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Analysis of delinquent firms using multi-state transitions*

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Abstract

This paper analyzes the behavior of firms with defaulted credits in terms of recovery or extinction. By defining classes for the severity of default, survival models for the multiple transitions from each class are estimated. The models are used to simulate the evolution of a firm's credit conditional on its characteristics. Estimates for the expected recovery or extinction rates are constructed from these simulations. They show that (i) the severity of default strongly influences the probability of extinction; (ii) for less severe default episodes, recovery is faster than extinction, and the opposite is true for more severe defaults; (iii) larger firms tend to display better outcomes; (iv) and the number of employees is the single most important determinant of the time profile of the extinction/recovery process. Estimates of a loss given default measure suggest that the supervision recommendations found in the literature are appropriate.

Keywords: credit default, survival analysis, firms

JEL: C15, C41, G28, G33

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1 Introduction

The assessment of credit risk taking by financial intermediaries evolved rapidly over the last two decades. The continuous improvement in the capacity to process information permitted major qualitative steps in the late 1990's. An example is the estimation of the ex ante propensity of firms to default, which became an alternative to the passive wait for the material observation of the default of each particular borrower.

The New Basel Accord (Basel II) set out by the Basel Committee on Banking Supervision (2004) incorporates the ex ante nature of credit risk, while requiring an interaction between capital adequacy rules and provisioning requirements. Specific provision requirements remain very diverse across countries and in most jurisdictions are likely not to coincide with the notion of "impairment adjustment" as set out in the IAS/IFRS.

Using information on credit for non-financial firms, as well as information concerning the type of firm, this paper proposes a method for measuring the long-run propensity of companies to remain in default, once it was objectively observed, or to evolve either to recovery or to definitive delinquency.

Beyond more sophisticated measures of loan losses, the model allows for the estimation of recovery and/or loss given default rates. Both measures are relevant for impairment assessment under IAS, calibration of provisioning rules, and capital adequacy assessment under the advanced version of the Basel II Internal Ratings-Based (IRB) method.

Due to the inherently private nature of credit exposures, there is not much published work with precise estimates of measures such as the probability of extinction or recovery of firms once a default episode has been recorded. The Internal Ratings-Based approach of the Basel Accord for banking supervision uses precisely this concept when defining *loss given default* (LGD) as the expected loss on a specific loan once default has occurred. The Basel Committee on Banking Supervision (2001) outlines different LGD calculation methods for a large array of exposures. The existence of collateral is explicitly acknowledged as an important mitigating factor on LGD estimates. Other factors include the type of exposure (corporate, retail, financial institutions) and maturity of loans, for instance. In the context of financial supervision, LGD may be calculated using the lender's internal methods (the "advanced" approach of the IRB method), or taken off-the-shelf for the purpose at hand (the "foundation" approach). In this case, the recommended value for the most common exposures is 50 percent. In our case, probabilities are calculated conditional on the state of the loan and other variables that characterize the firm. To obtain an LGD comparable to the values found in the supervision literature, we have to integrate across state distributions of the first occurrence of default, conditional on the firms' characteristics.

Beyond long-run measures such as the one reported by the Basel Committee on Banking Supervision, little is known about the time pattern of extinction and recovery of the firms. For instance, given that a firm is going to become extinct, when is that going to happen? Does recovery occur faster than extinction or is it the other way around? The answers to these and other questions are important in that they allow for a proper justification of the postponement or anticipation of specific provisions, for instance, and also because they allow a proper monitoring of the evolution of firms with a default record. If, for instance, we know that a particular type of firm typically becomes extinct relatively fast and recovers relatively slowly, one could view a long survival time as an indication that the firm is going to survive with a high probability. To answer this kind of questions, duration analysis presents obvious advantages over other possible approaches to this type of problem, such as probit estimates.

We use duration analysis with competing risks to assess the survival of firms in a given state. States are defined primarily in terms of the severity of the credit default episode. This is measured as the ratio between the amount of on-sheet overdue credit of a firm, and the total amount of on-sheet outstanding credit. Based on estimates of proportional hazard models for each state (where each competing risk is the transition to failure, recovery, or another state), implied probabilities for a semi-Markov process are calculated. We then simulate trajectories of credit history for a large number of firms and estimate probabilities of extinction and recovery conditional on the length of the observed credit episode and other characteristics of the firms. Standard errors for these estimates are calculated by performing multiple experiments, where the semi-Markov transition probabilities are calculated from realizations of the parameter vector that respect the distribution of the proportional hazard models estimated parameters.

