowers, SLB), 21 percent from two banks, 15 percent from a number of lenders ranging from 3 to 5 and the remaining 2 percent from more than 5 banks (Table 3). The share of SLBs fell from 68 to 60 percent between 2005 and 2006, remaining around this value until 2014 and then increasing, reaching 69 percent in 2016; however this increase could depend on the limited time until the end of the period of analysis that, according to the facts stylized in

<sup>26</sup> We recall that in the baseline model a bad loan sale is considered a censoring event. Thus the model focuses on closure times following ordinary procedures.

Figure 8, may not have been enough for all banks to signal bad loans.<sup>27</sup> These values are consistent with those that are achievable by analyzing the information drawn by the CCR, concerning the universe of loans to non-financial firms without aggregating them at banking group level.

**Table 3**

<b>Distribution of firms by the year of classification as bad loan (cohort) and number of lenders (1)</b> (percentage values)				
COHORT	SLB	borrowing from 2 banks	borrowing from 3-5 banks	borrowing from more than 5 banks
2005	67.8	18.6	12.1	1.5
2006	60.7	21.3	15.9	2.1
2007	58.7	21.9	16.9	2.5
2008	58.8	21.2	17.0	3.0
2009	57.3	21.7	17.5	3.5
2010	57.0	22.1	17.6	3.3
2011	55.8	23.1	18.0	3.1
2012	57.7	22.5	17.0	2.9
2013	60.3	21.3	15.6	2.8
2014	60.4	21.9	15.3	2.4
2015	65.1	19.7	13.2	2.0
2016	69.0	18.7	11.2	1.1

Source: Based on CCR data.

(1) For each firm, the number of lenders is calculated as the maximum number of banks reporting bad loans to the CCR from 2005 to 2016.

The number of lenders is positively correlated to the firm's size proxied by its overall gross exposure, as reported by all lenders at the end of the quarter in which the firm was classified as a bad borrower for the first time. Among SLBs, 46 percent of loans are granted to firms with an overall exposure lower than €15,000 (first quartile of the distribution). On the contrary, the share of loans granted to firms with high indebtedness (more than €300,000) increases with the number of lenders. However, Table 4 shows, on the one hand, the presence of SLBs with a high overall amount of bad loans and, on the other hand, the existence of MLBs with limited indebtedness. This allows us to disentangle the multi-lender borrowing effect from the exposure effect.

To estimate the effect on closure times of borrowing from a different number of lenders (multi-borrowing effect) we add the following variables to the baseline duration model estimated in Section 4. The first variable (*MLB*) is dichotomous and it takes the value 0 when the firm's bad loans are from only one lender and the value 1 whenever there are at least two lenders. The second variable (*exposure\_class*) is categorical and it considers four classes of MLBs: borrowing from 1 lender, borrowing from 2 lenders, borrowing from a number of lenders ranging from 3 to 5, and borrowing from more than 5 lenders. For both variables, the

<sup>27</sup> These shares are not significantly influenced by the way we handle merger and acquisitions among banks, making reference to the composition of banking groups at the end of 2016 (if we considered the composition at the beginning of the reference period, the shares would be equal to 54, 23, 19 and 4 per cent respectively).

borrowing class is defined at firm level and it is time invariant, i.e. it is equal for all bad loans of a given firm, irrespective of when the bad loan is registered.<sup>28</sup>

**Table 4**

<b>Distribution of positions (firm/banking group pairs) by firm exposure classes and number of lenders (1)</b> (percentage values)					
FIRM EXPOSURE CLASS (euros)	SLB	borrowing from 2 banks	borrowing from 3-5 banks	borrowing from more than 5 banks	total
lower than 15 thousand	45.6	29.6	15.2	2.3	27.8
from 15 to 65 thousand	29.6	27.7	17.1	3.2	22.5
from 65 to 300 thousand	17.7	28.8	32.0	10.9	24.1
from 300 thousand to 1 million	4.7	9.6	21.9	21.4	13.0
from 1 to 5 million	2.1	3.8	11.7	38.7	9.3
more than 5 million	0.4	0.6	2.1	23.6	3.4
total	100.0	100.0	100.0	100.0	100.0

Source: Based on CCR data.

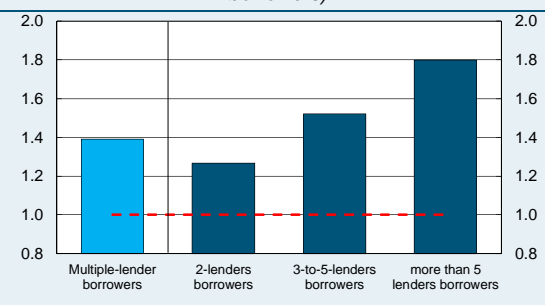
(1) For each firm, the number of lenders is calculated as the maximum number of banks reporting bad loans to the CCR from 2005 to 2016. The distribution of firms is developed according to their overall exposure (including performing loans) towards the banking system at the end of the quarter when they were first classified as bad borrowers. The first, second and third quartile of the overall exposure are respectively equal to 15, 65 and 300 thousand euros.

Results from the econometric estimates are shown in Table A13. In column 1, there is the baseline model with no multi-borrowing variable (see also column 1 in Table A10); in column 2, explanatory variables include the *exposure\_class* dummy (with SLB as reference category). In column 3, keeping SLB as the reference class, the variable *exposure\_class* is considered by adding 3 dummies for each multi-borrowing class. In columns 4 and 5, the models in columns 2 and 3 are augmented with proxy variables for the firm size in order to control for possible confounding factors on the identification of the multi-borrowing effect.<sup>29</sup>

These proxy variables are six size classes for the firm's overall exposure when the bad loan is initially reported to the CCR: up to €15 thousand (reference category); between €15 and 65 thousand; between €65 and 300 thousand; from €300 thousand to €1 million, from €1 to 5 million and above €5 million.<sup>30</sup>

**Figure 9**

**Closure times for bad business loans by cohort and number of lenders (1)**  
(as a ratio to the closure time of loans of single-lender borrowers)



Source: Based on CCR data.

(1) Estimated by a log-normal model of duration (columns 4 and 5 in Table A13 which represent, respectively, the dichotomous variable *MLB* and the classes of the variable *exposure\_class*). The dotted line stands for single-lender-borrowers (reference category).

<sup>28</sup> Although on the one hand this implies an approximation of when the number of bad loans may have varied in the sample period, on the other it has to be taken into account that our dataset is made up of bad loans only. Therefore, borrowers whose loans are registered as bad at different times were supposedly already multi-lender borrowers.

<sup>29</sup> Larger firms are more likely to borrow from more than one lender than smaller firms and this might introduce a confounding factor if the firm size has per se an effect on bad loan closure time.

<sup>30</sup> The first three classes roughly match the first three quartiles of the bad loans distribution in the estimated sample. The highest quartile, above €300 thousand, is split into the three sub-classes mentioned in the text.

In column 2, the *exposure\_class* dummy coefficient is positive and significant. In column 3, coefficients associated with *exposure\_class* are also positive and their magnitude increases with the number of lenders. In the AFT metric this implies that, *ceteris paribus*, closure times are higher for MLBs than for SLBs. These effects are confirmed and strengthened even after controlling for firm size (columns 4 and 5 for the specifications with the dichotomous variable and with the borrowing classes, respectively).<sup>31</sup>

Time ratios (i.e. the ratio between the expected closure times of each category with respect to SLBs) that result from specifications where firm size is controlled for are graphically shown in Figure 9. On average, the bad loans of MLBs are 39 per cent longer than those of SLBs.

