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FEMALE ENTREPRENEURS IN TROUBLE: DO THEIR BAD LOANS LAST LONGER?

by Juri Marcucci* and Paolo Emilio Mistrulli*

Abstract

We investigate the duration of bad loans for a unique data set of sole proprietorships in Italy, finding that bad loans for female firms last longer. However, this result is mainly due to the fact that loans granted to female firms are less frequently written off than those to male ones, suggesting that for banks female firms might be more creditworthy than male firms. These findings are robust to censoring, alternative specifications of the distribution of bad loan duration and other bank-specific control variables.

JEL Classification: C41, G21, G33.
Keywords: duration of bad loans, default status, survival analysis.

Contents

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* Bank of Italy, Economic Research and International Relations.

1 Introduction[1]

Credit risk encompasses a wide set of factors: the loss given default (LGD), the probability of default (PD), and the time needed for loan resolution. So far the debate in the credit risk literature has mostly been focused on the PD and the LGD, while much less is known about what happens once a loan becomes non-performing and in particular about the time it takes for banks to get rid of bad loans. Two notable exceptions are Dermine and Neto de Carvalho (2006, 2008) who rely on mortality analysis tools to investigate credit risk and in particular LGD by using data on loan losses obtained by one Portuguese bank. More recently Bonfim et al. (2012) look at the duration of financial distress and the ability of firms to re-access the credit market after default has been resolved.

In this paper we investigate the drivers of bad loans' duration. The duration of bad loans status, that by borrowing from biostatistics we can define as a kind of 'illness', depends on several factors. First of all, the ability of banks to get rid of bad loans depends on the degree of creditors protection and on judicial efficiency. These factors have important effects on the functioning of the credit market as shown by Jappelli, Pagano and Bianco (2005) suggesting that credit availability negatively correlates with judicial efficiency. Second, the duration of loan "illness" depends on banks' behavior. Banks may indeed ask borrowers for pledging collateral and, in that case, for some specific collateral, which may fasten the process of repossessing it. More in general, when borrowers are insolvent banks have to evaluate pros and cons of alternative recovering actions. In some cases the cost of loan contract enforcing expected by banks might be so high that banks write-off bad loans very quickly. Indeed, on the one hand, banks benefit from terminating bad loans early since by the time onwards they are not suffering any further costs related to the management of the foregone bad loans. The costs banks may incur are not only those related to the judicial process, i.e. legal costs, but also those related to asset substitution effects and to unexpected changes in the value of collateral. On the other hand, resolving bad loans early, which typically means selling or writing a loan off, entails quite often some credit losses. Third, the ability of banks to get rid of bad loans may depend on the nature of default. Indeed, a borrower may default because he is unable to pay (accidental default) or he is unwilling to pay (strategic default) and it seems reasonable to argue that, in the latter case, banks have less chance to be successful with their recovery actions.

In this paper we also explore whether the gender of insolvent borrowers affects the resolution of bad loans. Gender differences may affect both the behavior of banks and borrowers and then the time needed for bad loan resolution. This is in line with an expanding strand of literature on gender and banking investigating whether gender matters

[1]A previous version of this paper was presented at the conference "Women and the Italian Economy" organized by the Bank of Italy, held in Rome on March 7th, 2012. We would like to thank Magda Bianco, Francesca Lotti and Roberta Zizza for their comments on earlier versions of the paper. The views expressed are those of the authors and do not necessarily reflect those of the Bank of Italy. Emails: juri.marcucci@bancaditalia.it (Juri Marcucci, corresponding author), paoloemilio.mistrulli@bancaditalia.it (Paolo Emilio Mistrulli).

in the market for credit (e.g. Alesina et al., 2013; Beck et al., 2010; Beck et al., 2012; Bellucci et al., 2010). In general, the evidence suggests that banks are less prone to lend to female-run firms compared to other borrowers. Our paper complements previous contributions by investigating one of the determinants of credit risk, i.e. time in default. Comparing male versus female loan performance is crucial to assess whether banks have a taste for discrimination against women or it is just a matter of differences in default risk.

To this aim we use detailed information from the Italian Central Credit Register run by the Bank of Italy concerning loans which became non-performing after January 1997 and then tracking their changes of status until October 2010. In line with Alesina et al. (2013) we look at micro-firms (sole-proprietorships) since for those firms the identification of the entrepreneurs' gender is simply obtained by their tax code.

From a financial stability perspective, it is important to analyze the duration of bad loans and its drivers. Managing non performing loans implies some operating (e.g. employees dedicated to managing bad loans) and legal costs. At the same time, it is important to investigate how bad loans exit from their bad status. Indeed, it makes a lot of difference whether bad loans are paid back, sold to other financial intermediaries, securitized or written-off.

We find that the duration of bad loans granted to female firms is longer compared to male ones. However, this is mainly due to the fact that banks are less prone to write-off loans granted to female entrepreneurs. This is consistent with the view that banks' expectations about bad loan recovery for female businesses are better compared to those referred to males, otherwise they would not be willing to keep loans to female on their balance-sheets for longer. Consistently with this view, we also find that, among those firms that become solvent after being non-performing, female businesses tend to exit from their bad status much faster than males.

The paper is organized as follows: Section 2 describes the econometric approach to the analysis of duration data, while Seciton 3 illustrates the features of our dataset. In Section 4 we discuss the models employed and present the main empirical results. Finally, Section 5 gives some concluding remarks.

2 Duration models

We model the duration of bad loans as a time-dependent event using a hazard model that explicitly takes into account the timing of exit from the default status over the life of the bad loan.

We compute the number of months (duration) starting from the time a loan enters the bad status to the time it exits. Such exit may occur in different ways: a bad loan becomes a) performing or it is either b) sold, c) securitized, d) written off, or e) paid back.

We assume that the time to the exit from the default status is a realization of a random process in which the event time T (i.e. the end of the default status) is a random variable having a probability distribution. The probability distribution of the random variable T can be characterized by the cumulative distribution function $F(t) = \Pr(T \leq t)$. Alternatively, and more commonly the probability distribution can be characterized by the survivor function:

$$S(t) = \Pr(T > t) = 1 - F(t) \tag{1}$$

where t is time, $S(t)$ the survivor function, $\Pr(T > t)$ the probability that the timing of the event T is greater than some value t, and $F(t)$ is the cumulative density function, with a corresponding probability distribution function (pdf) denoted as $f(t)$, that represents the probability that the event time will be less than or equal to any value t.[2] These three formulations are mathematically equivalent so that one can be easily obtained from the others. However, they highlight different aspects of the bad loan lifetime. Put more simply, the survivor function identifies probability as default status survives (i.e. persists) after time t.

Alternatively, we can describe the same distribution of time to exit from default status using a hazard function (Kiefer, 1988). The hazard rate is a measure of the probability that a loan will default in time t, given that it has survived until that time. The hazard function is defined as:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t | T \geq t)}{\Delta t} = \lim_{\Delta t \to 0} \frac{F(t + \Delta t) - F(t)}{\Delta t S(t)} = \frac{f(t)}{S(t)} = -\frac{d \ln S(t)}{dt} \tag{2}$$

where $\Pr(\cdot|\cdot)$ is the conditional probability that the event takes place between t and $t + \Delta t$ as Δt approaches zero, and $F(t)$, $f(t)$, and $S(t)$ are as defined above. In this way we can quantify the instantaneous risk that an event will occur at time t.

We adopt some parametric regression models using three of the most common lifetime distributions. The typical starting point is the exponential distribution which has a constant hazard rate γ that does not vary with t (memoryless property). From equation (1) $S(t) = \exp(\int_0^t \gamma du) = \exp(\gamma t)$. In general the exponential distribution is too restrictive so we also adopt the more general and flexible Weibull distribution function which has a hazard $\lambda(t) = \gamma \alpha t^{\alpha - 1}$. This hazard is monotonically increasing if $\alpha > 1$ and monotonically decreasing if $\alpha < 1$ allowing for a great degree of flexibility. This is a special case of the proportional hazards (PH) family in which the hazard $\lambda(t)$ factors into a baseline component $\lambda_0(t)$ and a term γ that can be parameterized as a function of covariates only. The third distribution we use is the Gompertz distribution which has a hazard $\lambda(t) = \gamma \exp(\alpha t)$ and a survivor function $\exp(-(\gamma/\alpha)(e^{\alpha t} - 1))$. The Gompertz distribution is similar to the Weibull in that it has a hazard function that is monotonically increasing if $\alpha > 0$ or monotonically decreasing if $\alpha < 0$, with the exponential distribution as a special case ($\alpha = 0$). We decided to adopt the Gompertz distribution because it is usually the right model for mortality data and in fact it is more often used in biostatistics rather than in econometrics. All these models can be classified as PH models.

[2]The pdf is defined as $f(t) = dF(t)/dt$, where $F(t) = \int_0^1 f(s) ds$. Furthermore, $dS(t)/dt = -f(t)$.

A common problem in estimating survivor and hazard functions is the number of right censored observations. These occur when an item has "not failed" after the period of observation, which in our case corresponds to a bad debt that has neither become performing nor securitized, sold, written off or paid back. To introduce regressors one usually lets $\gamma = \exp(x'\beta)$ with α and σ^2 left constant. Typically the main issue in parametric modeling is the correct model specification for consistent parameter estimates.

Let T^* denote durations without censoring, with conditional density $f(t|x, \theta)$, where θ is a vector of parameters to be estimated and x are the regressors that can vary across subjects but do not vary over the spell for a given subject. The overall estimation is complicated by the presence of censoring that calls for a treatment similar to the Tobit model. For uncensored observations the contribution to the likelihood is $f(t|x, \theta)$. For right-censored observations we only know that the duration exceeded t, thus their contribution is

$$\Pr[T > t] = \int_t^\infty f(u|x, \theta)du = 1 - F(t|x, \theta) = S(t|x, \theta) \tag{3}$$

where $S(\cdot)$ is the survivor function. The density for the i-th observation becomes

$$f(t_i|x_i, \theta)^{\delta_i} S(t_i|x_i, \theta)^{1-\delta_i} \tag{4}$$

where δ_i is the right-censoring indicator with $\delta_i = 1$ if the subject is not censored and $\delta_i = 0$ if the subject is right-censored. Taking logs and summing, we find that the MLE $\hat{\theta}$ maximizes the log-likelihood

$$\ln L(\theta) = \sum_{i=1}^{N} [\delta_i \ln f(t_i|x_i, \theta) + (1 - \delta_i) \ln S(t_i|x_i, \theta)] \tag{5}$$

where we assume independence over i. The first term corresponds to the completed spells while the second one to right-censored spells.