The data come from two sources, the *Central de Responsabilidades de Crédito* (CRC) database, and an internal comprehensive database used for statistical purposes at Banco de Portugal. The CRC comprises monthly credit information on non financial, private firms reported to the Portuguese central bank. Reporting is mandatory. Only firms that have had a non-repayment episode are considered in the analysis. The internal statistical purpose database has yearly information on the firm's number of employees, sales, activity sector, and region. Both databases virtually represent the respective universe and their intersection spans the period from January 1995 to December 2000. In order to avoid misreported or absent data from the CRC, we use end-of-the-period, quarterly data.

The estimation and simulation procedures enable us to compute probabilities and other quantitative measures of the firms' recovery or extinction processes. We assess the severity of default using the ratio of due credit to total outstanding credit. We shall call this measure the "default ratio". The first broad conclusion is that the severity of default strongly and significantly influences the probability of extinction. For the least severe default episodes (the ones with a default ratio between 10 and 25 percent), recovery is faster than extinction, and the opposite is true for more severe cases. The simulations also suggest that larger firms tend to display better outcomes, and that the number of employees is the single most important determinant of the time profile of the extinction/recovery process. Estimates of a loss given default measure suggest that the supervision recommendations found in the literature are appropriate.

The characterization of deliquescent firms presented in this paper suffers from several shortcomings. The first is that credit data specific to each firm is aggregated across financial institutions. It is therefore impossible to distinguish between different loans of the same firm. This is unfortunate because loss given default estimates for supervisory purposes should, in principle, distinguish between types of credit and maturity. Moreover, the existence of collateral is not reported.

As for the estimation and the simulation strategies used, it is clear that the hypothesis of independence between the firm's history in the state space prior to entry in current state, and its duration of stay in the current state, merits some thoughts. However, the fact that we used four intermediate states mitigates this concern, as dependence across spells in different states is likely to be smaller if states are not too dissimilar. If, for instance, we defined a continuum of states, then we would end up with a perfect description of the underlying statistical process, should one exist.

The rest of the paper is organized as follows. Section 2 describes the estimation and simulation strategies. Section 3 describes the data used for estimation purposes. Section 4 presents the empirical results, and section 5 concludes.

2 Modelling transitions

2.1 Definition of states

Based primarily on the severity of the credit default episode r for a given firm in a known moment, we define J states. The severity of the credit episode is calculated as the ratio of on-sheet overdue credit, x, to the total amount of outstanding credit d.

There are two absorbing states in our analysis. A state is absorbing if a firm stays there forever once it enters that state. The two states correspond to extinction and recovery. A firm is defined as extinct if r exceeds 90 percent and the amount of overdue credit is higher than 100 euros. Recovery occurs whenever r is lower than 10 percent or d is smaller than 100 euros. Sensitivity analysis for these thresholds will be provided in appendix A.

We define four non absorbing states. Provided d is higher than 100 euros, we use thresholds for r of 25, 50 and 75 percent. Table 1 summarizes the definitions of states.

The motivation for definition of extinction comes from the fact that firms often stay in a database such as the CRC long after they became effectively bankrupt, or at least in a situation where claims on outstanding debt are already fully provisioned. An alternative criterion for firm extinction would lie, for instance, in the use of databases with information on firms that were declared to have ended legal activity. This kind of database exists in many countries. In the Portuguese case, however, the information is updated at a much lower frequency than the CRC, and often with a considerable lag.

It is worth noting that the fact that recovery is an absorbing state in the statistical analysis does not imply that, for instance, a real world firm recovering from a bad credit episode will never default again. We assume that once a firm recovers, the probability that it again enters the pool of financially stressed firms is statistically not different from that of any other firm with the same characteristics.