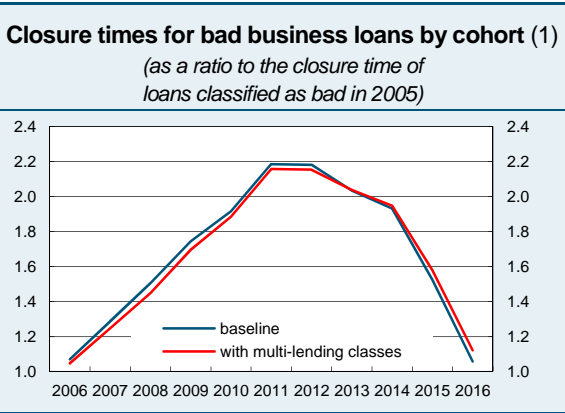
Coefficients of multi-borrowing classes show that the duration lengthening ranges from 27 per cent for borrowers with 2 lenders to 80 per cent for those who borrow from more than 5 lenders; for the class of borrowers with 3 to 5 lenders, closure times lengthened by 52 per cent. Differences between classes are statistically significant.

Finally, it is possible to observe that including information on the number of lenders generally does not bring about relevant changes for the other coefficients shown in Table A13 in terms of sign, magnitude and significance. From a quantitative viewpoint, in the model accounting for multi-borrowing, the implied time ratios for the cohort dummies (which measure the evolution of the expected closure times year by year) are basically aligned with those predicted by the baseline model in column 1 of Table A10 (Figure 10). This confirms that bad loan duration has increased up to the 2012 cohort to then decline to the levels recorded in 2005-06.

**7. Conclusions**

We have analyzed the temporal evolution of bank loans to firms that were classified as bad loans from 2005 to 2016. The analysis shows that during the economic crisis the speed at which positions were closed slowed down significantly, not only because the propensity to

**Figure 10**



Source: Based on CCR data.  
 (1) Estimated by a log-normal model of duration (columns 1 and 3 in Table A13, representing, respectively, the baseline and the specification augmented with multi-borrowing classes). Time ratios resulting from the specification in column 2 with *exposure\_class* dummy are not plotted as they basically overlap with those resulting from the specification in column 3.

<sup>31</sup> Coefficients show that larger firm sizes (proxied by the overall exposure) are associated with lower closure times. Since size is positively correlated with the number of lending banks, without controlling for size multi-borrowing (positive) coefficients are attenuated as they partly pick up the (negative) size effect.

sell bad debts on the market lessened, but also because the length of ordinary work-out procedures increased.

However, an econometric estimation suggests that the slowdown partly depends on changes in the composition of the debts that progressively entered bad loan status. Controlling for the effects of the positions' characteristics, such as sector, amount, location, presence of collateral and multiple borrowing, it turns out that the duration of work-out procedures actually lengthened only until 2012. In the years that followed, the expected closure times seem to have diminished, nearing the values that prevailed in the pre-crisis period. This reduction may have benefited either from the improvements in banks' internal NPL management policies, or from advancements in judicial recovery proceedings.

This evidence is consistent with the data published by Cerved (2016 and 2017) on the decline in the duration of bankruptcy and foreclosure proceedings, although that data are based on proceedings that were closed irrespective of when the initial actions were opened. It is also consistent with the reduction in the duration of enforcement procedures (Department of Justice, 2017; Giacomelli, Orlando and Rodano, 2018).

It has to be underlined that the estimation of closure times is based on the evidence for closure rates available in the period under analysis; hence, they should be interpreted more carefully for the 2015 and 2016 cohorts, for which the observable number of closures is limited. In the future, however, the approach proposed in this work can be applied to extend the evaluation to a longer period.

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## Tables

**Table A1**

### Number of positions and distribution of their starting values by cohort and type of guarantee

COHORT	Positions (banking group-firm) by type of collateral					
	Positions totally secured by mortgages		Other positions secured by collateral (1)		Positions unsecured by collateral	
	Number	Average value (euros)	Number	Average value (euros)	Number	Average value (euros)
2005	1,862	229,738	3,372	413,631	46,731	67,620
2006	2,376	251,939	4,612	462,233	62,975	69,358
2007	2,628	330,967	4,878	389,697	66,144	65,490
2008	2,672	329,854	5,002	606,874	60,601	88,264
2009	3,340	400,597	6,501	704,136	75,874	107,191
2010	4,236	375,186	7,643	675,024	80,947	105,452
2011	3,944	474,529	8,384	770,214	73,772	106,222
2012	4,654	498,898	10,064	792,016	89,986	106,455
2013	5,669	626,046	11,548	939,323	91,454	124,725
2014	5,911	634,318	13,215	848,409	113,962	98,804
2015	5,656	576,379	13,817	877,366	101,964	102,480
2016	5,248	537,430	14,486	798,692	106,794	92,013
Tot. period 2005-2016	48,196	482,969	103,522	757,131	971,204	97,030

Source: Based on CCR data.

(1) Positions partially secured by collateral or totally secured by collateral other than mortgages (pledges and liens).



Table A2

**Overall amount of bad business loans by cohort and outcome of the recovery action**  
(millions of euros and percentage values)

COHORT	standard work-out procedures (1)		sales on the market	still classified as bad at the end of 2016	total
	of which: total write-offs with losses	of which: other closures			
	<i>(millions of euros)</i>				
2005	1,532	479	2,225	747	4,982
2006	1,860	622	3,349	1,268	7,098
2007	1,605	713	2,724	2,060	7,102
2008	1,798	740	3,439	3,289	9,266
2009	2,640	955	3,182	7,272	14,049
2010	2,224	794	3,381	8,885	15,285
2011	1,491	537	3,557	10,580	16,165
2012	1,702	620	3,792	13,758	19,872
2013	1,571	955	4,904	18,373	25,803
2014	1,125	660	3,882	20,554	26,221
2015	825	388	2,118	22,501	25,832
2016	205	139	211	23,662	24,217
Total	18,577	7,602	36,765	132,948	
	<i>(percentage values with respect to newly classified bad loans per year)</i>				
2005	30.7	9.6	44.7	15.0	100.0
2006	26.2	8.8	47.2	17.9	100.0
2007	22.6	10.0	38.4	29.0	100.0
2008	19.4	8.0	37.1	35.5	100.0
2009	18.8	6.8	22.6	51.8	100.0
2010	14.6	5.2	22.1	58.1	100.0
2011	9.2	3.3	22.0	65.4	100.0
2012	8.6	3.1	19.1	69.2	100.0
2013	6.1	3.7	19.0	71.2	100.0
2014	4.3	2.5	14.8	78.4	100.0
2015	3.2	1.5	8.2	87.1	100.0
2016	0.8	0.6	0.9	97.7	100.0
Total	9.5	3.9	18.8	67.9	100.0
	<i>(percentage values with respect to outcome type)</i>				
2005	8.2	6.3	6.1	0.6	2.5
2006	10.0	8.2	9.1	1.0	3.6
2007	8.6	9.4	7.4	1.5	3.6
2008	9.7	9.7	9.4	2.5	4.7
2009	14.2	12.6	8.7	5.5	7.2
2010	12.0	10.4	9.2	6.7	7.8
2011	8.0	7.1	9.7	8.0	8.3
2012	9.2	8.2	10.3	10.3	10.1
2013	8.5	12.6	13.3	13.8	13.2
2014	6.1	8.7	10.6	15.5	13.4
2015	4.4	5.1	5.8	16.9	13.2
2016	1.1	1.8	0.6	17.8	12.4
Total	100.0	100.0	100.0	100.0	100.0

Source: Based on CCR data. The values refer to the total exposure of the firm towards the bank (or of the banking group for banks belonging to banking groups) at the beginning of the quarter in which the position was first classified as a bad loan.

(1) Bad loans that were not sold on the market to third parties and that were closed by the originating bank through an internal recovery procedure.