3 Data

3.1 Sources

While there is no internationally recognized definition of "woman entrepreneur" or "female-run firm", the definition used by countries to disseminate data on male and female entrepreneurship includes concepts such as owners, managers, the self-employed and employers. For the purposes of the present paper, we rely on sole proprietorship firms because in this case it is more straightforward to identify the owner's gender. The data used in our analysis come from the Central Credit Register ('Centrale dei Rischi') run by the Bank of Italy, containing detailed information on firms and individuals whose loans are above the threshold level of Euro 75,000 (reduced to Euro 30,000 since January 2009). However, bad loans are reported without any threshold meaning that we are able to observe the whole population of bad loans granted to sole proprietorships in Italy.

Data are collected monthly from January 1997 through October 2010 and refer to each bank-firm relationship. We record the first time a loan was reported as bad and we follow it until it exits from the 'bad loan' status either because the debtor becomes solvent and pays back the loan or the bank grants him a new (performing) loan or, alternatively, the bad loan is i) securitized; ii) sold to another bank or financial institution or iii) written off, which typically implies some losses for the lender.

We start with a dataset containing 784,778 bank-firm relationships for 318,659 firms and 1,078 financial intermediaries (both banks and other credit intermediaries). We clean the dataset by dropping those observations that have incomplete records remaining with 538,759 bank-firm relationships for the sample from January 1997 through October 2010. Moreover, since the Central Credit Register records the type of exit from the bad loan status only from 2005 onwards, we form a second smaller dataset for the period January 2005 through October 2010 (we refer to it as the 'short sample') where we have 254,236 bank-firm relationships, for 138,324 firms and 859 credit institutions. For this sub-sample information on the way bad loans terminate is available. In particular, we focus on the following cases: i) bad loans become performing again ($EXIT\ 1 = 1$), ii) they are written off ($EXIT\ 2 = 1$), iii) they are paid back ($EXIT\ 3 = 1$), iv) ($EXIT\ 4 = 1$) bad loans either become performing or are paid back, and v) ($EXIT\ 5 = 1$) other exits (they include loan sales and securitizations).

3.2 Summary Statistics

In Table 1 we define all the variables used in the empirical analysis. We have three firm-specific variables: *Gender* is a dummy variable that takes value 1 if the entrepreneur is a woman, 0 otherwise; *Sector* is a full set of seven sectorial dummies (Manufacturing, Construction, Wholesale and Retail trade, Hotel and Restaurants, Transportation and Communication, Financial and Insurance activities, and Professional, Scientific, Technical and Real Estate activities). *Area* is a full set of dummy variables for the geographical areas of Italy (Center, Islands, North East, North West and South) where firms are headquartered.

Among the bank-specific variables, the dummy *Bank* equals 1 if the lender is a bank and 0 for non-bank financial institutions. *Bank_Size* takes value 1 for "major" banks (total assets greater than 60 billion euro), 2 for "big" banks (between 26 and 60 billion euro), 3 for "medium" banks (between 9 and 26 billion euro), 4 for "small" banks (between 1,3 and 9 billion euro), 5 for "minor" banks (less than 1,3 billion euro), 6 for foreign banks' branches. *Start_date* and *End_date* are respectively the date in which the loan is recorded as 'bad' and the date in which the loan exits from the bad status. *Cohort* represents the first year the loan has become bad, *Amount* is the value of the bad loan in log of euro. *Exit_type* takes five values depending on the type of exit from the bad loan status and $EXIT\ j$, $j = 1, 2, 3, 4, 5$ is a dummy variable indicating the type of exit.[3] $D\_mortgage$ is a dummy variable that takes value of 1 if loans are guaranteed by a mortgage and zero otherwise. $D\_postcrisis$ is a dummy variable that takes the value of 1 if loans have become bad after the beginning of the financial crisis and 0 otherwise.

Table 2 classifies the bad loan in our sample by their observed duration. The first column shows the observed duration in months. The second column lists the cumulative distribution of all bad loans sorted by the number of months each bad loan survives in our sample. The third and fourth column show the same distribution of bad loans across owner gender, the fifth and sixth report, respectively, loans backed by a real guarantee (Mort.) and those without (No Mort.). From the seventh to the tenth column we list the distribution of the duration of bad loans broken down by gender/presence of real guarantee: female firms are reported in the first two columns (F/Mort.,F/No Mort.), male firms in the ninth and tenth one (M/Mort.;M/No Mort.). We have two panels in the table. The upper one is based on the whole sample and it refers to a non-specified type of exit from the bad loan status. The bottom one is instead referred to write-offs and, given that this information is available since January 2005, it is based on a shorter sample. We focus on this specific type of exit since it is clearly a case in which "illness" turns out into "death", i.e. into loan losses for banks.

The median duration of all bad loans in our sample is 41 months which is lower, even if we are looking at a shorter sample period, compared with the case of write-offs (49 months) indicating that banks tend to first resort to other ways to be paid back and only in case they expect a relatively high loss given default they write-off part or all the loan exposure. Looking across owner gender, we notice that there are no big differences in the duration of bad loans between female and male firms when the exit is generic (49 per cent of all bad loans do not extend beyond the two years). Interestingly we find some differences when we take into account whether borrowers are backed or not by real guarantees. In that case, we see that female firms backed by a real guarantee (F/Mort.) exhibit a shorter persistence in a bad shape compared to their male counterparts (M/Mort.). On other hand, for both female and male borrowers we find that the duration of bad loans is longer when they are backed by real guarantees compared to the case in which they are not, consistently with the hypothesis that banks expect a lower loss given default from secured loans and then try to be paid back for a longer time. It is also interesting to note that, for unsecured bad loans, we do not observe any differences across gender.

Some differences across gender are observed when we concentrate on write-offs. In this case, the duration of bad loans granted to female firms is greater than the one computed for male firms. The median duration of bad loans to female firms is 50 months and therefore slightly longer than that for male firms (49 months) and consistently we observe that 58 per cent of bad loans to female firms do not survive after the second year, while this happens for 60 per cent of bad loans to male ones. The longer duration observed

[3] $EXIT\ 1 = 1$ if bad loans become performing; $EXIT\ 2 = 1$ if bad loans are written off; iii) $EXIT\ 3 = 1$ if bad loans are paid back; iv) $EXIT\ 4 = 1$ if bad loans either become performing or are paid back; and v) $EXIT\ 5 = 1$ if bad loans are either sold or securitized.

for female firms is mainly due to unsecured bad loans that exhibit a longer duration for female borrowers (49 months) compared to male ones (47), while the opposite is observed for secured bad loans (respectively, 61 and 63 months). In general, bad secured loans last longer (63 months) than unsecured ones (47), confirming the evidence found for the whole sample on a generic exit type. This suggests that banks tend to go on with legal actions for longer in case of secured loans since their expections on the loss given default are less pessimitic when loans are backed by a real guarantee.

Table 3 shows the gender decomposition of our data by regions of Italy (North-East, North-West, Center and South) both across firms and bad loans for the full sample (January 1997 through October 2010). The fraction of female-owned businesses is about 21% of the total, and the fraction of non-performing loans for these businesses is slightly less, at 20%. This may hint at the possibility that female firms are more creditworthy, especially if we recall that one firm out of four is female-run, according to the business register. Interestingly, the share of female businesses which have at least a bad loan with one bank within the Italian financial system is very similar between the North and the South of Italy and the geographical distribution of shares is similar. However, we have to notice that even though there are more firms in the more populated North of Italy, the total number of firms (and bank-firm relationships) characterized by a bad loan is much higher for the South of Italy.[4] Note that the female entrepreneurial rates are especially large in the South compared to labor participation rates. In any event, our results are not driven by observations in the South.

Table 4 shows the gender decomposition by type of exit from the bad loan status for the short sample (January 2005 through October 2010) where we have information on the type of exit. As we can see, the distribution across exit types is rather similar both in terms of loans and in terms of firms. For bad loans that go back to a performing status ($EXIT\ 1 = 1$), the percentage of female businesses is around 24%. For those bad loans that are written off ($EXIT\ 2 = 1$), paid back ($EXIT\ 3 = 1$), either paid back or became performing ($EXIT\ 4 = 1$), either securitized or sold ($EXIT\ 5 = 1$), the percentage of female businesses is around 21%. These percentages are not too far away from the 21-22% for the full sample, but they show that in general bad loans from female businesses are slightly more likely to become performing. We should also notice that bad loans which become performing are much less than those sold, securitized, paid back or written off.

Table 5 illustrates the sectorial composition of the Italian 'bad' borrowers by gender for the full sample. In line with Alesina et al. (2013), we find that women and men are not distributed evenly in all sectors; women are almost non-existent in Construction, but make up around a third of the Tourism industry, the industry that comprises Professional, Scientific, Technological and Real Estate activities and the Wholesale and Retail one. Needless to say, in our regression below we control for sectors using sectoral fixed

[4] For the short sample the fraction of female-owned businesses is similar to the full sample (about 21% of the total), and the fraction of bad loans for these businesses is again similar, at 21%. We have decided not to report these results for the sake of brevity but they are available from the authors upon request.

effects. Notice that both in terms of firms and bad loans, Construction, Manufacturing and Wholesale and Retail trade are the most populated sectors.[5]

Table 6 depicts the gender distribution across sectors and cohorts for the full sample. We can notice some variation across cohorts in the distribution between owner's gender but nothing noteworthy. Female firms again make up around a third of the Tourism industry, the industry that comprises Professional, Scientific, Technological and Real Estate activities and the Wholesale and Retail one even across the different cohorts of bad loans. The same happens for the short sample where the exit is given by a write off.