The fact that many firms simply disappear from the CRC database, and therefore cannot be labelled as "extinct" or "recovered", means in practical terms that these observations are censored. The mere observation that they were present in the CRC for some period is taken into account in the parameter estimation, even though the destination state is not observed.

Another observation is that different definitions of recovery or extinction could have been used in this analysis. For instance, one might have considered that a firm was basically bankrupt from the moment when some bank wrote off its liabilities. This may be seen as an indication of definitive non-recoverability of overdue claims. However, the correlation between an indicator of the existence of write-offs above the 100 euros and the first occurrence of the recovery state is only -8.5 percent. (The correlation with the indicator of extinction is the same but positive.) This amounts to saying that many firms that essentially have a small amount of overdue credit experience write-offs.

The assumption that extinction is absorbing is acceptable because it implies that the extinction probability calculated in this paper is an upper bound for its real counterpart. As for the recovery rate, its definition is sufficiently conservative to make sure that no significant impact on the bank's balance sheet occurs for a threshold lower than 10 percent. See appendix A for more details on this.

The thresholds chosen for r are motivated by the accounting rules of many countries, which establish different provisioning procedures based on r being less (or more) than 25 percent, 50 percent, or 75 percent.

State number	State label	Conditioning event
1	"Recovery"	$r \leq 0.1$ or $x \leq 100$
2	"Extinction"	$r \geq 0.9$ and $x > 100$
3		$0.1 < r < 0.25$ and $x > 100$
4		$0.25 \leq r < 0.5$ and $x > 100$
5		$0.5 \leq r < 0.75$ and $x > 100$
6		$0.75 \leq r < 0.9$ and $x > 100$

Table 1: Definition of states. Amount of defaulted credit x in euros, r in natural units.

2.2 Duration models

We assume that the current state and the firm's vector of characteristics, as well as the duration of the firm's stay in that state, determine the probability of transition to another state per unit of time. For expositional purposes, suppose for now that there are only two states, the origin and the destination states, and that all firms are equal. Define T as the random variable describing the moment when the transition occurs. Assuming that the firm enters the origin state at time 0, T is the duration of the firm's stay in the origin state. Define $P(t \leq T < t + dt | T \geq t)$ as the probability that a transition to the destination state occurs between instants t and $t + dt$, given that the firm survived in the origin state up to moment t. The *hazard function* associated with the probability measure P is defined as

$$h(t) = \lim_{dt \to 0} \frac{P(t \leq T < t + dt | T \geq t)}{dt}.$$

If there is a large number of firms, $h(t)$ is, among all the firms that have not transited to the destination state by moment t, the fraction of those transiting between t and $t + dt$. Also of interest is the *survival function*. It is defined as the fraction of firms that have not yet transited to the destination state by time t, and can be calculated from h through

$$\overline{F}(t) = \exp\left\{ -\int_0^t h(u) du \right\}. \tag{1}$$

From the definitions of the hazard and survival functions, it is easily seen that the probability density function of random variable T is $f(t) = h(t)\overline{F}(t)$.

The classical approach outlined in the previous paragraphs cannot be used in the context of multiple states and transitions. A firm is allowed to transit to a series of states before recovering or becoming extinct. If a given firm is in, say, state i, then it will stay in that state for a while, and eventually jump to state $k \neq i$. Since we do not know ex ante to which state will the firm jump to, we say that there are *competing risks*: when it occurs, the transition will be to one of the different possible destination states. Since we have J states, there are $J-1$ different hazard functions associated to state i, $h_{ik}(t)$, with $k \neq i$. As there are competing risks, the interpretation of function h_{ik} is tricky: it is the probability per unit of time of transition to state k given that the firm has been in state i for t units of time. Each of these functions has an associated random variable T_{ik}. Defining the survival function of state i as

$$h_i(t) = \sum_{k \neq i} h_{ik}(t), \tag{2}$$

the associated random variable is $T_i = \min_{k \neq i}\{T_{ik}\}$. This is the sense in which we say that we are in the presence of competing risks. A survival function $\overline{F}_i(t)$ associated to this hazard function is calculated similarly to expression (1).