Table A3

**Cumulated share of positions still classified as bad at the end of 2016 by cohort and size class**  
(percentage values)

COHORT	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
	<i>I quartile</i>											
year t	81.9	77.2	82.5	78.2	84.8	85.4	85.1	88.6	86.9	88.0	87.2	88.2
year t+1	44.9	48.5	43.1	53.8	63.2	63.0	70.6	70.0	66.8	55.9	51.7	
year t+2	31.6	29.8	31.8	43.7	46.2	49.3	57.8	49.0	45.7	36.2		
year t+3	24.0	20.5	25.8	32.7	38.5	41.7	41.8	37.2	29.2			
year t+4	18.0	15.8	22.0	28.7	34.3	28.8	31.9	26.9				
year t+5	15.4	13.3	20.0	24.1	24.0	23.0	24.0					
year t+6	12.9	11.9	16.5	19.9	20.1	18.0						
year t+7	11.7	10.8	14.4	16.9	15.4							
year t+8	11.0	9.4	12.1	14.2								
year t+9	9.9	8.1	10.5									
year t+10	8.2	6.7										
year t+11	7.0											
	<i>II quartile</i>											
year t	89.6	86.7	89.4	81.2	93.3	93.3	93.9	95.0	93.5	94.4	92.8	92.5
year t+1	63.3	63.5	55.2	65.7	79.3	79.8	85.8	84.6	80.3	69.0	65.4	
year t+2	47.1	37.7	46.9	56.1	68.7	68.9	78.1	69.9	65.1	53.5		
year t+3	34.4	30.7	39.8	48.4	59.6	62.7	65.7	58.9	51.0			
year t+4	29.0	25.6	35.6	42.4	54.8	52.0	56.1	47.1				
year t+5	26.0	22.3	31.7	36.9	45.4	44.5	48.7					
year t+6	22.8	19.4	27.8	32.2	39.7	38.1						
year t+7	19.7	17.8	25.2	28.3	33.7							
year t+8	18.3	16.1	22.2	23.6								
year t+9	16.6	14.1	19.1									
year t+10	14.3	11.9										
year t+11	12.0											
	<i>III quartile</i>											
year t	92.9	92.6	92.4	83.8	95.5	95.6	96.5	96.7	96.8	96.7	96.8	95.4
year t+1	75.5	70.2	61.9	72.9	86.0	87.1	90.8	89.4	88.9	81.1	78.2	
year t+2	55.4	42.0	55.1	65.3	78.4	78.7	84.7	81.7	78.9	67.4		
year t+3	38.5	36.9	49.2	59.1	69.6	73.4	77.7	73.0	66.5			
year t+4	34.2	32.2	44.8	51.6	65.1	67.6	70.0	60.4				
year t+5	30.9	28.7	39.7	47.6	59.4	60.2	61.1					
year t+6	27.2	25.2	36.4	43.0	53.5	51.3						
year t+7	23.7	23.1	33.3	38.4	44.7							
year t+8	21.7	21.1	29.5	31.5								
year t+9	19.7	18.5	24.7									
year t+10	17.7	15.1										
year t+11	14.4											
	<i>IV quartile</i>											
year t	93.7	93.4	92.9	84.3	95.2	96.5	97.1	97.6	97.7	98.4	98.0	97.4
year t+1	79.7	72.5	67.3	76.6	89.2	91.4	92.7	91.5	92.2	90.1	88.3	
year t+2	59.0	49.2	61.8	71.1	84.9	86.4	86.6	87.1	86.3	79.4		
year t+3	41.3	44.7	57.2	66.9	79.3	79.4	81.4	82.0	75.5			
year t+4	37.9	41.2	53.6	60.9	72.5	75.0	75.9	72.3				
year t+5	34.9	37.8	48.7	55.3	68.3	69.1	66.4					
year t+6	31.8	33.4	44.0	51.0	62.4	59.7						
year t+7	27.9	29.2	40.7	46.1	53.6							
year t+8	24.5	26.9	36.7	38.0								
year t+9	22.6	23.8	30.3									
year t+10	20.0	19.0										
year t+11	15.7											

Source: Based on CCR data.

(1) For every cohort, the size classes are defined according to the distribution of the value of the positions in the quarter in which they were first classified as a bad debt. Each column indicates, for the positions (firm/banking group pairs) first classified as bad in any one of the quarters of the year indicated by the column, the ratio between the number of positions still classified as bad at the end of the year  $t+1$ ,  $t+2$ , etc., and the number of positions first classified as bad in any of the quarters of the year indicated by the column.

Table A4

**Cumulated share of the positions by cohort, size class and outcome of the recovery action (1)**  
(percentage values)

COHORT	2005			2009			2013					
	standard work-out procedures	sales on the market	still classified as bad debts at the end of 2016	standard work-out procedures	sales on the market	still classified as bad debts at the end of 2016	standard work-out procedures	sales on the market	still classified as bad debts at the end of 2016			
	of which: total write-offs with losses	of which: other closures		of which: total write-offs with losses	of which: other closures		of which: total write-offs with losses	of which: other closures				
	<i>I quartile</i>											
year t	7.4	6.3	4.1	81.9	5.2	5.4	4.6	84.8	3.6	2.8	6.6	86.9
year t+1	21.7	13.9	19.1	44.9	14.4	11.1	11.3	63.2	10.0	7.9	15.2	66.8
year t+2	26.6	17.1	24.3	31.6	19.1	13.6	21.0	46.2	12.9	9.7	31.7	45.7
year t+3	29.2	18.5	28.0	24.0	20.9	15.2	25.3	38.5	16.8	10.8	43.2	29.2
year t+4	30.8	19.9	31.1	18.0	22.3	16.2	27.1	34.3				
year t+5	32.5	20.2	31.7	15.4	23.4	16.9	35.6	24.0				
year t+6	34.1	20.5	32.4	12.9	24.5	17.4	38.1	20.1				
year t+7	34.6	20.7	32.8	11.7	25.5	17.8	41.3	15.4				
year t+8	34.9	21.0	33.0	11.0								
year t+9	35.3	21.1	33.7	9.9								
year t+10	35.7	21.3	34.8	8.2								
year t+11	36.1	21.6	35.3	7.0								
	<i>II quartile</i>											
year t	4.4	3.5	2.2	89.6	2.8	1.3	2.5	93.3	2.0	1.3	3.0	93.5
year t+1	15.8	8.8	11.9	63.3	9.7	5.7	5.2	79.3	6.9	3.8	8.9	80.3
year t+2	22.1	11.2	19.5	47.1	14.2	7.2	9.6	68.7	10.4	4.7	19.8	65.1
year t+3	25.8	12.5	27.1	34.4	16.3	8.6	15.4	59.6	13.6	5.6	29.8	51.0
year t+4	28.0	13.8	29.1	29.0	18.3	9.9	16.9	54.8				
year t+5	29.9	14.4	29.6	26.0	20.1	10.8	23.6	45.4				
year t+6	31.8	15.0	30.3	22.8	22.1	11.5	26.6	39.7				
year t+7	32.8	15.7	31.8	19.7	23.8	12.2	30.3	33.7				
year t+8	33.5	16.1	32.1	18.3								
year t+9	34.1	16.4	32.9	16.6								
year t+10	34.8	16.7	34.2	14.3								
year t+11	35.6	17.1	35.3	12.0								
	<i>III quartile</i>											
year t	3.6	2.4	0.7	92.9	1.9	1.0	1.0	95.5	1.3	0.8	0.8	96.8
year t+1	13.8	6.2	4.3	75.5	7.4	3.8	2.1	86.0	4.8	2.3	3.7	88.9
year t+2	21.4	8.4	14.6	55.4	11.9	5.0	4.0	78.4	8.0	3.2	9.7	78.9
year t+3	25.3	9.7	26.3	38.5	13.8	6.2	9.8	69.6	10.9	4.0	18.5	66.5
year t+4	27.8	10.5	27.3	34.2	15.9	7.4	11.1	65.1				
year t+5	30.2	11.1	27.6	30.9	18.3	8.3	13.6	59.4				
year t+6	32.5	11.8	28.4	27.2	20.6	9.0	16.4	53.5				
year t+7	33.5	12.4	30.3	23.7	23.6	9.9	21.7	44.7				
year t+8	34.6	13.0	30.7	21.7								
year t+9	35.2	13.6	31.4	19.7								
year t+10	36.0	14.0	32.3	17.7								
year t+11	37.1	14.7	33.8	14.4								
	<i>IV quartile</i>											
year t	2.6	1.7	0.9	93.7	1.6	0.7	1.0	95.2	0.6	0.3	0.8	97.7
year t+1	9.8	4.9	4.9	79.7	5.3	2.4	1.7	89.2	2.2	1.4	3.7	92.2
year t+2	15.7	6.4	18.3	59.0	8.3	3.3	2.3	84.9	4.2	2.2	6.9	86.3
year t+3	19.9	7.3	31.0	41.3	10.0	3.9	5.9	79.3	6.8	2.7	15.0	75.5
year t+4	22.1	7.9	31.8	37.9	12.0	4.7	10.0	72.5				
year t+5	24.4	8.6	32.1	34.9	14.0	5.3	11.8	68.3				
year t+6	26.5	9.1	32.5	31.8	16.7	5.8	14.5	62.4				
year t+7	27.6	9.6	35.1	27.9	20.0	6.4	20.1	53.6				
year t+8	28.8	9.9	36.8	24.5								
year t+9	29.8	10.3	37.3	22.6								
year t+10	30.8	10.8	38.4	20.0								
year t+11	32.6	11.3	40.4	15.7								

Source: Based on CCR data.