Table 7 illustrates the median and average (both restricted and unrestricted) duration of bad loans for the full sample, for relationships with banks only or non-banking financial institutions and, within these two groups, for bad loans under the threshold (i.e. those that, before entering the bad status, were not recorded in the Credit Register because the loan amount was below the recording threshold of euro 75,000 until December 2008 and 30,000 afterwards) and above it (i.e. the higher loans). We can notice that in median terms in the overall sample the median duration of bad loans is around 41 months with no differences across gender. We also notice that when loans are granted by banks the median duration of bad loans is around 35 months for both female and male firms. Instead, with other financial institutions (non-banks) the median duration increases substantially at 62 months for female and 60 for male businesses. It is important to note also that small loans (those with an amount under the recording threshold for the CR) tend to stay less in bad status with respect to larger ones. Actually, for banks, the median duration of small non-performing loans is 32 months for female firms and 31 months for male firms, while for large bad loans the median duration is 39 months for female and 38 for male businesses. Across sectors, for banks there are not so many differences in the median duration (which is between 34 and 37 months), except for industries such as Financial & Insurance, Transportation & Communication and Professional, Scientific, Technological and Real Estate (with median durations between 31 and 34 months). On the contrary, for non-bank financial institutions the median duration across sectors is always between 52 and 66 months, except for the Transportation & Communication sector where the median duration is around 40 months.[6]

We also test for the equality of the survivor across gender using typical tests such as log-rank, Wilcoxon, Tarone-Ware and Peto-Peto. The main finding is that survivor in the bad loan status is significantly different across entrepeneurs' gender. This holds also for loans granted by banks but only for the more populated sectors.

[5] Similar results also hold for the sectorial decomposition by gender over the short sample (available upon request).

[6] This substantial difference between banks and non-bank financial intermediaries could be due to the fact that among the latter there are some bad banks.

4 Empirical Results

Before turning to the cross-sectional estimates of the hazard functions, we first run a round of non-parametric estimates of the survivor functions using the Kaplan-Meier estimators. These estimates are useful to plot the distributions of bad loan spells. Figure 1 depicts the estimated survivor functions, $S(t) = \Pr[T \geq t]$. The plot illustrates the differences among cohorts between the spell duration of bad loans to female and male businesses. In general, it seems that the exit of loans entered in a bad status during the crisis tends to slow down compared to older cohorts. We can also notice that there are some differences between female and male entrepreneurs for the last three cohorts in the full sample (i.e. 2007, 2008 and 2009): female firms seem to persist longer in their bad status. Similarly, Figure 2 shows the estimated survivor functions for the short sample by cohort when the exit is a write off. We notice that the survivor functions tend to be slightly different for male and female firms from the cohort of 2007 onwards.[7]

Table 8 shows the estimated results from the Cox proportional hazard model and some other parametric models (Exponential, Weibull and Gompertz) for the full sample with generic exit. The table depicts the estimation results for the four distributions of the basic model on the left (specifications from 1a to 4a) and those of the basic model plus the dummy for those loans which became bad after the recent crisis (specifications from 1b to 4b). We can notice that female firms stay longer in a 'bad loan' status compared to male ones. In fact, the hazard for female businesses is from 3 to 4% significantly lower compared to that of male ones in all models. This result is robust to alternative specifications and distributional hypotheses. As far as other covariates are concerned we find that firms' total amount of bad debt ($Amount$) reduces the hazard between 16 and 18% over the baseline one. This is consistent with the view that for larger loans banks recovery costs are lower and then banks tend to prosecute with legal actions for longer until they write-off all or part of the firms' debt. We also find that when bad loans are backed by real guarantees ($D\_Mortgage = 1$) they exit faster from the bad status. This result suggests that real guarantees are more easily seized by creditors compared to other types of collateral or that creditors are more prone to pay back their debt in case they have posted a real guarantee. We have also tested whether the effect of real guarantees depends on borrower gender. Indeed, we find that in that case, contrary to the result we found on average for female firms, female borrowers backed by a real guarantee stay shorter in bad status. This could be due to the fact that female businesses are more prone to repay their bad debts to avoid that banks could seize their collateral, in line with the most recent experimental evidence on the different behaviors of males and females toward risk (Jianakoplos and Bernasek, 1998; Schubert et al., 1999; Eckel and Grossman, 2008; Croson and Gneezy, 2009). For sectors such as Transportation & Communication, Financial & Insurance and Professional, Scientific, Technological and Real Estate the

[7] Additional figures available upon request from the authors show similar differences across gender that can be even higher for particular cases or sectors. This indicates that there are some differences in the duration of bad loan spells across owners' gender.

hazard increases between 2 and 14%. On the contrary, for Wholesale & Retail and Hotel & Restaurants the hazard slightly decreases with respect to the baseline. Regarding the area where borrowers are headquartered our results confirm that in the North, due to a higher judicial efficiency (Banca d'Italia, 2008), the duration of bad loans is, everything being equal, around 10% shorter compared to the Center and even more compared to the South where it takes longer for banks to resolve loan defaults. Looking at the size of lenders we find that foreign bank branches are able to get rid of bad loans much faster than other intermediaries. However, this result might be due to the very low number of sole proprietorships that borrow from those banks, that are typically more oriented to corporate borrowers instead of retail ones. Moreover, we find that small banks tend to get rid of bad debts faster than larger banks.

One potential objection to the results we obtain about the longer duration in bad status of loans granted to female firms is that this might be due to the crisis and, in particular, to the fact that banks could have unevenly passed through the financial shocks to their customers. According to Cesaroni et al. (2012), banks would have tightened credit conditions more intensively for female than for male businesses. To this aim we have defined a dummy variable related with the time a loan starts not being performing. $D\_postcrisis$ equals 1 if loans became bad during the crisis, i.e. after July 2007, and 0 otherwise. When we include such dummy (models 1b to 4b) we obtain results similar to the previous ones indicating that loans to female firms stay longer in bad status compared to those to men (the hazard of the latter is 2% higher than the baseline).In general, we notice that those bad loans which entered in the bad status during the crisis tend to exit much faster than those entered in bad status before the crisis ($D\_postcrisis = 1$)

In Table 9 we report the estimation results from the Weibull model with the whole set of dummies and different interactions between gender and the other dummies. Our previous results are confirmed. We notice that loans to female firms stay longer in bad status compared to male ones: the hazard for female businesses is from 2 to 7% lower compared to that of male ones in all models. This result is robust to alternative specifications. Again firms' total amount of bad debt reduces the hazard by about 18% over the baseline. As before, the hazard for bad loans to borrowers headquartered in the North is, everything being equal, around 10% higher compared to the Center and even more if compared to the South and Islands. Across different specifications, small banks tend again to get rid of bad debts faster than larger banks. As we have found before for the full sample in the basic model, when bad loans are backed by real guarantees ($D\_Mortgage = 1$) banks tend to get rid of those loans faster. Looking at the various interactions with the *Gender* dummy we notice that there is no difference across gender with respect to the amount of bad debt. On the contrary, in case loans are backed by real guarantees female businesses exit faster from their bad loan status if compared to male firms. When we look at the interactions between bank size and gender we find that all types of banks tend to get rid of the bad loans to male businesses faster than those to female entrepreneurs, confirming that loans to female firms are kept longer in banks' balance sheets. Finally, as we can see from Tables 8 and 9 the fit of the Weibull model exhibits a positive state dependence ($\alpha > 1$), indicating that in all specifications the probability of the spell terminating increases as the spell lengthens. As far as female firms are concerned, the evidence that they stay longer in a default status does not trivially mean that female businesses are riskier than male ones. By using a metaphor coming from the medical science, we can liken a loan insolvency to a disease. Now, the fact that a disease persists may be a good or a bad news depending on how much dangerous is the illness. Indeed, in case of a trivial disease the fact that it resists to some treatment signals that it might be not so trivial as expected. On the contrary, in case of a potentially lethal disease, as firm insolvency is, the fact that the disease does not terminate might signal that the probability of healing is higher than expected. In our case, banks should always choose between terminating or holding a bad loan. In general, there are some pros and cons that have to be evaluated when taking such a decision. On the one hand, banks benefit from terminating bad loans early (i.e. pulling the plug) since by the time onwards they are not suffering any further costs related to the management of the bad loans exited. On the other hand, resolving bad loans early, which typically means selling or writing a loan off, entails some immediate credit losses. Thus, the fact that we observe female entrepreneurs staying longer in a bad status might be due to banks' better expectations in terms of their recovery rates compared to male firms so that it is worthwhile to persevere with legal actions to be at least partially paid back.

To assess this view we concentrate on the cases in which bad loans are written off banks' balance sheets. Indeed, write-offs are a good proxy for loss rates and then, in this way, we can test whether the longer duration of bad loans that we observe for female firms is due to a greater difficulty to be paid back or, at the opposite, to better expectations about their recovery rates. Since the information about the type of exit is available only for those bad loans resolved since January 2005 in what follows we focus on a sub-sample.

Table 10 presents the same results of Table 9 for the short sample with exit given by a write off ($EXIT\ 2 = 1$). Again, loans to female firms stay longer in a 'bad loan' status compared to male ones. In fact, the hazard for female businesses is from 4 to 6% lower than male ones. This result reinforces our view that female firms are better borrower than male ones. Indeed, the fact that banks take more time before writing off loans granted to female firms is consistent with less pessimistic expectations on their loss rates. Thus, banks tends to rely later on debt forbearance when a loan has been granted to a female borrower since the higher cost due to the continuation of enforcement actions are compensated by a higher expected recovery rate. The other results are similar to those presented for the full sample and will not be commented further. The only difference is that as expected bad loans backed by real guarantees present lower hazards, indicating that banks tend to go on for longer with enforcement actions before writing them off.

4.1 Unobserved heterogeneity and frailty models

In all the models considered so far, all the differences between individuals are captured by observed explanatory variables. In this section we allow for unobserved individual effects. In the presence of unobserved heterogeneity even individuals with the same values for all covariates may have different hazards. When unobserved heterogeneity is ignored, its impact might be confounded with that of the baseline hazard. This kind of models are usually called 'frailty' models in bio-medical sciences. In the estimates that follow we consider gamma frailty models where the unobserved heterogeneity is modeled multiplicatively assuming a gamma distribution.

Considering the possible implications of unobserved heterogeity, a picture similar to the one outlined so far arises. Table 11 depicts the empirical results for the Weibull model with and without gamma frailty and with gamma frailty shared by banks and firms for the full sample (1997-2010). The first thing to notice is that the introduction of unobserved heterogeneity has a substantial impact on the duration dependence parameter (α), which increases from 1.2 to 1.3/1.6. The latter implies a more steeply rising hazard rate out of the bad loan status.

The estimate of θ shows that there is intra-correlation within the same bank and the same firm but that within the same firm such correlation is much higher. The hazard for male businesses increases significantly between 2 and 5% indicating that their bad loans have shorter survival before the generic exit or before being written off. As before, higher amounts of bad debt reduce the hazard between 10 and 25%. In addition, the hazard increases significantly for the crisis period (cohorts from 2007 to 2010). The hazard is higher if there is a real guarantee on the bad loan except for the short sample case.