From a computational point of view, it is useful to transform survival models into a semi-Markov process that can be used to simulate the underlying dynamics of state transitions. A semi-Markov process is identical to a regular Markov chain except that the transition probabilities depend on the elapsed time in the current state. The departure from state i of a firm is characterized along two dimensions: (i) when does it occur; and (ii) to which state does the firm go.

The first dimension is governed by the probability density function $f_i(t)$. The probability density function of random variable T_i is simply $f_i(t) = h_i(t)\overline{F}_i(t)$, where $h_i(t)$ is given by equation (2) and $\overline{F}_i(t)$ is obtained using expression (1) with index i in h and $\overline{F}$.

The second dimension is determined by the probability that the transition, when it occurs, is to state k. This is calculated using expression

$$\pi_{ik} = \int_0^\infty \overline{F}_i(u) h_{ik}(u) du. \tag{3}$$

To characterize the dynamics of firms across states we have to estimate hazard functions for every possible transition, then obtain overall hazard and survivor functions specific to the current state, and finally compute ex ante probabilities for every possible transition.

Now suppose that each firm is described by a vector x of characteristics. For simplicity, assume again that there are only two states: an origin and a destination state. The proportional hazards hypothesis states that the conditional hazard function of a firm is proportional to a baseline function that is valid for the entire population,

$$h(t|x) = e^{x\beta} h(t),$$

where β is a vector of parameters. From an estimation viewpoint, several functional forms for $h(t)$ have been used in the literature. Lancaster (1992) provides an analytic treatment of several of those functions. Here we shall use a parametric approach based on the Weibull function (and the associated survival function) for the baseline hazard:

$$\begin{aligned} h(t) &= \alpha \lambda^{\alpha} t^{\alpha - 1} \\ \overline{F}(t) &= e^{-(\lambda t)^{\alpha}}. \end{aligned}$$

There are essentially two reasons for this choice. First, the Weibull function is flexible enough to allow for increasing as well as decreasing hazards. Second, we want to simulate the evolution of the credit of firms in order to compute recovery and extinction probabilities. The adoption of a non-parametric hazard would limit us to the longest spell of a firm in the state transition under study. This would require additional hypotheses about the posterior behavior of the hazard.

For the estimation of the proportional hazards models, we only consider the first episode of each firm in each state. Successive jumps from one state to another are thus eliminated as this might bias the results towards too much high-frequency dynamics, and also to accommodate the hypothesis that two of the states are absorbing.

2.3 Simulation of firms' behavior

To calculate the transition probabilities of the semi-Markov process that will be used to simulate the credit evolution of a large number of firms, we first need to estimate conditional hazards $h_{ik}(t|x)$, where i is an index of a non absorbing state, and k an index of any state. We then use the $(J-2)(J-1)$ functions to generate the transition probabilities conditional on x, $\pi_{ik}(x)$, and, for every non absorbing state, the probability density function of departure time, $f_i(t|x)$. Finally, we simulate the evolution of 100 identical firms across states and compute the overall probability of extinction (or recovery) conditional on the characteristics of the firm x and survival to time t. We shall call this overall extinction probability $\pi_i(t,x)$. Naturally, a lot more information can be extracted from these simulations.

To calculate the standard deviation of these estimates, this procedure is then repeated 1000 times for different parameter draws from a distribution that respects the variance matrix of the estimated parameters. A total of 100000 trajectories is therefore used.

3 The data

The first data source used was the *Central de Responsabilidades de Crédito* database. Portuguese banks and other financial institutions are required to report credit information on an individual basis to the Portuguese central bank, which is gathered in the *Central de Responsabilidades de Crédito* (CRC) database. This information is centralized monthly and is used by the participating financial institutions to assess the risk profile of current or potential borrowers. The reported information is the total amount of credit for each firm disaggregated by credit type. The credit type characterizes the loan and its repayment status (see table 2). To study stressed firms, one resorts to delinquency situations, including restructured loans and legally enforceable written off loans, which correspond to credit types 7, 8, 9 and 10.