(1) For every cohort, the size classes are defined according to the distribution of the value of the positions in the quarter in which they were first classified as a bad debt. Each column indicates, for the positions (firm/banking group pairs) first classified as bad in any one of the quarters of the year indicated by the column, the ratio between the number of positions closed with standard work-out procedures in the year  $t+1$ ,  $t+2$ , etc., or sold on the market in the year  $t+1$ ,  $t+2$ , etc., or still classified as bad at the end of the year  $t+1$ ,  $t+2$ , etc., and the number of positions first classified as bad in any of the quarters of the year indicated by the column. See the Methodological Appendix for the definition of the different types of closures.

Table A5

**Bad business loans reported to the CCR by Italian banks at the end of 2016  
by cohort and type of guarantee (1)**  
(percentage values to the overall amount of bad loans and millions of euros)

COHORT	Positions totally secured by mortgages		Other positions secured by collateral (2)		Positions unsecured by collateral		Total	
	millions of euros	%	millions of euros	%	millions of euros	%	millions of euros	%
2005	97	0.1	139	0.1	407	0.3	643	0.5
2006	135	0.1	326	0.3	613	0.5	1,073	0.9
2007	205	0.2	599	0.5	953	0.8	1,757	1.4
2008	368	0.3	939	0.7	1,230	1.0	2,537	2.0
2009	679	0.5	2,269	1.8	3,288	2.6	6,236	5.0
2010	978	0.8	2,844	2.3	4,128	3.3	7,950	6.3
2011	1,312	1.0	3,974	3.2	4,052	3.2	9,339	7.4
2012	1,741	1.4	5,257	4.2	5,792	4.6	12,790	10.2
2013	2,819	2.2	7,293	5.8	7,282	5.8	17,393	13.8
2014	3,127	2.5	8,811	7.0	8,480	6.8	20,418	16.3
2015	2,831	2.3	10,492	8.4	9,101	7.2	22,423	17.9
2016	2,725	2.2	11,359	9.0	8,976	7.1	23,060	18.4
Total	17,017	13.5	54,301	43.2	54,302	43.2	125,620	100.0

Source: Based on CCR data.

(1) The overall amount of bad loans at the end of 2016 (€126 billion) is lower than the value of bad loans to the universe of Italian non-financial firms (€177 billion) because our sample does not include loans granted by financial intermediaries, loans sold to entities not belonging to the same banking group or to securitization companies and loans that were already classified as bad at the beginning of 2005 (for further details see the Methodological Appendix). The values of the positions shown in this table refer to the end of 2016 and generally differ from their starting values. – (2) Positions partially secured by collateral or totally secured by collateral other than mortgages (pledges and liens).

Table A6

**Cumulated share of positions sold on the market by cohort**  
(percentage values)

COHORT	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
year t	2.2	4.9	3.0	12.0	2.5	2.5	2.8	2.0	3.0	2.5	2.4	3.0
year t+1	11.0	14.9	24.7	17.0	5.8	7.1	5.7	6.6	8.3	17.3	18.1	
year t+2	19.7	31.6	27.5	19.0	10.6	13.1	10.0	14.6	17.9	28.1		
year t+3	28.0	34.7	28.7	21.5	15.4	16.2	16.9	21.1	27.6			
year t+4	29.9	35.6	29.9	24.8	17.5	22.1	22.3	29.1				
year t+5	30.4	36.4	31.9	27.4	22.9	25.9	27.8					
year t+6	31.0	37.9	34.1	30.0	25.6	30.5						
year t+7	32.5	38.6	35.5	32.2	29.9							
year t+8	33.1	39.4	37.4	35.4								
year t+9	33.7	40.7	39.5									
year t+10	34.8	42.2										
year t+11	36.0											

Source: Based on CCR data.

(1) Each column indicates, for the positions (firm/banking group pairs) first classified as bad in any one of the quarters of the year indicated by the column, the ratio between the number of the positions sold on the market in the year  $t+1$ ,  $t+2$ , etc., and the number of the positions first classified as bad in any of the quarters of the year indicated by the column. See the Methodological Appendix for the definition of sales on the market.

Table A7

**Cumulated share of positions closed following standard work-out procedures by cohort**  
(percentage values)

COHORT	<i>positions closed following standard work-out procedures</i>											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
year t	8.5	8.2	7.8	6.1	5.6	5.2	4.3	3.6	3.4	3.3	3.9	3.6
year t+1	25.0	22.6	19.7	16.7	16.2	13.9	10.0	10.1	10.3	9.3	11.3	
year t+2	33.5	29.5	25.3	23.3	22.1	17.9	14.4	14.8	14.3	13.8		
year t+3	38.3	33.3	30.2	28.5	25.2	21.6	18.2	17.8	18.4			
year t+4	41.4	37.1	33.0	31.0	28.1	24.8	21.3	21.1				
year t+5	44.0	39.5	34.8	33.4	30.6	27.6	24.3					
year t+6	46.4	40.9	36.4	35.3	33.1	30.4						
year t+7	47.8	42.2	37.8	37.0	35.9							
year t+8	48.9	43.2	39.0	39.3								
year t+9	49.9	44.1	40.8									
year t+10	50.9	45.5										
year t+11	52.3											
	<i>of which: total write-offs with losses</i>											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
year t	4.8	5.1	4.8	3.8	3.1	3.0	2.8	1.7	2.0	1.8	2.4	2.6
year t+1	16.0	15.1	12.9	10.3	9.8	8.7	6.2	5.5	6.2	5.9	7.9	
year t+2	22.1	20.2	16.7	14.9	14.1	11.0	8.9	8.6	9.1	9.3		
year t+3	25.6	22.9	20.3	18.0	15.9	13.2	11.4	10.9	12.3			
year t+4	27.6	25.3	22.6	19.6	17.8	15.4	13.7	13.4				
year t+5	29.7	27.2	23.7	21.2	19.5	17.5	16.0					
year t+6	31.6	28.2	24.9	22.5	21.4	19.7						
year t+7	32.5	29.1	25.7	23.7	23.5							
year t+8	33.2	29.7	26.6	25.2								
year t+9	33.8	30.4	27.7									
year t+10	34.6	31.3										
year t+11	35.5											
	<i>of which: other closures</i>											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
year t	3.8	3.1	3.0	2.3	2.5	2.2	1.5	1.9	1.4	1.4	1.4	1.1
year t+1	9.0	7.5	6.8	6.4	6.4	5.2	3.8	4.6	4.1	3.4	3.4	
year t+2	11.5	9.3	8.6	8.4	8.0	7.0	5.5	6.2	5.2	4.4		
year t+3	12.8	10.5	9.8	10.5	9.2	8.3	6.8	6.9	6.1			
year t+4	13.8	11.7	10.5	11.4	10.3	9.4	7.6	7.7				
year t+5	14.3	12.2	11.1	12.2	11.1	10.0	8.3					
year t+6	14.8	12.7	11.6	12.8	11.7	10.7						
year t+7	15.3	13.1	12.0	13.3	12.3							
year t+8	15.7	13.5	12.4	14.0								
year t+9	16.1	13.7	13.0									
year t+10	16.3	14.1										
year t+11	16.8											

Source: Based on CCR data.