Tables 12 and 13 illustrate the results for the Weibull model with gamma frailty shared by firms for the full sample and the short sample, respectively. The estimate of θ shows that there is intra-correlation within the same firm in particular over the full sample. The results across gender still hold. In fact, the hazard for male entrepreneurs increases significantly indicating that their bad loans have a shorter survival before exiting for a generic exit or because they are written off. Again, the higher hazard for the dummy related to the post-crisis period indicates that as the effects of the financial crisis exacerbate banks are more prone to clean their balance sheet from bad loans.

4.2 Competing risks

We also check whether our previous results are confirmed when we estimate the duration of bad loans in a competing risk setting. By estimating competing risks models, we compare the effects of included covariates on the alternative probabilities to end the bad loan status. The only difference with respect to the previous case is that in the estimation of exits, all spells that end by exiting in a different way with respect to a specific exit considered (in this case a write off) are treated as being censored.

Tables 14 illustrates the same Weibull models estimated considering competing risks for the short sample. Actually, leaving as right censored the other exits, we considered as a possible exit the fact that a bad loan exits from a bank's balance sheet because it is written off ($EXIT\ 2 = 1$). Then we estimated the same model with the same distributional assumptions for the duration of bad loans, reporting only the results for the Weibull distribution. We can notice that when the exit is a write off (Table 14) the hazard for bad loans to male firms is still greater than one, suggesting that banks tend to keep longer bad loans to female businesses. The duration of bad loans is longer also for loans characterized by a larger amount. Those loans which became bad after July 2007 tend to be written off faster by banks' balance sheets. However, if the loan is backed by collateral banks tend to keep the bad loan longer. We should also notice that when interacted with bank's size, bad loans to male firms tend to exit from banks' balance sheets faster with respect to those to female firms.

In addition the state dependence is positive ($\alpha > 1$), suggesting that the probability of a bad loan to be terminated increases as the time elapses. Furthermore, small and minor banks seem to be faster in getting rid of bad loans from their balance sheets.

Therefore, it seems that when a bad loan is written off, female entrepreneurs are considered more creditworthy and their bad loans are kept on hold longer than those of male entrepreneurs.

All in all, these results seem to support our view that the reason why loans to female firms stay longer in bad status is that banks expect less losses in case of their default. Therefore, banks are willing to wait longer to be paid back, securitize, sell or write off a bad loan granted to a female firm with respect to the same loan granted to a male business.

5 Conclusion

Credit risk depends on several factors. Among them, a quite unexplored one relates to how successful are the enforcement actions banks rely on once loans do not perform anymore. In this paper, by using detailed data obtained from the Italian Credit Register, we investigate how long does it take for a bank to get rid of bad loans. In particular, we concentrate on Italian sole-proprietorships to assess whether firm owner's gender might affect the duration of bad loans.

We find that loans to female firms stay more in bad status compared to male ones. These findings are robust to censoring, alternative specifications of the distribution of bad loan duration and other bank-specific control variables. However, this has not to be necessarily interpreted as evidence supporting the view that female firms are riskier. In fact, we find that, in case loans are written-off, loans to female firms exit later from banks' balance sheet than those granted to male ones. This is consistent with the view that banks may expect to recover more from female firms and, as consequence, they persist with costly enforcement actions for longer in case they have granted a loan to a female firm.

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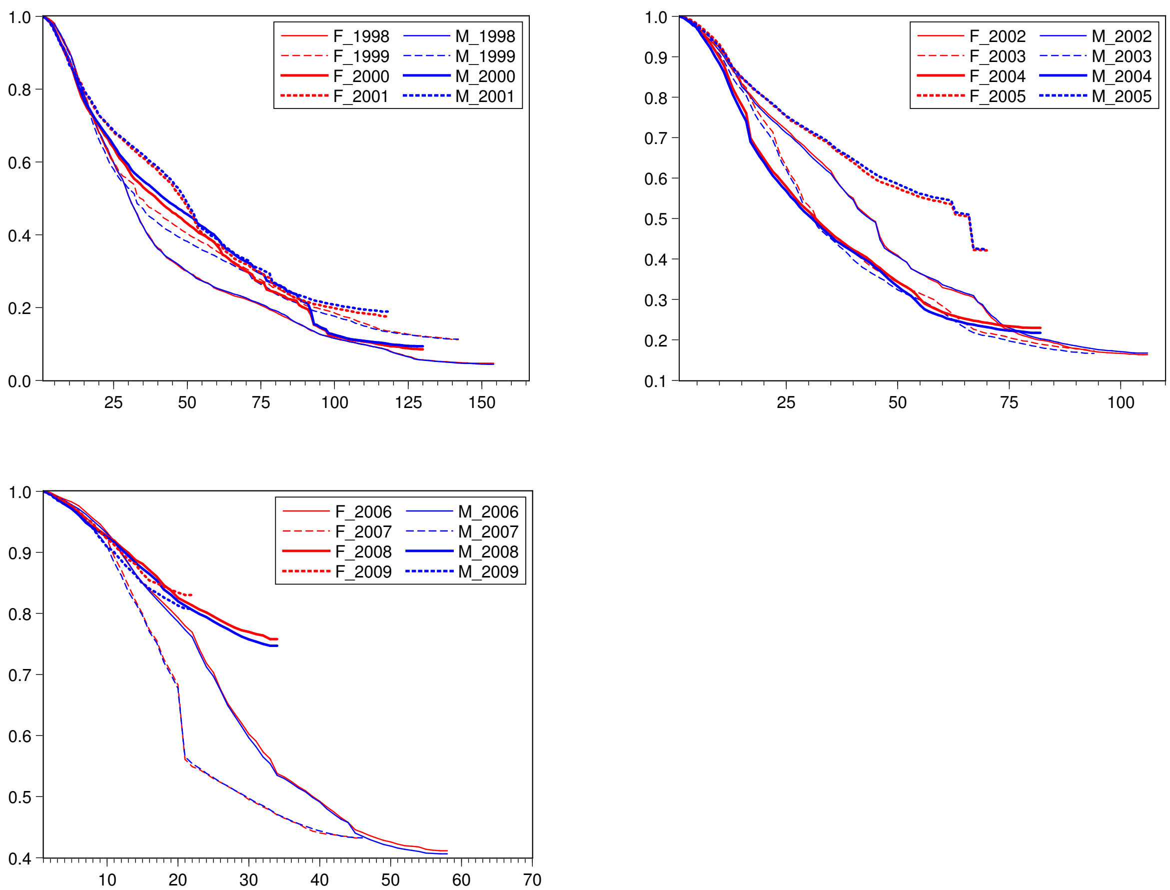
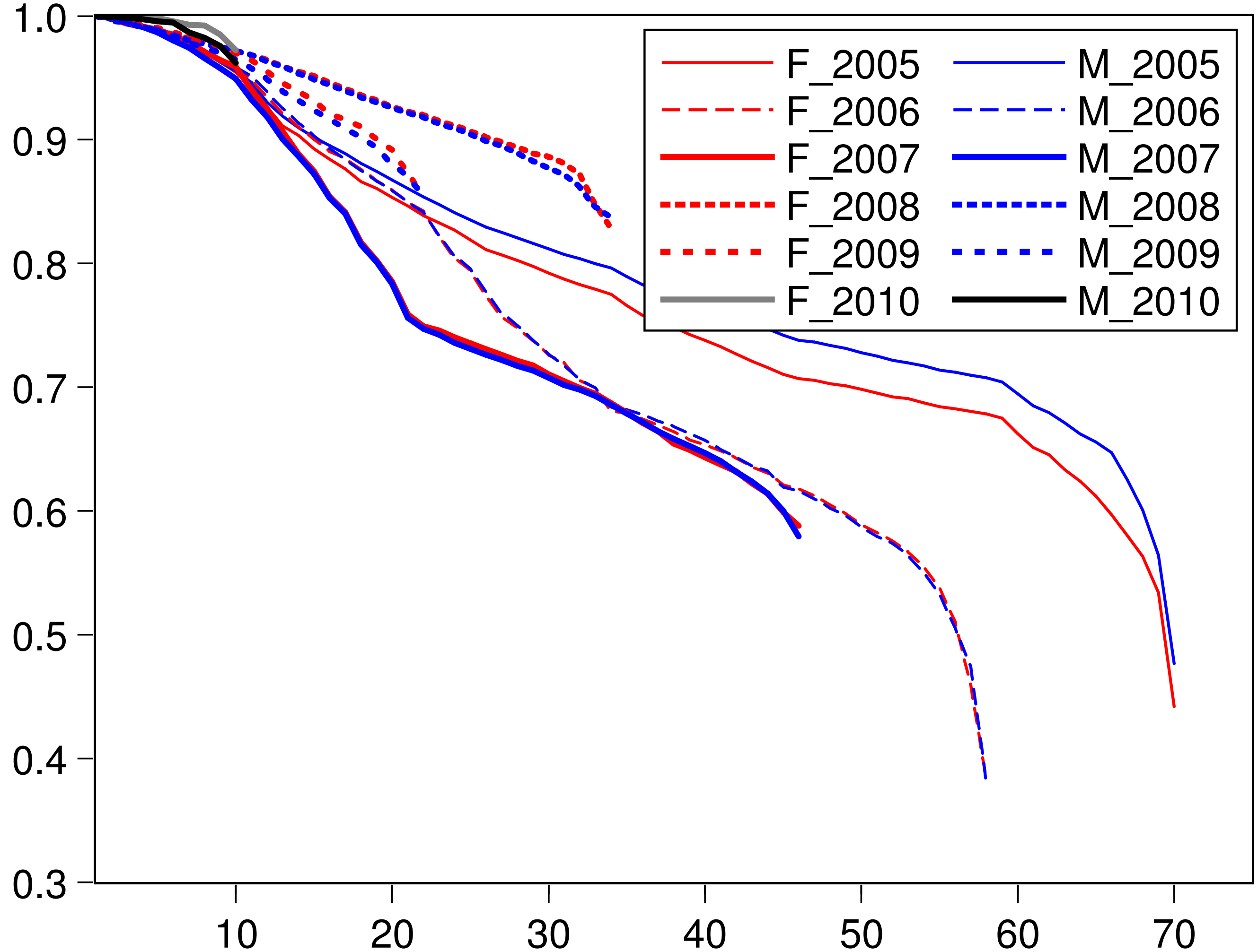
Figure 1: Kaplan-Meier estimates for all cohorts and all financial institutions (both banks and non-banks). Full sample: January 1997 through October 2010.