The available data is the complete credit history of each non-financial corporation for which at least one record of overdue or written off loans exists between 1995 and 2001,

Credit type	Description
1	Commercial liabilities
2	Financing liabilities at discount
3	Other short-term financing liabilities
4	Medium- and long-term financing liabilities
5	Other liabilities
6	Off-sheet liabilities
7	Overdue credit liabilities
8	Credit liabilities under litigation
9	Credit write-offs
10	Renegotiated credits

Table 2: Credit types, Banco de Portugal.

starting from the date of the first record. Each bad credit episode must be qualified by its severity. This is defined as the portion of on-balance sheet outstanding credit that is overdue.

We exclude write-offs from the severity measure. If the total liabilities of a firm are write-offs, then the firm is basically in the absorbing state labelled "extinction" and no analysis is performed over that firm. Table 3 presents summary statistics for the available data. There are 85322 firms in the database, which generate 1824695 monthly observations. The average total credit is around 421 thousand euros. Bad credit is, on average, roughly 150 thousand euros, that is, just above one third of total credit.

Variable	Mean	Std. Dev.
Regular credit	264.1	5359.7
Overdue credit liabilities	40.6	374.1
Credit liabilities under litigation	65.4	405.5
Renegotiated credits	0.1	9.3
Total	421.8	5474.8
Obs.	1824695	
Months in database	29.258	30.347
Firms	85322	

Table 3: Summary statistics, CRC database, monthly data, 1995–2001. Figures for credit type in thousands of euros. Source: Banco de Portugal.

The second data source is an internal database used for statistical purposes at Banco de Portugal. It contains information on every firm registered in Portugal with at least one paid employee. It is updated every year with information on the activity sector, yearly sales, number of employees, and location.The available data covers the period from 1995 to 2000. See table 4 for summary statistics on some of the variables available in this database. There are 430830 firms in the database and a total of 1345178 observations. The average number of employees per firm is roughly 12.

Variable	Mean	Std. Dev.
Employees	10.8	92.6
Sales	817.8	17713
Capital	250.6	12505.6
Obs.	1345178	
Years in database	2.2	2
Firms	430830	

Table 4: Summary statistics, internal database, yearly data, 1995–2000. Money figures in thousands of euros.

The two databases have quite disjoint universes. The CRC has only firms that have had at least one credit episode (as defined above) in period 1995–2001, including those that have no employees. Most of these firms are run by a single entrepreneur who is not registered as an employee. The internal database has only firms with at least one employee, regardless of the firms' credit history. Moreover, the available internal data ends by 2000, whereas the CRC ends in 2001.

As a consequence of the disjoint data sets, the number of overlapping firms is 34980 (with a total of 324136 monthly observations), which is just above one third of the firms in the CRC, and less than 10 percent of the firms in the internal database. We can thus estimate that around two thirds of firms with a delinquency episode have no employees, and more than 90 percent of firms with at least one employee had no bad credit episodes during the period under analysis.

4 Empirical results

The model $h_{ik}(t|x)$ underlying each state transition was estimated using standard maximum likelihood maximization. The vector of covariates contains variables related to credit, sales, number of employees, activity sector, location of the headquarters, and year first in current state. Table 6 in appendix B presents the estimations of the 20 models needed to perform the simulations. The global test on the proportional hazards hypothesis was not rejected in all but two regressions (Grambsch and Therneau, 1994). This suggests that the proportional hazards hypothesis is a reasonable one in this application.

Notice that many of the variables lack significance in the regressions. This uncertainty of estimation is taken into account through the variance matrix of the associated coefficients.

Concerning the results of regressions, a few aspects are worth pointing out. First, firms with larger loans are less likely to become extinct than smaller ones. This behavior is in many instances statistically significant and does not depend on the original default ratio. Second, in 2000 transitions to extinction are less likely to occur relative to previous years. There are other significant variables for the different transitions, but general patterns are relatively difficult to obtain. This might be related to the fact that a lot of observations with spells started in 2000 are censored.

4.1 Probability of extinction and recovery

In the context of this model, only two long-run outcomes may occur: extinction or recovery. In order to compute the probability of extinction (and the associated total loss) of a firm, we used the duration models described above to calculate a random set of trajectories. By "extinction" we mean a transition of the default ratio to 0.1 or lower from above. (We only consider observations for which the total defaulted amount is higher than 100 euros.) Using this definition, we computed probabilities of extinction and recovery conditional of the firm's covariates, state, and duration of stay in the current state. We then repeated this procedure for different random draws of the model parameters. We were thus able to calculate both the probabilities and the confidence interval associated to the uncertainty in the estimation of parameters.