(1) Bad loans that were not sold on the market to third parties and closed by the originating bank through an internal recovery procedure. Each column indicates, for the positions (firm/banking group pairs) first classified as bad in any one of the quarters of the year indicated by the column, the ratio between the number of the positions closed following standard work-out procedures in the year  $t+1$ ,  $t+2$ , etc., and the number of the positions first classified as bad in any of the quarters of the year indicated by the column.

Table A8

**Cumulated share of positions by cohort, outcome of the recovery action and type of guarantee (1)**  
(percentage values)

COHORT	2005			2009			2013					
	standard work-out procedures	sales on the market	still classified as bad at the end of 2016	standard work-out procedures	sales on the market	still classified as bad at the end of 2016	standard work-out procedures	sales on the market	still classified as bad at the end of 2016			
	of which: total write-offs with losses	of which: other closures		of which: total write-offs with losses			of which: total write-offs with losses					
<i>positions totally secured by mortgages</i>												
year t	1.5	4.5	1.1	92.3	1.1	2.2	0.9	95.3	0.4	0.9	0.1	98.3
year t+1	6.9	14.4	4.0	73.7	3.8	7.0	1.5	86.9	2.2	3.1	2.7	91.7
year t+2	12.3	20.1	7.1	59.2	6.7	9.7	1.7	80.9	3.9	4.8	4.2	86.9
year t+3	17.3	24.2	14.5	42.9	8.0	11.6	4.9	74.7	6.4	5.8	10.6	77.3
year t+4	20.0	26.4	15.5	37.2	10.2	13.6	5.7	69.8				
year t+5	22.5	28.5	15.7	32.6	12.8	14.7	7.2	64.9				
year t+6	24.7	30.4	15.8	28.2	15.5	15.9	9.4	59.0				
year t+7	26.1	31.3	17.4	24.6	18.7	16.9	14.2	50.2				
year t+8	27.0	32.6	18.3	21.7								
year t+9	27.7	33.2	18.7	20.1								
year t+10	28.8	33.7	19.4	18.1								
year t+11	30.0	34.3	21.4	14.3								
<i>other positions secured by collateral</i>												
year t	2.5	2.8	1.9	91.1	1.1	1.1	1.4	95.1	0.5	0.6	0.3	98.1
year t+1	10.0	7.7	6.0	74.6	4.1	3.3	2.0	89.2	1.9	2.0	3.1	92.5
year t+2	15.4	9.6	17.0	56.6	6.4	4.5	2.5	85.2	3.7	3.0	6.6	86.2
year t+3	18.5	11.2	29.3	39.9	8.0	5.3	6.8	78.9	6.1	3.7	14.3	75.9
year t+4	21.1	12.3	30.7	35.0	9.7	6.3	9.2	74.0				
year t+5	22.9	13.3	31.0	32.1	11.7	7.2	10.8	69.6				
year t+6	25.1	14.0	31.3	29.1	14.0	7.7	13.7	64.2				
year t+7	25.9	14.4	34.0	25.5	16.7	8.7	19.2	55.4				
year t+8	26.9	15.0	35.5	22.5								
year t+9	27.9	15.3	36.0	20.7								
year t+10	29.0	15.7	37.2	18.1								
year t+11	30.0	16.3	38.5	15.1								
<i>positions unsecured by collateral</i>												
year t	5.1	3.8	2.3	88.3	3.4	2.6	2.7	90.9	2.3	1.5	3.5	92.4
year t+1	16.8	8.9	11.7	62.3	10.6	6.6	6.3	76.2	7.0	4.4	9.3	79.1
year t+2	22.9	11.3	20.4	45.2	15.1	8.2	11.6	64.6	10.1	5.5	20.2	64.0
year t+3	26.4	12.4	28.4	32.6	17.0	9.5	16.7	56.6	13.5	6.4	30.4	49.8
year t+4	28.4	13.4	30.4	27.7	18.8	10.5	18.8	51.6				
year t+5	30.4	13.8	30.9	24.8	20.5	11.3	24.6	43.4				
year t+6	32.3	14.3	31.6	21.7	22.3	11.8	27.4	38.3				
year t+7	33.2	14.7	33.0	19.1	24.3	12.5	31.5	31.7				
year t+8	33.9	15.1	33.5	17.5								
year t+9	34.5	15.4	34.1	15.9								
year t+10	35.2	15.7	35.3	13.8								
year t+11	36.1	16.1	36.4	11.3								

Source: Based on CCR data.

(1) Each column indicates, for the positions (firm/banking group pairs) first classified as bad in any one of the quarters of the year indicated by the column, the ratio between the number of the positions closed with standard work-out procedures in the year  $t+1$ ,  $t+2$ , *Etc.*, or sold on the market in the year  $t+1$ ,  $t+2$ , *etc.*, or still classified as bad at the end of the year  $t+1$ ,  $t+2$ , *etc.*, and the number of positions first classified as bad in any of the quarters of the year indicated by the column. See the Methodological Appendix for the definition of the different types of closures. The presence of collateral refers to the beginning of the quarter in which the position was first classified as bad. Personal guarantees are not included.

Table A9

**Bad business loan closure time – comparison of distributions**

*Survival analysis* in AFT metric. The failure event is defined as the bad loan's closure after a standard work-out procedure (write-offs with or without losses); sales on the market are considered a censoring event. Standard errors (reported in parenthesis) are clustered by debtor code recorded in the CCR. Reference categories are unsecured positions and the top five banking groups. Sector dummy variables are defined at 2-digit Ateco level.

	(1) Weibull	(2) Log Logistic	(3) Log-Normal	(4) Generaliz-Gamma
partially secured	0.059 (0.009) ***	0.060 (0.008) ***	0.062 (0.008) ***	0.062 (0.008) ***
totally secured (no mortgage)	-0.015 (0.018)	-0.031 (0.019) *	-0.035 (0.018) *	-0.039 (0.018) **
totally secured (only mortgage)	-0.126 (0.009) ***	-0.125 (0.009) ***	-0.117 (0.009) ***	-0.111 (0.009) ***
log of amount	0.435 (0.009) ***	0.505 (0.009) ***	0.491 (0.009) ***	0.488 (0.009) ***
squared log of amount	-0.010 (0.000) ***	-0.013 (0.000) ***	-0.012 (0.000) ***	-0.012 (0.000) ***
other large and medium banks	-0.129 (0.005) ***	-0.145 (0.005) ***	-0.152 (0.004) ***	-0.156 (0.004) ***
small banks	-0.388 (0.004) ***	-0.380 (0.004) ***	-0.375 (0.004) ***	-0.366 (0.004) ***
foreign banks	-0.805 (0.012) ***	-0.793 (0.013) ***	-0.799 (0.013) ***	-0.790 (0.013) ***
cohort_2006	0.031 (0.008) ***	0.070 (0.009) ***	0.068 (0.009) ***	0.071 (0.009) ***
cohort_2007	0.216 (0.009) ***	0.276 (0.009) ***	0.253 (0.009) ***	0.244 (0.009) ***
cohort_2008	0.320 (0.009) ***	0.423 (0.010) ***	0.409 (0.009) ***	0.408 (0.009) ***
cohort_2009	0.421 (0.008) ***	0.566 (0.009) ***	0.556 (0.009) ***	0.560 (0.009) ***
cohort_2010	0.483 (0.008) ***	0.651 (0.009) ***	0.650 (0.009) ***	0.660 (0.009) ***
cohort_2011	0.586 (0.009) ***	0.767 (0.009) ***	0.782 (0.009) ***	0.797 (0.009) ***
cohort_2012	0.572 (0.009) ***	0.753 (0.009) ***	0.780 (0.009) ***	0.801 (0.009) ***
cohort_2013	0.481 (0.009) ***	0.669 (0.009) ***	0.710 (0.009) ***	0.737 (0.009) ***
cohort_2014	0.430 (0.009) ***	0.607 (0.009) ***	0.658 (0.009) ***	0.687 (0.009) ***
cohort_2015	0.182 (0.010) ***	0.360 (0.010) ***	0.422 (0.009) ***	0.456 (0.009) ***
cohort_2016	-0.127 (0.014) ***	0.008 (0.013)	0.055 (0.012) ***	0.081 (0.011) ***
Sector Dummy (Ateco 2dgt)	YES	YES	YES	YES
Province Dummy	YES	YES	YES	YES
Firm's legal form Dummy	YES	YES	YES	YES
$\rho$	1.163 (0.002) ***			
$\gamma$		0.716 (0.001) ***		
$\sigma$			1.294 (0.002) ***	1.402 (0.003) ***
$k$				-0.298 (0.008) ***
AIC	1,509,912	1,488,016	1,474,549	1,472,816
Units	1,078,652	1,078,652	1,078,652	1,078,652
Number of failures	275,343	275,343	275,343	275,343
Observations	3,773,142	3,773,142	3,773,142	3,773,142