Notes: The figure depicts the Kaplan-Meier estimates of the survival functions for all cohorts (from 1998 through 2009) by gender (F=Female firm; M=Male firm) for bad loans by banks and non-banks.

Figure 2: Kaplan-Meier estimates by cohorts. Short Sample: January 2005 through October 2010.



Notes: The figure depicts the Kaplan-Meier estimates of the survival functions by cohorts and gender (F=Female firm; M=Male firm) for the short sample. Exit is a write off ($EXIT\,2 = 1$).

Table 1: Variable Names and Definitions

Firm specific variables	**Description**	**Source**
Gender	Dummy variable that takes value 1 if the owner's gender is female (2 if male)	Central Credit Register
Sector	Full set of seven sectorial dummies (Manufacturing, Construction, Wholesale & Retail, Hotel & Restaurant, Trasportation & Communication, Financial & Insurance Activities and Professional, Scientific, Technological activities)	Central Credit Register
Area	Full set of five geographical dummies (Center, Islands, North-East, North-West, and South)	Central Credit Register

Bank specific variables	**Description**	**Source**
Bank	Dummy variable that takes value 1 if the lender is a bank (0 if financial institution)	Central Credit Register
Bank_Size	Dummy variable for bank size that takes value 1 for major banks, 2 for big banks, 3 for medium banks, 4 for small banks, 5 for minor banks, 6 for foreign banks, 88 for financial institutions	Central Credit Register
Start_date	Date in which loan becomes 'bad'	Central Credit Register
End_date	Date in which loan exits the bad status	Central Credit Register
Cohort	First year loan becomes 'bad'	Central Credit Register
Amount	Amount of bad loans in logarithm	Central Credit Register
Exit_type	Type of exit from the 'bad loan' status	Central Credit Register
EXIT1	Dummy variable that takes value 1 if a bad loan exits because it becomes performing (0 otherwise)	Central Credit Register
EXIT2	Dummy variable that takes value 1 if a bad loan exits because it is written off (0 otherwise)	Central Credit Register
EXIT3	Dummy variable that takes value 1 if a bad loan exits because it is paid back (0 otherwise)	Central Credit Register
EXIT4	Dummy variable that takes value 1 if a bad loan exits because it is either paid back or becomes performing (0 otherwise)	Central Credit Register
EXIT5	Dummy variable that takes value 1 if a bad loan exits because it is either securitized or sold (0 otherwise)	Central Credit Register
D_Mortgage	Dummy that takes value 1 if loans are guaranteed by a mortgage (0 otherwise)	Central Credit Register
D_postcrisis	Dummy that takes value 1 if loans enter the bad loan status after July 9, 2007 (0 otherwise)	Central Credit Register
D_Threshold	Dummy that takes value 1 if loans are under the recording threshold in the Central Credit Register (0 otherwise)	Central Credit Register

Table 2: Distribution of observed duration of bad loans.

Observed duration	Bad loans terminated with a generic exit (1997-2010)								
(in months)	Total	F	M	Mort.	No Mort.	F/Mort.	F/No Mort.	M/Mort.	M/No Mort.
0 - 3	1.90	1.69	1.95	0.91	1.97	0.74	1.76	0.95	2.03
3 - 6	6.45	6.02	6.55	3.43	6.67	3.70	6.19	3.36	6.79
6 - 12	20.24	19.65	20.39	12.68	20.81	13.44	20.12	12.49	20.98
12 - 18	35.84	35.40	35.95	24.34	36.71	25.42	36.15	24.07	36.84
18 - 24	48.89	48.72	48.93	37.63	49.73	38.55	49.49	37.41	49.79
24 - 36	65.73	66.07	65.64	58.51	66.27	60.86	66.47	57.94	66.22
36 - 48	77.29	77.82	77.16	70.66	77.79	72.89	78.19	70.11	77.69
48 - 60	84.95	85.42	84.83	79.23	85.38	81.75	85.69	78.60	85.30
> 60	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Mean duration	56.30	56.38	56.28	64.28	55.65	61.88	55.96	64.85	55.57
Median duration	41.00	41.00	41.00	52.00	40.00	48.00	41.00	53.00	40.00

Observed duration	Bad loans terminated with a write-off (2005-2010)								
(in months)	Total	F	M	Mort.	No Mort.	F/Mort.	F/No Mort.	M/Mort.	M/No Mort.
0 - 3	4.05	3.80	4.12	3.98	4.06	3.43	3.83	4.12	4.12
3 - 6	10.93	10.22	11.12	10.90	10.93	10.72	10.18	10.95	11.13
6 - 12	27.55	26.60	27.80	26.50	27.64	26.79	26.58	26.43	27.92
12 - 18	44.88	43.78	45.17	40.53	45.25	39.93	44.10	40.68	45.56
18 - 24	59.25	57.72	59.66	54.06	59.70	53.29	58.09	54.26	60.13
24 - 36	77.47	76.35	77.77	73.22	77.84	73.32	76.60	73.19	78.17
36 - 48	89.12	88.58	89.26	87.37	89.27	87.15	88.70	87.43	89.42
48 - 60	95.97	95.68	96.05	95.56	96.00	95.05	95.74	95.69	96.08
> 60	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Mean duration	45.09	45.27	45.04	53.43	44.41	52.63	44.70	53.64	44.33
Median duration	49.00	50.00	49.00	63.00	47.00	61.00	49.00	63.00	47.00

Notes: Cumulative distributions for the observed durations of bad loans in months. Median and average observed duration of bad loans by owner gender and by collateral. Bad loans exit is generic for the full sample (January 1997 through October 2010) and a write-off (EXIT2=1) for the short sample (January 2005 through October 2010).

Table 3: Bad loans by gender: geographical distribution (in %) - Full sample: Jan. 1997 - Oct. 2010

	Share of loans			Share of firms		
Area	F	M	Total	F	M	Total
Center	22.2	77.9	119,332	23.6	76.4	44,903
North East	18.2	81.8	88,864	19.3	80.7	35,348
North West	20.3	79.7	122,973	21.2	78.8	51,150
South & Islands	19.3	80.8	207,590	21.2	78.9	86,770
Total	20.0	80.0	538,759	21.4	78.6	218,171

Notes: Distribution by gender and by geographical area (percentage) of firms with a bad loan and firm-bank relationships recorded as bad loans. Generic exit. Sample: January 1997 through October 2010

Table 4: Exit from bad loan status by gender: distribution (in %) - Short sample: Jan. 2005 - Oct. 2010

	Share of loans			Share of firms		
	F	M	Total	F	M	Total
$EXIT\ 1 = 1$	24.3	75.7	523	22.8	77.2	470
$EXIT\ 2 = 1$	21.3	78.7	53,657	21.7	78.4	43,030
$EXIT\ 3 = 1$	20.9	79.1	21,584	21.3	78.7	17,292
$EXIT\ 4 = 1$	21.0	79.0	22,107	21.3	78.7	17,762
$EXIT\ 5 = 1$	21.5	78.5	32,729	21.8	78.2	25,484
Total	21.3	78.7	108,493	21.6	78.4	86,276

Notes: Distribution by gender and by type of exit from bad loan status (percentage) of firms with a bad loan and firm-bank relationships recorded as bad loans. $EXIT\ 1 = 1$ if a bad loan becomes performing; $EXIT\ 2 = 1$ if bad loan is written off; $EXIT\ 3 = 1$ if a bad loan is paid back; $EXIT\ 4 = 1$ if a bad loan is either paid back or becomes performing; $EXIT\ 5 = 1$ if a bad loan is either securitized or sold. Sample: January 2005 through October 2010

Table 5: Bad loans by gender: sectorial distribution (in %) - Full sample: Jan. 1997 - Oct. 2010

	Share of loans			Share of firms		
Sector	F	M	Total	F	M	Total
Construction	4.6	95.4	44,884	4.4	95.6	107,885
Financial & Insurance Activities	18.5	81.5	13,879	17.3	82.7	37,415
Hotel & Restaurant	35.0	65.0	14,171	32.8	67.2	32,737
Manufacturing	24.6	75.4	48,428	23.7	76.3	120,917
Professional, Scientific, Technological and Real Estate activities	34.0	66.0	3,743	32.5	67.5	8,735
Transportation & Communication	10.8	89.2	14,204	10.3	89.7	38,309
Wholesale & Retail	28.3	71.7	78,862	26.0	74.0	192,761
Total	21.4	78.6	218,171	20.0	80.0	538,759

Notes: Distribution of firms by gender and by sector (percentage) and total number of firm-bank relationships recorded as non-performing. Generic exit. Sample: January 1997 through October 2010.

Table 6: Firms' owner gender and duration of bad loans: sectorial distribution across cohorts (in %). Full sample: January 1997 through October 2010.

	1997		1998		1999		2000		2001		2002		2003	
Sector	F	M	F	M	F	M	F	M	F	M	F	M	F	M
Construction	2.6	97.4	3.7	96.4	3.3	96.7	4.0	96.0	4.3	95.7	4.5	95.6	5.1	94.9
Fin. & Ins. Activities	14.4	85.6	15.2	84.8	16.0	84.0	16.7	83.3	19.7	80.3	17.4	82.6	17.9	82.2
Hotel & Restaurant	31.0	69.0	30.1	69.9	32.8	67.2	32.1	68.0	31.5	68.5	31.5	68.5	31.1	68.9
Manufacturing	22.0	78.0	23.3	76.7	21.8	78.2	23.4	76.6	22.6	77.4	24.4	75.6	25.8	74.2
Prof., Scient., Tech. & RE Activities	23.4	76.6	34.9	65.1	28.1	71.9	36.4	63.6	32.5	67.5	30.6	69.4	29.4	70.6
Transportation & Communication	6.5	93.5	7.3	92.7	7.5	92.5	9.0	91.1	8.3	91.7	10.9	89.1	9.6	90.4
Wholesale & Retail	23.7	76.3	23.0	77.0	23.9	76.1	24.2	75.8	23.7	76.3	24.8	75.2	26.6	73.4
Total	18.4	81.6	18.6	81.4	18.8	81.2	19.5	80.5	19.4	80.6	19.9	80.1	20.7	79.3

	2004		2005		2006		2007		2008		2009		2010	
Sector	F	M	F	M	F	M	F	M	F	M	F	M	F	M
Construction	4.1	95.9	4.6	95.4	5.2	94.8	4.8	95.2	4.5	95.5	4.8	95.2	5.0	95.0
Fin. & Ins. Activities	16.5	83.5	16.2	83.8	18.6	81.4	17.5	82.5	19.0	81.0	17.0	83.0	18.3	81.7
Hotel & Restaurant	32.6	67.4	32.1	67.9	34.9	65.1	35.7	64.3	34.0	66.0	33.7	66.3	32.9	67.1
Manufacturing	24.9	75.1	24.0	76.0	25.1	74.9	25.0	75.0	23.1	76.9	22.7	77.3	22.6	77.4
Prof., Scient., Tech. & RE Activities	30.3	69.7	34.4	65.6	32.2	67.8	33.7	66.3	34.1	65.9	33.7	66.3	35.7	64.4
Transportation & Communication	10.9	89.1	9.6	90.4	12.7	87.3	12.3	87.7	11.7	88.3	11.4	88.6	11.4	88.6
Wholesale & Retail	26.6	73.4	25.3	74.7	28.0	72.1	28.6	71.4	28.5	71.5	27.8	72.2	27.7	72.3
Total	20.4	79.6	20.0	80.0	21.5	78.5	21.2	78.8	20.5	79.5	19.3	80.7	19.4	80.6

Notes: Sectorial distribution of firms by owner gender and by cohort (percentage). The cohort year indicates the year in which the bad loan was recorded as non-performing for the first time. Generic exit. Sample: January 1997 through October 2010

Table 7: Descriptive statistics for duration of bad loans. Full sample January 1997 through October 2010.