Figure 1 presents extinction probabilities conditional on the current state (defined in terms of r), and on the duration of stay in the current state. We are using the baseline hazard functions, which means that all covariates are zero. As expected, the probability of extinction increases as r increases. For instance, the ex ante probability of extinction of a firm in state 3 (with r between 10 and 25 percent) at the end of the first quarter is 34 percent. At the end of the fourth quarter in state 3, that probability is 38 percent. It should be noted that the semi-Markov process is memoryless regarding previous transitions, that is, the transition probabilities to other states depend only on the covariates and the duration of stay in the current state. It does not depend on the history of the firm it terms of states visited. This means that if after 3 months in state 3 a firm jumps to state 4, the extinction probability becomes 48 percent at the end of the first quarter in state 4, and not 53 percent, which is the extinction probability of a firm at the end of the fifth quarter in state 4.

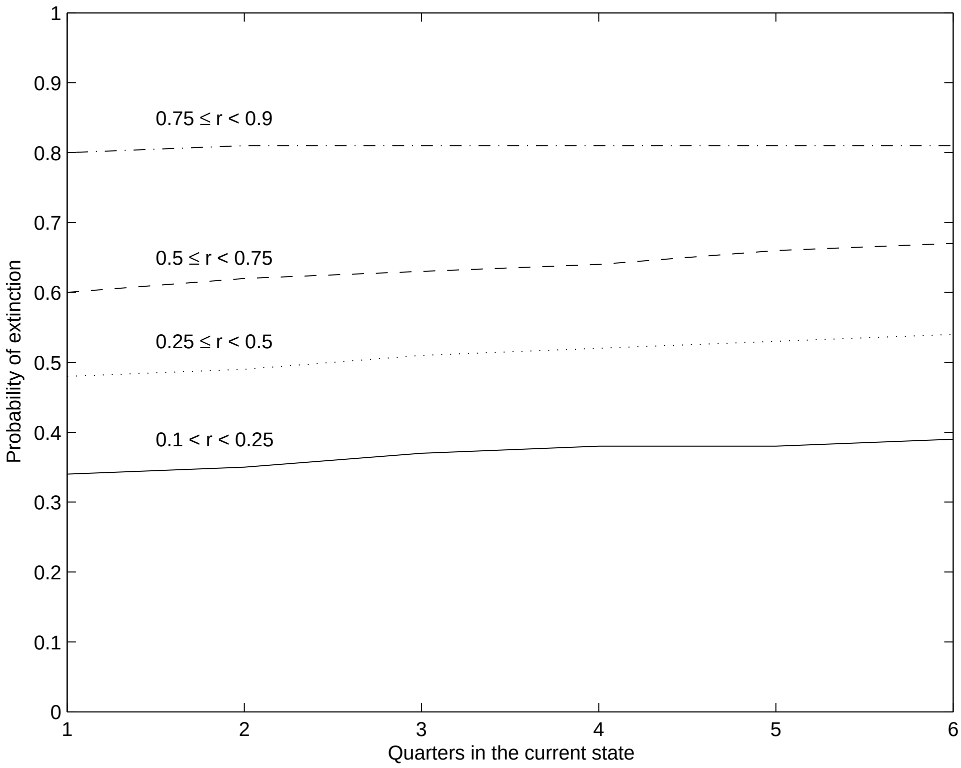

Figure 1: Median extinction probabilities for different states in terms of r, the default ratio. Results using 100 simulated firms per each of 1000 parameter draws.

Another interesting feature of the data is that, as long as $r \leq 0.75$, the probability of extinction is only mildly increasing in the duration of stay in the current state. This implies that the semi-Markov setting we used could be substituted by a pure Markov chain, for which transition probabilities are constant. A fully memoryless chain thus seems to be a reasonable first approximation of the evolution of firms in terms of the default ratio.