Table A10

### Bad business loan closure times

*Survival analysis* in AFT metric. The failure event is defined as the bad loan's closure after a standard work-out procedure (write-offs with or without losses); sales on the market are considered a censoring event. Standard errors (reported in parenthesis) are clustered by debtor code recorded in the CCR. Reference categories are unsecured positions and the top five banking groups. Sector dummy variables are defined at 2-digit Ateco level. In column 2, reference categories for macro-areas, macro-sectors, and legal forms are respectively: North-West, Construction, and Legal forms with unlimited liability.

	<i>(1) Full-model</i>			<i>(2) Short-model</i>		
partially secured	0.062	(0.008)	***	0.089	(0.008)	***
totally secured (no mortgage)	-0.035	(0.018)	*	-0.045	(0.018)	**
totally secured (only mortgage)	-0.117	(0.009)	***	-0.098	(0.009)	**
log of amount	0.491	(0.009)	***	0.495	(0.009)	***
squared log of amount	-0.012	(0.000)	***	-0.013	(0.000)	***
other large and medium banks	-0.152	(0.004)	***	-0.139	(0.005)	***
small banks	-0.375	(0.004)	***	-0.384	(0.004)	***
foreign banks	-0.799	(0.013)	***	-0.797	(0.013)	***
cohort_2006	0.068	(0.009)	***	0.070	(0.009)	***
cohort_2007	0.253	(0.009)	***	0.263	(0.009)	***
cohort_2008	0.409	(0.009)	***	0.421	(0.010)	***
cohort_2009	0.556	(0.009)	***	0.567	(0.009)	***
cohort_2010	0.650	(0.009)	***	0.660	(0.009)	***
cohort_2011	0.782	(0.009)	***	0.792	(0.009)	***
cohort_2012	0.780	(0.009)	***	0.793	(0.009)	***
cohort_2013	0.710	(0.009)	***	0.722	(0.009)	***
cohort_2014	0.658	(0.009)	***	0.669	(0.009)	***
cohort_2015	0.422	(0.009)	***	0.432	(0.009)	***
cohort_2016	0.055	(0.012)	***	0.059	(0.012)	***
Centre				0.279	(0.006)	***
South				0.282	(0.005)	***
North-East				0.014	(0.005)	**
Other sectors				-0.155	(0.009)	***
Manufacturing				-0.122	(0.007)	***
Services				-0.104	(0.005)	***
Limited liability legal form				-0.166	(0.004)	***
Sector dummy (Ateco 2dgt)	YES			NO		
Province dummy	YES			NO		
Firm's legal form Dummy	YES			NO		
$\sigma$	1.294	(0.002)	***	1.304	(0.002)	***
AIC		1,474,549			1,442,167	
Units		1,078,652			1,052,767	
Number of failures		275,343			267,532	
Observations		3,773,142			3,685,652	



Table A11

### Bad business loan closure times – robustness analysis concerning sales on the market

*Survival analysis* in AFT metric. In columns 1 and 2, the *failure event* is defined as the bad loan's closure after a standard work-out procedure (write-offs with or without losses); sales on the market are considered a censoring event. In columns 3 and 4, the *failure event* is defined as the bad loan's closure after a standard work-out procedure (write-offs with or without losses) or a sale on the market. Standard errors (reported in parenthesis) are clustered by debtor code recorded in the CCR. Reference categories are unsecured positions and the top five banking groups. Sector dummy variables are defined at 2-digit Ateco level. In columns 2 and 4, reference categories for macro-areas, macro-sectors, and legal forms are respectively: North-West, Construction, and Legal forms with unlimited liability.

	<i>Failure event: standard work-out procedures</i>		<i>Failure event: standard work-out procedures and sales on the market</i>	
	<i>(1) Full-model</i>	<i>(2) Short-model</i>	<i>(3) Full-model</i>	<i>(4) Short-model</i>
partially secured	0.062 (0.008) ***	0.089 (0.008) ***	0.180 (0.005) ***	0.191 (0.005) ***
tot secured (no mortgage)	-0.035 (0.018) *	-0.045 (0.018) **	0.061 (0.012) ***	0.058 (0.012) ***
tot secured (only mortgage)	-0.117 (0.009) ***	-0.098 (0.009) **	0.195 (0.007) ***	0.200 (0.007) ***
log of amonunt	0.491 (0.009) ***	0.495 (0.009) ***	0.503 (0.005) ***	0.520 (0.005) ***
squared log of amount	-0.012 (0.000) ***	-0.013 (0.000) ***	-0.015 (0.000) ***	-0.016 (0.000) ***
other large and medium banks	-0.152 (0.004) ***	-0.139 (0.005) ***	0.140 (0.003) ***	0.139 (0.003) ***
small banks	-0.375 (0.004) ***	-0.384 (0.004) ***	-0.138 (0.003) ***	-0.140 (0.003) ***
foreign banks	-0.799 (0.013) ***	-0.797 (0.013) ***	-0.530 (0.008) ***	-0.536 (0.008) ***
cohort_2006	0.068 (0.009) ***	0.070 (0.009) ***	-0.074 (0.006) ***	-0.075 (0.006) ***
cohort_2007	0.253 (0.009) ***	0.263 (0.009) ***	0.067 (0.006) ***	0.067 (0.006) ***
cohort_2008	0.409 (0.009) ***	0.421 (0.010) ***	0.151 (0.007) ***	0.154 (0.007) ***
cohort_2009	0.556 (0.009) ***	0.567 (0.009) ***	0.458 (0.006) ***	0.459 (0.006) ***
cohort_2010	0.650 (0.009) ***	0.660 (0.009) ***	0.475 (0.006) ***	0.476 (0.006) ***
cohort_2011	0.782 (0.009) ***	0.792 (0.009) ***	0.549 (0.006) ***	0.551 (0.006) ***
cohort_2012	0.780 (0.009) ***	0.793 (0.009) ***	0.464 (0.006) ***	0.466 (0.006) ***
cohort_2013	0.710 (0.009) ***	0.722 (0.009) ***	0.329 (0.006) ***	0.329 (0.006) ***
cohort_2014	0.658 (0.009) ***	0.669 (0.009) ***	0.153 (0.006) ***	0.153 (0.006) ***
cohort_2015	0.422 (0.009) ***	0.432 (0.009) ***	0.010 (0.006) *	0.013 (0.006) *
cohort_2016	0.055 (0.012) ***	0.059 (0.012) ***	-0.213 (0.008) ***	-0.212 (0.008) ***
Centre		0.279 (0.006) ***		0.100 (0.003) ***
South		0.282 (0.005) ***		0.121 (0.003) ***
North-East		0.014 (0.005) **		0.018 (0.004) ***
Other sectors		-0.155 (0.009) ***		-0.028 (0.005) ***
Manufacturing		-0.122 (0.007) ***		-0.029 (0.004) ***
Services		-0.104 (0.005) ***		-0.042 (0.003) ***
Limited liability legal form		-0.166 (0.004) ***		-0.054 (0.003) ***
Secotr dummy (Ateco 2dgt)	YES	NO	YES	NO
Province dummy	YES	NO	YES	NO
Firm's legal form Dummy	YES	NO	YES	NO
$\sigma$	1.294 (0.002) ***	1.304 (0.002) ***	0.996 (0.001) ***	0.999 (0.002) ***
AIC	1,474,549	1,442,167	2,171,532	2,121,921
Units	1,078,652	1,052,767	1,078,652	1,052,767
Number of failures	275,343	267,532	579,213	564,615
Observations	3,773,142	3,685,652	3,773,142	3,685,652