	Median		Restricted Mean		Unrestricted mean		Testing equality of survivor			
	F	M	F	M	F	M	Log-rank	Wilcoxon	Tarone-Ware	Peto-Peto
Overall	41.0	41.0	56.4	56.3	61.5	61.3	1.63	9.81***	5.31**	6.65***
Only banks	35.0	35.0	49.6	49.2	52.5	51.9	4.78**	8.72***	6.76***	7.65***
Only non-bank	62.0	60.0	71.5	70.9	86.2	83.8	19***	35.96***	29.57***	30.14***
Under Threshold/only banks	32.0	31.0	47.3	46.3	50.1	48.9	14.09***	13.94***	14.58***	14.55***
Under Threshold/non banks	55.0	50.0	63.1	61.9	77.4	67.4	51.66***	60.14***	59.56***	60.77***
Over Threshold/only banks	39.0	38.0	52.8	52.0	55.9	55.0	7.92***	17.05***	12.88***	14.5***
Over Threshold/non banks	65.0	64.0	74.1	74.0	90.6	90.1	5.21**	11.1***	8.72***	9.02***
Sectors/Banks										
Manufacturing	35.0	35.0	51.0	49.5	54.6	52.3	9.27***	8.1***	7.96***	8.22***
Construction	37.0	35.0	52.7	50.2	57.9	53.3	6.33**	7.53***	7.04***	7.26***
Wholesale & Retail Trade	35.0	35.0	49.6	49.5	52.4	52.1	0.29	1.45	0.87	1.13
Hotel & Restuarants	35.0	34.0	48.6	48.5	50.0	51.4	0.56	1.62	1.25	1.41
Transportation & Communication	34.0	33.0	48.8	48.1	49.5	51.1	1.74	1.9	2.01	1.98
Financial & Insurance activities	31.0	33.0	45.8	46.4	48.3	48.2	1.63	3.16*	2.94*	3.09*
Prof., Scient., Techn and RE Activities	31.0	32.0	45.8	47.4	47.7	50.0	0.8	0.12	0.37	0.25
Sectors/Non Banks										
Manufacturing	60.0	58.0	68.3	69.1	72.8	82.6	1.13	2.16	1.92	2.04
Construction	62.0	62.0	67.0	71.5	87.1	83.7	0.25	0.19	0.2	0.25
Wholesale & Retail Trade	66.0	66.0	75.8	75.7	101.1	89.1	0.14	0.56	0.28	0.36
Hotel & Restuarants	62.0	61.0	68.3	71.9	74.8	84.7	0.2	0.03	0.06	0.06
Transportation & Communication	40.0	39.0	54.4	54.7	61.5	61.7	0.46	0.73	0.7	0.73
Financial & Insurance activities	58.0	60.0	68.1	70.6	85.2	81.6	0.71	0.03	0.04	0.06
Prof., Scient., Techn and RE Activities	52.0	53.0	63.2	62.9	80.7	78.7	0	0.07	0.02	0.01

Notes: Median and average duration of non-performing loans by owner gender and by sector (percentage). Generic exit. Sample: January 1997 through October 2010. ***, ** and * indicate rejection of the null at 1, 5 and 10%, respectively.

Table 8: Estimation results for some parametric models. Full sample

	(1a) Exp.	(2a) Weib.	(3a) Gomp.	(4a) Cox	(1b) Exp.	(2b) Weib.	(3b) Gomp.	(4b) Cox
Gender (Male)	1.0331***	1.0354***	1.0340***	1.0342***	1.0327***	1.0351***	1.0337***	1.0339***
	(0.0047)	(0.0052)	(0.0049)	(0.0049)	(0.0047)	(0.0052)	(0.0049)	(0.0049)
Amount	0.8370***	0.8242***	0.8320***	0.8307***	0.8364***	0.8235***	0.8314***	0.8300***
	(0.0011)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0011)	(0.0011)
Bank size								
Large	0.8119***	0.7919***	0.8024***	0.8075***	0.8112***	0.7910***	0.8016***	0.8066***
	(0.0055)	(0.0060)	(0.0058)	(0.0057)	(0.0055)	(0.0060)	(0.0058)	(0.0057)
Medium	0.7638***	0.7472***	0.7559***	0.7601***	0.7623***	0.7455***	0.7543***	0.7583***
	(0.0054)	(0.0059)	(0.0056)	(0.0056)	(0.0054)	(0.0059)	(0.0056)	(0.0056)
Small	1.0162***	1.0149***	1.0132***	1.0244***	1.0127***	1.0111***	1.0096***	1.0207***
	(0.0077)	(0.0085)	(0.0080)	(0.0081)	(0.0077)	(0.0085)	(0.0080)	(0.0081)
Minor	0.9080***	0.8999***	0.9031***	0.9100***	0.9067***	0.8985***	0.9017***	0.9085***
	(0.0066)	(0.0072)	(0.0068)	(0.0068)	(0.0066)	(0.0072)	(0.0068)	(0.0068)
Foreign	2.1362***	2.2581***	2.1900***	2.1682***	2.1183***	2.2375***	2.1716***	2.1490***
	(0.0412)	(0.0475)	(0.0432)	(0.0443)	(0.0409)	(0.0472)	(0.0430)	(0.0441)
Fin. Inst.	0.6718***	0.6559***	0.6649***	0.6660***	0.6688***	0.6529***	0.6619***	0.6627***
	(0.0030)	(0.0031)	(0.0030)	(0.0030)	(0.0029)	(0.0031)	(0.0030)	(0.0030)
$D\_Mortgage$	1.0185***	1.0250***	1.0224***	1.0185***	1.0224***	1.0295***	1.0264***	1.0226***
	(0.0078)	(0.0086)	(0.0082)	(0.0080)	(0.0079)	(0.0087)	(0.0083)	(0.0080)
Female × $D\_Mortgage$	1.0873***	1.0932***	1.0896***	1.0895***	1.0839***	1.0894***	1.0862***	1.0858***
	(0.0180)	(0.0198)	(0.0188)	(0.0184)	(0.0179)	(0.0198)	(0.0188)	(0.0184)
$D\_postcrisis$					1.4303***	1.4848***	1.4440***	1.4642***
					(0.0170)	(0.0186)	(0.0173)	(0.0181)
Constant	0.1149***	0.0572***	0.1075***		0.1156***	0.0573***	0.1082***	
	(0.0017)	(0.0010)	(0.0016)		(0.0017)	(0.0010)	(0.0016)	
α		1.2007***	0.0030***			1.2022***	0.0030***	
		(0.0016)	(0.0001)			(0.0016)	(0.0001)	
N	532,986	532,986	532,986	532,986	532,986	532,986	532,986	532,986
$\log L$	-600,367	-593,241	-599,411	-3,923,131	-599,936	-592,714	-598,956	-3,922,642
AIC	1,200,802	1,186,552	1,198,892	7,846,327	1,199,941	1,185,500	1,197,984	7,845,351
BIC	1,201,182	1,186,944	1,199,283	7,846,696	1,200,333	1,185,903	1,198,387	7,845,732

Notes: Full sample: 1997:1-2010:10. Generic exit. In all panels ***, ** and * indicate rejection at 1, 5 and 10%, respectively. Standard errors are in parentheses. A set of fixed effects for cohorts (the first year a loan becomes 'bad'), geographical area and sector are also included. $D\_Mortgage$ is 1 if loans are guaranteed by a mortgage. For additional details on the variable definitions see Table 1.

Table 9: Estimation results for the Weibull model with interactions. Full

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender (Male)	1.029***	1.070***		1.035***	0.824***	1.021***		
	(0.005)	(0.034)		(0.005)	(0.001)	(0.007)		
Amount	0.824***	0.827***		0.824***		0.824***	0.824***	
	(0.001)	(0.003)		(0.001)		(0.001)	(0.001)	
Bank size								
Large	0.792***	0.792***	0.792***	0.792***	0.792***	0.808***	0.808***	
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.014)	(0.014)	
Medium	0.747***	0.747***	0.747***	0.747***	0.747***	0.764***	0.764***	
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.013)	(0.013)	
Small	1.015***	1.015***	1.015***	1.015***	1.015***	0.966***	0.966***	
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.018)	(0.018)	
Minor	0.900***	0.900***	0.900***	0.900***	0.900***	0.911***	0.911***	
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.017)	(0.017)	
Foreign	2.257***	2.257***	2.257***	2.258***	2.258***	2.522***	2.522***	
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.124)	(0.124)	
Fin. Inst.	0.656***	0.656***	0.656***	0.656***	0.656***	0.636***	0.636***	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	
D_Mortgage	1.043***	1.043***	1.043***	1.025***		1.043***	1.043***	
	(0.008)	(0.008)	(0.008)	(0.009)		(0.008)	(0.008)	
Female×Amount			0.822***	1.093***				0.824***
			(0.001)	(0.020)				(0.003)
Male×Amount		0.996***	0.825***					0.824***
		(0.003)	(0.001)					(0.001)
No Mort. × Male					1.035***			0.680***
					(0.005)			(0.023)
Mort. × Female					1.121***			1.116***
					(0.019)			(0.019)
Mort. × Male					1.061***			0.698***
					(0.010)			(0.025)
Bank size×Gender								
Major × Male							1.021***	1.513***
							(0.007)	(0.008)
Large × Female								0.808***
								(0.014)