Table A12

## Bad business loan closure times – heterogeneous cohort effects

*Survival analysis* in AFT metric. In columns 1 and 2, the *failure event* is defined as the bad loan's closure after a standard work-out procedure (write-offs with or without losses); sales on the market are considered a censoring event. In columns 3 and 4, the *failure event* is defined as the bad loan's closure after a standard work-out procedure (write-offs with or without losses) or a sale on the market. Standard errors (reported in parenthesis) are clustered by debtor code recorded in the CCR. Reference categories are unsecured positions, the top five banking groups, the North-West, the construction sector and unlimited liability legal forms. Column (1) shows estimates from the baseline model in Table A10 column 2. Columns 2 to 5 consider interactions of cohort dummies with the following variables: area, sector, collateral type, bank class. For the sake of brevity, coefficients of interaction variables are not shown but are available from the authors upon request.

	Baseline short model (1)			Interact. cohort-area (2)			Interact. cohort sector (3)			Interact. cohort collateral (4)			Interact. cohort bank class(5)		
partially secured	0.089	(0.008)	***	0.090	(0.008)	***	0.089	(0.008)	***	-0.078	(0.030)	**	0.089	(0.008)	***
tot secured (no mortgage)	-0.045	(0.018)	**	-0.045	(0.018)	**	-0.045	(0.018)	**	-0.032	(0.065)		-0.052	(0.018)	***
tot secured (only mortgage)	-0.098	(0.009)	**	-0.098	(0.009)	***	-0.098	(0.009)	***	-0.307	(0.032)	***	-0.100	(0.009)	***
log of amount	0.495	(0.009)	***	0.495	(0.009)	***	0.494	(0.009)	***	0.499	(0.009)	***	0.494	(0.009)	***
squared log of amount	-0.013	(0.000)	***	-0.013	(0.000)	***	-0.013	(0.000)	***	-0.013	(0.000)	***	-0.013	(0.000)	***
other large and medium banks	-0.139	(0.005)	***	-0.140	(0.005)	***	-0.139	(0.005)	***	-0.139	(0.005)	***	-0.122	(0.016)	***
small banks	-0.384	(0.004)	***	-0.385	(0.004)	***	-0.384	(0.004)	***	-0.383	(0.004)	***	-0.345	(0.015)	***
foreign banks	-0.797	(0.013)	***	-0.798	(0.013)	***	-0.796	(0.013)	***	-0.794	(0.013)	***	-0.393	(0.087)	***
Centre	0.279	(0.006)	***	0.158	(0.019)	***	0.280	(0.006)	***	0.279	(0.006)	***	0.280	(0.006)	***
South	0.282	(0.005)	***	0.283	(0.018)	***	0.282	(0.005)	***	0.282	(0.005)	***	0.281	(0.005)	***
North-East	0.014	(0.005)	**	-0.019	(0.019)		0.014	(0.005)	**	0.013	(0.005)	***	0.015	(0.005)	***
Other sectors	-0.155	(0.009)	***	-0.156	(0.009)	***	-0.065	(0.031)	**	-0.154	(0.009)	**	-0.155	(0.009)	***
Manufacturing	-0.122	(0.007)	***	-0.122	(0.006)	***	-0.046	(0.023)	**	-0.120	(0.007)	***	-0.121	(0.006)	***
Services	-0.104	(0.005)	***	-0.104	(0.005)	***	-0.038	(0.019)	*	-0.103	(0.005)	***	-0.104	(0.005)	***
Limited liability legal form	-0.166	(0.004)	***	-0.166	(0.004)	***	-0.166	(0.004)	***	-0.166	(0.004)	***	-0.164	(0.004)	***
cohort_2006	0.07	(0.009)	***	0.049	(0.017)	***	0.100	(0.022)	***	0.069	(0.009)	***	0.046	(0.012)	***
cohort_2007	0.263	(0.009)	***	0.214	(0.018)	***	0.321	(0.023)	***	0.257	(0.010)	***	0.260	(0.013)	***
cohort_2008	0.421	(0.010)	***	0.377	(0.018)	***	0.507	(0.023)	***	0.407	(0.010)	***	0.470	(0.014)	***
cohort_2009	0.567	(0.009)	***	0.522	(0.017)	***	0.654	(0.021)	***	0.545	(0.009)	***	0.668	(0.013)	***
cohort_2010	0.66	(0.009)	***	0.620	(0.017)	***	0.749	(0.021)	***	0.638	(0.009)	***	0.718	(0.013)	***
cohort_2011	0.792	(0.009)	***	0.712	(0.018)	***	0.887	(0.022)	***	0.765	(0.010)	***	0.833	(0.013)	***
cohort_2012	0.793	(0.009)	***	0.759	(0.017)	***	0.865	(0.022)	***	0.766	(0.009)	***	0.774	(0.013)	***
cohort_2013	0.722	(0.009)	***	0.701	(0.018)	***	0.797	(0.022)	***	0.691	(0.010)	***	0.692	(0.013)	***
cohort_2014	0.669	(0.009)	***	0.647	(0.017)	***	0.701	(0.021)	***	0.659	(0.009)	***	0.677	(0.013)	***
cohort_2015	0.432	(0.009)	***	0.405	(0.018)	***	0.436	(0.022)	***	0.417	(0.010)	***	0.388	(0.014)	***
cohort_2016	0.059	(0.012)	***	0.041	(0.022)	*	0.057	(0.028)	*	0.046	(0.012)	***	0.022	(0.018)	
Interaction cohort-area	NO			YES			NO			NO			NO		
Interaction cohort-sector	NO			NO			YES			NO			NO		
Interaction cohort-collateral type	NO			NO			NO			YES			NO		
Interaction cohort-bank class	NO			NO			NO			NO			YES		
$\sigma$	1.304	(0.002)	***	1.304	(0.002)	***	1.304	(0.002)	***	1.304	(0.002)		1.300	(0.002)	***
AIC	1,442,167			1,442,025			1,442,119			1,441,897			1,440,439		
Units	1,052,767			1,052,767			1,052,767			1,052,767			1,052,767		
Number of failures	267,532			267,532			267,532			267,532			267,532		
Observations	3,685,652			3,685,652			3,685,652			3,685,652			3,685,652		

Table A13

## Bad business loan closure times

*Survival analysis* performed in the AFT metric. The *failure event* is defined by standard work-out procedures; sales on the market are considered a censoring event. Standard errors, clustered at firm level as registered in the CCR, are shown in brackets. Reference categories are uncollateralized positions, the top five banking groups, single-lender borrowers (for columns 2-5) and firms with a total exposure below €15,000 (for columns 4-5). Sector dummies are defined at the Ateco two-digit level.

	Baseline (1)	No control for overall exposure		With control for overall exposure	
		MLB dummy (2)	MLB classes (3)	MLB dummy (4)	MLB classes (5)
MLB		0.276*** (0.004)		0.330*** (0.004)	
2-lender borrower			0.195*** (0.005)		0.238*** (0.005)
3-to-5- lender borrower			0.323*** (0.005)		0.420*** (0.005)
>5-lender borrower			0.424*** (0.008)		0.587*** (0.010)
total exposure: 15-65k€				-0.105*** (0.005)	-0.113*** (0.005)
total exposure: 65-300k€				-0.237*** (0.006)	-0.279*** (0.006)
total exposure: 300k-1 mln€				-0.234*** (0.008)	-0.342*** (0.009)
total exposure: 1-5mln€				-0.218*** (0.011)	-0.402*** (0.012)
total exposure: >5 mln €				-0.256*** (0.019)	-0.514*** (0.020)
partially collateralized	0.062*** (0.008)	0.095*** (0.008)	0.116*** (0.008)	0.112*** (0.008)	0.130*** (0.008)
totally collat. (no mortgage)	-0.035* (0.018)	-0.021 (0.018)	-0.012 (0.018)	-0.016 (0.018)	-0.008 (0.018)
totally collat. (mortgage)	-0.117*** (0.009)	-0.053*** (0.009)	-0.030*** (0.009)	-0.028*** (0.009)	-0.003 (0.009)
log amount loaned	0.491*** (0.009)	0.476*** (0.009)	0.493*** (0.009)	0.504*** (0.009)	0.465*** (0.009)
sq log amount loaned	-0.012*** (0.000)	-0.012*** (0.000)	-0.013*** (0.000)	-0.012*** (0.000)	-0.010*** (0.000)
other medium/big groups	-0.152*** (0.004)	-0.166*** (0.004)	-0.174*** (0.004)	-0.162*** (0.004)	-0.169*** (0.004)
small groups	-0.375*** (0.004)	-0.396*** (0.004)	-0.404*** (0.004)	-0.395*** (0.004)	-0.402*** (0.004)
foreign groups	-0.799*** (0.013)	-0.843*** (0.013)	-0.859*** (0.013)	-0.836*** (0.013)	-0.849*** (0.013)
cohort_ 2006	0.068*** (0.009)	0.050*** (0.009)	0.046*** (0.009)	0.052*** (0.009)	0.046*** (0.009)
cohort_ 2007	0.253*** (0.009)	0.226*** (0.009)	0.220*** (0.009)	0.229*** (0.009)	0.220*** (0.009)
cohort_ 2008	0.409*** (0.009)	0.377*** (0.009)	0.368*** (0.009)	0.380*** (0.009)	0.370*** (0.009)
cohort_ 2009	0.556*** (0.009)	0.522*** (0.009)	0.513*** (0.009)	0.535*** (0.009)	0.528*** (0.009)
cohort_ 2010	0.65*** (0.009)	0.620*** (0.009)	0.614*** (0.009)	0.636*** (0.009)	0.633*** (0.009)
cohort_ 2011	0.782*** (0.009)	0.753*** (0.009)	0.749*** (0.009)	0.769*** (0.009)	0.768*** (0.009)
cohort_ 2012	0.78*** (0.009)	0.752*** (0.009)	0.748*** (0.009)	0.767*** (0.009)	0.766*** (0.009)
cohort_ 2013	0.71*** (0.009)	0.691*** (0.009)	0.689*** (0.009)	0.708*** (0.009)	0.712*** (0.009)
cohort_ 2014	0.658*** (0.009)	0.644*** (0.009)	0.643*** (0.009)	0.660*** (0.009)	0.667*** (0.009)
cohort_ 2015	0.422*** (0.009)	0.424*** (0.009)	0.427*** (0.009)	0.444*** (0.009)	0.457*** (0.009)
cohort_ 2016	0.055*** (0.012)	0.074*** (0.012)	0.078*** (0.012)	0.098*** (0.012)	0.114*** (0.012)
Sector dummy (Ateco 2dgt)	YES	YES	YES	YES	YES
Province dummy	YES	YES	YES	YES	YES
Corporate type	YES	YES	YES	YES	YES
$\sigma$	1.294*** (0.002)	1.289*** (0.002)	1.287*** (0.002)	1.287*** (0.002)	1.284*** (0.002)
Subjects	1,078,652	1,078,652	1,078,652	1,078,652	1,078,652
Numbers of failures	275,343	275,343	275,343	275,343	275,343
Observations	3,773,142	3,773,142	3,773,142	3,773,142	3,773,142

## Methodological Appendix

In this paper we use data drawn from the Italian Central Credit Register (CCR) concerning loans to non-financial firms that were first classified as bad by banks between 2005 and 2016. We cannot consider the previous period because data about write-offs and sales on the market are not available. Firms whose debts were already classified as bad at the beginning of 2005 are excluded. For banks belonging to banking groups we consider the overall exposure of the firm towards the group and make reference to the banking group's composition at the end of 2016.

A loan classified by a bank as a bad debt at time  $t$ , at time  $t+x$  can be alternatively: a) still classified as a bad debt; b) still reported by the bank to the CCR but no longer classified as bad; c) closed after a standard work-out procedure and written off; d) closed after a standard work-out procedure without it being recorded as a loss; or e) sold on the market. Given the information recorded in the CCR, we can always observe cases a), c), d) and e). We can also observe case b) unless the bank no longer reports the loan because the exposure fell below the recording threshold (€75,000 until December 2008 and €30,000 thereafter) that applies only to credit other than bad loans. However, this circumstance is not common in our dataset. Also in the event of the sale of bank branches, loans are no longer reported by the originating banking group.

In the event of a merger, we identify the positions that are 'technically' closed by the target bank (bank A) and opened by the acquirer (bank B). To avoid overestimating both new debts and closed positions, we consider bank A as having been acquired by bank B for the whole reference period and aggregate the positions at banking group level making reference to the composition of the groups at the end of 2016. Given that we cannot trace mergers among financial intermediaries, we exclude loans reported by these entities.

Positions involved in sales on the market are also 'technically' closed by the selling bank and opened by the acquiring one. We consider positions involved in infra-group sales as having been continuously held by the banking group. The CCR does not indicate which bank acquired a loan sold by another bank; we reconstruct this information using an indicator that signals whether a bank has acquired a loan from or sold a loan to a given firm. Exploiting this indicator, we reconstruct every sale by matching, for each firm, new loans reported by a bank and loans closed by another bank at the same date. Furthermore, given that banks can sell loans to intermediaries that do not participate in the CCR (for example, foreign institutions), extra-group sales also include positions for which we observe the following conditions: a) at the beginning of the reference quarter, the originating bank reported the loan as a bad debt; b) at the end of the reference quarter, the originating bank did not signal the loan; c) during the reference quarter the indicator signaling that the bank sold the loan is flagged; and d) a new bad debt for another intermediary and the corresponding flag signaling the acquisition is not observed during the reference quarter.

We also identify the sale of bank branches among banks not belonging to the same group. As described above with mergers and infra-group sales, the sale of bank branches leads to a 'technical' closure for the selling bank and a 'technical' opening for the acquiring one.

However, unlike market sales of individual loans, sales of bank branches are not reported to the CCR. We therefore reconstruct these operations by assuming that the sale of a bank branch has occurred if a loan that is not signaled by a bank at the beginning of a given quarter is signaled as a bad debt at the end of the quarter and at least one of the following conditions is met: a) the new report is not caused by a merger operation; b) the value of the position, gross of provisions, is above the CCR reporting threshold. These positions (banking group/firm pairs) represent 4 per cent of the total number of positions reported to the CCR and are excluded from our dataset.

Finally, we used the following **definitions at banking group level**:

- **Bad loan:** for each quarter, we consider the overall exposure of the firm towards the group classified as bad if at least one bank in the group classifies its credit as bad.
- **Date on which the loan was first classified as bad (cohort or vintage):** the first date on which any member of the group classified the loan as such.
- **Losses:** for each quarter, we consider that the group writes off the exposure if at least one member writes-offs the position.
- **Positions still classified as a bad loan:** at the end of each year of the reference period, we consider the position still classified as bad by the group if at least one member classifies it as bad.
- **Sales on the market:** for each quarter, we consider the position sold on the market by the group if at least one member sold it to an intermediary not belonging to the same group.
- **Other closures:** positions no longer classified as bad for reasons other than write-offs and sales on the market, as of the quarter during which all the banks of the group stop classifying it as bad.