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Table 9 – continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large × Male						0.976***	0.996***	1.193***
						(0.018)	(0.018)	(0.011)
Medium × Female								0.765***
								(0.013)
Medium × Male						0.972***	0.993***	1.124***
						(0.019)	(0.018)	(0.010)
Small × Female								0.967***
								(0.018)
Small × Male						1.063***	1.086***	1.554***
						(0.022)	(0.021)	(0.015)
Minor × Female								0.910***
								(0.016)
Minor × Male						0.984***	1.006***	1.359***
						(0.020)	(0.019)	(0.013)
Foreign × Female								2.454***
								(0.122)
Foreign × Male						0.873***	0.892***	3.354***
						(0.047)	(0.048)	(0.078)
Fin.Inst. × Female								0.636***
								(0.007)
Fin.Inst. × Male						1.039***	1.061***	
						(0.012)	(0.010)	
Constant	0.057***	0.056***	0.059***	0.057***		0.058***	0.058***	0.057***
	(0.001)	(0.002)	(0.001)	(0.001)		(0.001)	(0.001)	(0.002)
α	1.201***	1.201***	1.201***	1.201***	0.183***	1.201***	1.201***	1.201***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
N	532,986	532,986	532,986	532,986	532,986	532,986	532,986	532,986
$\log L$	-593,254	-593,253	-593,256	-593,241	-593,241	-593,233	-593,233	-593,222
AIC	1,186,576	1,186,576	1,186,580	1,186,552	1,186,552	1,186,547	1,186,547	1,186,528
BIC	1,186,956	1,186,968	1,186,960	1,186,944	1,186,944	1,186,994	1,186,994	1,186,998

Notes: Full sample: 1997:1-2010:10. Generic exit. In all panels ***, ** and * indicate rejection at 1, 5 and 10%, respectively. Standard errors are in parentheses. A set of fixed effects for cohorts (the first year a loan becomes 'bad'), geographical area and sector are also included. D_Mortgage is 1 if loans are guaranteed by a mortgage. For additional details on the variable definitions see Table 1.

Table 10: Estimation results for the Weibull model with interactions. Shor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender (Male)	1.038***	1.057***		1.044***		1.036***		
	(0.012)	(0.078)		(0.012)		(0.014)		
Amount	0.834***	0.835***		0.834***	0.834***	0.834***	0.834***	
	(0.003)	(0.006)		(0.003)	(0.003)	(0.003)	(0.003)	
Bank size								
Large	0.605***	0.605***	0.605***	0.604***	0.604***	0.627***	0.627***	
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.021)	(0.021)	
Medium	0.565***	0.565***	0.565***	0.565***	0.565***	0.624***	0.624***	
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.021)	(0.021)	
Small	0.872***	0.872***	0.872***	0.872***	0.872***	0.819***	0.819***	
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.027)	(0.027)	
Minor	0.683***	0.683***	0.683***	0.683***	0.683***	0.632***	0.632***	
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.025)	(0.025)	
Foreign	0.745***	0.745***	0.745***	0.745***	0.745***	0.778***	0.778***	
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.120)	(0.120)	
D_Mortgage	0.732***	0.732***	0.732***	0.714***		0.731***	0.731***	
	(0.016)	(0.016)	(0.016)	(0.017)		(0.016)	(0.016)	
Gender×Amount								
Female			0.831***					0.832***
			(0.003)					(0.006)
Male		0.998***	0.835***	1.127***				0.835***
		(0.008)	(0.003)	(0.055)				(0.003)
D_Mortgage×Gender								
No Mort. × Male					1.044***			0.743***
					(0.012)			(0.079)
Mort. × Female					0.804***			0.812***
					(0.035)			(0.037)
Mort. × Male					0.745***			0.528***
					(0.019)			(0.059)
Bank size×Gender								
Major × Male								1.356***
								(0.100)
Large × Female								0.626***
								(0.021)

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Table 10 – continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large × Male						0.955***	1.036***	0.812***
						(0.036)	(0.014)	(0.061)
Medium × Female								0.624***
								(0.021)
Medium × Male						0.882***	0.990***	0.746***
						(0.034)	(0.034)	(0.056)
Small × Female								0.818***
								(0.027)
Small × Male						1.081***	0.914***	1.201***
						(0.039)	(0.033)	(0.090)
Minor × Female								0.630***
								(0.025)
Minor × Male						1.103***	1.121***	0.946***
						(0.048)	(0.038)	(0.072)
Foreign × Female								0.779***
								(0.120)
Foreign × Male						0.948***	1.143***	
						(0.162)	(0.047)	
Fin.Inst. × Female								
Fin.Inst. × Male							0.982	
							(0.167)	
Constant	0.016***	0.016***	0.017***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
α	1.445***	1.445***	1.445***	1.445***	1.445***	1.445***	1.445***	1.445***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N	174,064	174,064	174,064	174,064	174,064	174,064	174,064	174,064
$\log L$	-122,170	-122,170	-122,171	-122,168	-122,168	-122,157	-122,157	-122,154
AIC	244,391	244,392	244,391	244,387	244,387	244,374	244,374	244,371
BIC	244,642	244,654	244,643	244,649	244,649	244,676	244,676	244,694

Notes: Short sample: 2005:1-2010:10. Exit is a write-off. In all panels ***, ** and * indicate rejection at 1, 5 and 10%, respectively. Standard errors are in parentheses. A set of fixed effects for cohorts (the first year a loan becomes 'bad'), geographical area and sector are also included. D_Mortgage is 1 if loans are guaranteed by a mortgage. For additional details on the variable definitions see Table 1.

Table 11: Estimation results for Weibull model with and without frailty. Full sample

		w/ Frailty	w/ Frailty by bank	w/ Frailty by firm		w/ Frailty	w/ Frailty by bank	w/ Frailty by firm
Gender (Male)	1.035***	1.051***	1.026***	1.038***	1.035***	1.051***	1.026***	1.038***
	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)	(0.007)	(0.005)	(0.007)
Amount	0.824***	0.757***	0.818***	0.799***	0.823***	0.753***	0.818***	0.797***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bank size								
Large	0.792***	0.750***	0.721***	0.794***	0.791***	0.746***	0.721***	0.792***
	(0.006)	(0.008)	(0.147)	(0.006)	(0.006)	(0.008)	(0.147)	(0.006)
Medium	0.747***	0.750***	0.896***	0.734***	0.746***	0.746***	0.898***	0.731***
	(0.006)	(0.007)	(0.147)	(0.006)	(0.006)	(0.007)	(0.147)	(0.006)
Small	1.015***	1.141***	0.786***	1.061***	1.011***	1.135***	0.784***	1.056***
	(0.009)	(0.012)	(0.125)	(0.009)	(0.009)	(0.012)	(0.124)	(0.009)
Minor	0.900***	0.937***	0.778***	0.919***	0.899***	0.933***	0.780***	0.917***
	(0.007)	(0.010)	(0.084)	(0.007)	(0.007)	(0.010)	(0.084)	(0.007)
Foreign	2.258***	2.746***	1.582***	2.286***	2.237***	2.725***	1.581***	2.259***
	(0.047)	(0.088)	(0.347)	(0.058)	(0.047)	(0.088)	(0.347)	(0.057)
Fin. Inst.	0.656***	0.578***	1.726***	0.628***	0.653***	0.566***	1.729***	0.623***
	(0.003)	(0.004)	(0.190)	(0.003)	(0.003)	(0.004)	(0.190)	(0.003)
D_Mortgage	1.025***	1.027***	0.964***	1.041***	1.029***	1.033***	0.965***	1.046***
	(0.009)	(0.012)	(0.009)	(0.010)	(0.009)	(0.012)	(0.009)	(0.010)
Gender×Amount								
Female	1.093***	1.147***	1.068***	1.113***	1.089***	1.143***	1.067***	1.109***
	(0.020)	(0.028)	(0.019)	(0.022)	(0.020)	(0.028)	(0.019)	(0.022)
D_postcrisis					1.485***	1.920***	1.202***	1.648***
					(0.019)	(0.031)	(0.016)	(0.022)
Constant	0.057***	0.053***	0.042***	0.061***	0.057***	0.053***	0.042***	0.061***
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)
α	1.201***	1.575***	1.336***	1.316***	1.202***	1.590***	1.336***	1.320***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
θ		0.805***	0.551***	0.274***		0.832***	0.551***	0.279***
		(0.009)	(0.027)	(0.003)		(0.009)	(0.027)	(0.003)
N	532,986	532,986	532,986	532,986	532,986	532,986	532,986	532,986
$\log L$	-593,241	-586,030	-536,381	-585,847	-592,714	-585,196	-536,287	-585,155
AIC	1,186,552	1,172,133	1,072,834	1,171,766	1,185,500	1,170,466	1,072,648	1,170,385

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Table 11 – continued

		w/ Frailty	w/ Frailty by bank	w/ Frailty by firm		w/ Frailty	w/ Frailty by bank	w/ Frailty by firm
BIC	1,186,944	1,172,536	1,073,236	1,172,169	1,185,903	1,170,880	1,073,062	1,170,799

Notes: Full sample: 1997:1-2010:10. Generic exit. In all panels ***, ** and * indicate rejection at 1, 5 and 10%, respectively. Standard errors are in parentheses. A set of fixed effects for cohorts (the first year a loan becomes 'bad'), geographical area and sector are also included. D_Mortgage is 1 if loans are guaranteed by a mortgage and D_Postcrisis is 1 if loans became bad after July 2007. For additional details on the variable definitions see Table 1.

Table 12: Estimation results for the Weibull model with frailty across firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender (Male)	1.030***	1.106***		1.038***		1.023***		
	(0.006)	(0.037)		(0.006)		(0.008)		
Amount	0.799***	0.804***		0.799***	0.799***	0.799***	0.799***	
	(0.001)	(0.003)		(0.001)	(0.001)	(0.001)	(0.001)	
Bank size								
Large	0.794***	0.794***	0.794***	0.794***	0.794***	0.810***	0.810***	
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.014)	(0.014)	
Medium	0.734***	0.734***	0.734***	0.734***	0.734***	0.767***	0.767***	
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.013)	(0.013)	
Small	1.061***	1.061***	1.061***	1.061***	1.061***	0.999***	0.999***	
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.018)	(0.018)	
Minor	0.919***	0.919***	0.919***	0.919***	0.919***	0.938***	0.938***	
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.017)	(0.017)	
Foreign	2.285***	2.285***	2.285***	2.286***	2.286***	2.609***	2.609***	
	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.149)	(0.149)	
Fin. Inst.	0.628***	0.629***	0.628***	0.628***	0.628***	0.607***	0.607***	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	
D_Mortgage	1.063***	1.063***	1.063***	1.041***		1.063***		
	(0.009)	(0.009)	(0.009)	(0.010)		(0.009)		
Gender×Amount								
Female			0.797***					0.801***
			(0.001)					(0.003)
Male		0.992***	0.799***					0.798***
		(0.004)	(0.001)					(0.001)
D_Mortgage×Gender								
No Mort. × Male					1.038***			0.670***
					(0.006)			(0.024)
Mort. × Female				1.113***	1.158***			1.149***
				(0.010)	(0.021)			(0.022)
Mort. × Male					1.081***			0.699***
					(0.012)			(0.026)
Bank size×Gender								
Major × Male							1.023***	1.578***
							(0.008)	(0.009)

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Table 12 – continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large × Female								0.809***
								(0.014)
Large × Male						0.976***	0.998***	1.247***
						(0.019)	(0.019)	(0.012)
Medium × Female								0.768***
								(0.013)
Medium × Male						0.948***	0.969***	1.147***
						(0.018)	(0.017)	(0.010)
Small × Female								1.001***
								(0.018)
Small × Male						1.078***	1.103***	1.699***
						(0.022)	(0.021)	(0.016)
Minor × Female								0.935***
								(0.017)
Minor × Male						0.976***	0.998***	1.446***
						(0.020)	(0.019)	(0.014)
Foreign × Female								2.539***
								(0.146)
Foreign × Male						0.850***	0.869***	3.523***
						(0.054)	(0.055)	(0.099)
Fin. Inst. × Female								0.607***
								(0.007)
Fin. Inst. × Male						1.043***	1.067***	
						(0.013)	(0.011)	
Constant	0.061***	0.058***	0.063***	0.061***	0.061***	0.062***	0.062***	0.060***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
α	1.316***	1.316***	1.316***	1.316***	1.316***	1.317***	1.317***	1.317***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
θ	0.274***	0.274***	0.274***	0.274***	0.274***	0.274***	0.274***	0.274***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
N	532,986	532,986	532,986	532,986	532,986	532,986	532,986	532,986
$\log L$	-585,861	-585,859	-585,864	-585,847	-585,847	-585,836	-585,836	-585,823
AIC	1,171,793	1,171,790	1,171,797	1,171,766	1,171,766	1,171,753	1,171,753	1,171,731
BIC	1,172,184	1,172,193	1,172,189	1,172,169	1,172,169	1,172,212	1,172,212	1,172,212

Notes: Full sample: 1997:1-2010:10. Generic exit. In all panels ***, ** and * indicate rejection at 1, 5 and 10%, respectively. Standard errors are in parentheses. A set of fixed effects for cohorts (the first year a loan becomes 'bad'), geographical area and sector are also included. D_Mortgage is 1 if loans are guaranteed by a mortgage. For additional details on the variable definitions see Table 1.

Table 13: Estimation results for the Weibull model with frailty across firms. Short

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender (Male)	1.033***	1.000***		1.039***		1.032***	0.793***	
	(0.016)	(0.087)		(0.016)		(0.019)	(0.003)	
Amount	0.793***	0.790***		0.793***	0.793***	1.032***		
	(0.003)	(0.007)		(0.003)	(0.003)	(0.019)		
Bank size								
Large	0.529***	0.529***	0.529***	0.529***	0.529***	0.559***	0.559***	
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.023)	(0.023)	
Medium	0.510***	0.510***	0.510***	0.510***	0.510***	0.583***	0.583***	
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.023)	(0.023)	
Small	0.907***	0.907***	0.907***	0.907***	0.907***	0.817***	0.817***	
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.030)	(0.030)	
Minor	0.680***	0.680***	0.680***	0.680***	0.680***	0.630***	0.630***	
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.027)	(0.027)	
Foreign	0.763***	0.763***	0.763***	0.763***	0.763***	0.778***	0.778***	
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.127)	(0.127)	
D_Mortgage	0.721***	0.721***	0.721***	0.705***		0.720***	0.720***	
	(0.018)	(0.018)	(0.018)	(0.020)		(0.018)	(0.018)	
Gender×Amount								
Female			0.790***					0.785***
		1.004***	(0.003)					(0.007)
Male		(0.009)	0.793***					0.795***
			(0.003)					(0.004)
D_Mortgage×Gender								
No Mort. × Male					1.039***			0.708***
					(0.016)			(0.085)
Mort. × Female				1.115***	0.786***			0.801***
				(0.065)	(0.041)			(0.043)
Mort. × Male					0.733***			0.496***
					(0.023)			(0.063)
Bank size×Gender								
Major × Male							1.032***	1.315***
							(0.019)	(0.103)
Large × Female								0.558***
								(0.023)

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Table 13 – continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large × Male						0.931***	0.961***	0.685***
						(0.043)	(0.042)	(0.055)
Medium × Female								0.582***
								(0.023)
Medium × Male						0.844***	0.871***	0.648***
						(0.038)	(0.037)	(0.052)
Small × Female								0.814***
								(0.030)
Small × Male						1.138***	1.175***	1.226***
						(0.046)	(0.044)	(0.097)
Minor × Female								0.630***
								(0.027)
Minor × Male						1.099***	1.134***	0.912***
						(0.053)	(0.052)	(0.073)
Foreign × Female								0.777***
								(0.126)
Foreign × Male						0.977	1.008	
						(0.176)	(0.181)	
Constant	0.017***	0.018***	0.018***	0.017***	0.017***	0.017***	0.017***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
α	1.651***	1.651***	1.651***	1.651***	1.651***	1.652***	1.652***	1.652***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
θ	0.752***	0.752***	0.752***	0.752***	0.752***	0.753***	0.753***	0.753***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
N	174,064	174,064	174,064	174,064	174,064	174,064	174,064	174,064
$\log L$	-119,760	-119,760	-119,760	-119,758	-119,758	-119,742	-119,742	-119,740
AIC	239,572	239,574	239,572	239,571	239,571	239,547	239,547	239,545
BIC	239,834	239,846	239,834	239,843	239,843	239,859	239,859	239,878

Notes: Short sample: 2005:1-2010:10. Exit is a write-off. In all panels ***, ** and * indicate rejection at 1, 5 and 10%, respectively. Standard errors are in parentheses. A set of fixed effects for cohorts (the first year a loan becomes 'bad'), geographical area and sector are also included. D_Mortgage is 1 if loans are guaranteed by a mortgage. For additional details on the variable definitions see Table 1.

Table 14: Estimation results for the Weibull model. Competing risks ($EXIT$ 2 - Wri

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gender (Male)	1.038***	1.048***		1.044***		1.036***		
	(0.012)	(0.083)		(0.012)		(0.014)		
Amount	0.833***	0.834***		0.833***	0.833***	0.833***	0.833***	
	(0.003)	(0.006)		(0.003)	(0.003)	(0.003)	(0.003)	
Bank size								
Large	0.604***	0.604***	0.604***	0.604***	0.604***	0.628***	0.628***	
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.021)	(0.021)	
Medium	0.553***	0.553***	0.553***	0.553***	0.553***	0.609***	0.609***	
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.021)	(0.021)	
Small	0.868***	0.868***	0.868***	0.868***	0.868***	0.815***	0.815***	
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.027)	(0.027)	
Minor	0.682***	0.682***	0.682***	0.682***	0.682***	0.630***	0.630***	
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.025)	(0.025)	
Foreign	0.738***	0.738***	0.738***	0.738***	0.738***	0.780***	0.780***	
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.120)	(0.120)	
$D\_Mortgage$	0.733***	0.733***	0.733***	0.715***		0.732***	0.732***	
	(0.016)	(0.016)	(0.016)	(0.017)		(0.016)	(0.016)	
Gender×Amount								
Female			0.831***					0.830***
			(0.003)					(0.006)
Male		0.999***	0.834***					0.834***
		(0.008)	(0.003)					(0.003)
D_Mortgage×Gender								
No Mort. × Male					1.044***			0.726***
					(0.012)			(0.081)
Mort. × Female				1.121***	0.802***			0.811***
				(0.055)	(0.035)			(0.037)
Mort. × Male					0.747***			0.517***
					(0.019)			(0.060)
Bank size×Gender								
Major × Male							1.036***	1.371***
							(0.014)	(0.101)
Large × Female								0.627***
								(0.021)

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Table 14 – continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large × Male						0.952***	0.987***	0.819***
						(0.036)	(0.034)	(0.062)
Medium × Female								0.609***
								(0.021)
Medium × Male						0.883***	0.915***	0.738***
						(0.034)	(0.033)	(0.056)
Small × Female								0.814***
								(0.027)
Small × Male						1.081***	1.120***	1.209***
						(0.039)	(0.038)	(0.091)
Minor × Female								0.629***
								(0.025)
Minor × Male						1.104***	1.144***	0.955***
						(0.048)	(0.047)	(0.072)
Foreign × Female								0.780***
								(0.120)
Foreign × Male						0.935***	0.969***	
						(0.160)	(0.165)	
D_Postcrisis	1.205***	1.205***	1.205***	1.204***	1.204***	1.205***	1.205***	1.205***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Constant	0.018***	0.018***	0.019***	0.018***	0.018***	0.018***	0.018***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
α	1.447***	0.018***	1.447***	1.447***	1.447***	1.447***	1.447***	1.447***
	(0.005)	(0.001)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N	174,537	174,537	174,537	174,537	174,537	174,537	174,537	174,537
$\log L$	-122,202	-122,202	-122,202	-122,200	-122,200	-122,189	-122,189	-122,186
AIC	244,456	244,458	244,456	244,453	244,453	244,439	244,439	244,437
BIC	244,718	244,730	244,718	244,725	244,725	244,751	244,751	244,769

Notes: Short sample: 2005:1-2010:10. Bad loans exit because they become performing (EXIT2=1). In all panels ***, ** and * indicate rejection at 1, 5 and 10%, respectively. Standard errors are in parentheses. A set of fixed effects for cohorts (the first year a loan becomes 'bad'), geographical area and sector are also included. D_Mortgage is 1 if loans are guaranteed by a mortgage. For additional details on the variable definitions see Table 1.