One might also be interested on the average duration of stay in a given state, and also on the survival time to extinction and recovery. The number of firms in any given state decays sharply over time. Figure 2 documents this aspect of the simulations. It can be observed that the probability that a firm is still in state 3 after 6 quarters is less than 1 percent. It should be noted, however, that not all the transitions from a non-absorbing state have the two absorbing states as destination.

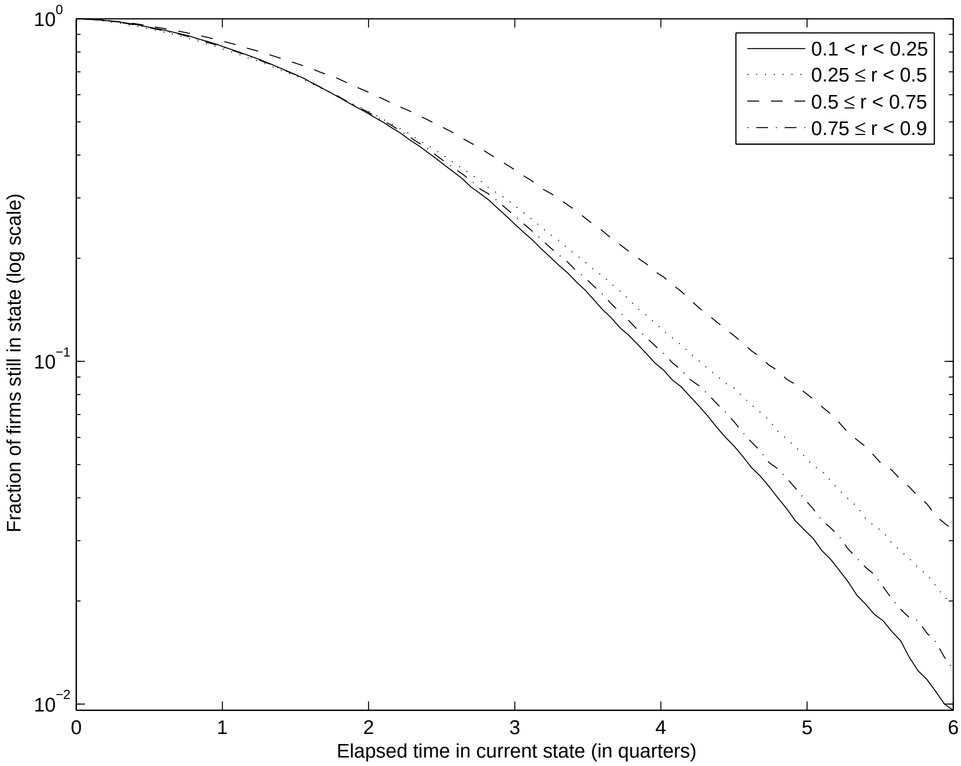

Figure 2: Fraction of firms still in the original state. The results are obtained simulating 100000 firms for each initial state.

It is therefore useful to characterize the intertemporal profile of extinction and recovery conditional on the initial state, *but unconditional on the subsequent trajectory of the firm in the state space.* Figure 3 presents the fraction of firms that either are extinct or have recovered, irrespective of their subsequent trajectory in terms of the state space, conditional on the event that at time zero they enter one of the non-absorbing states.[1] We see that almost all transitions to one of the absorbing states have occurred by the fourth year after default. An interesting feature of these graphs is that recovery is much faster than extinction for the least severe episodes, and the opposite is true for the most severe episodes. For instance, half of the firms initially in state 3 that will recover do it during the first three quarters; this figure is over two years for firms that are bound to

[1] The fact that the firm enters state i at time zero does not mean that the default occurs at time zero, but rather that either the firm was previously in another non-absorbing state, or it had not defaulted yet. This is a consequence of the assumption that the behavior of a firm after it enters a non-absorbing state does not depend on its previous history in the state space; it only depends on the firm's length of stay in the current state and on its current covariates. For this reason, we shall often identify the moment a firm enters one of the non-absorbing states as the moment it defaults.

become extinct.

This graph also documents an important aspect of the debate on *loss given default* (LGD), a measure used in financial supervision practices. The fact that the speed of recovery and/or extinction depends on the severity of the default episode means that such measure should be calculated over a sufficiently large time span. In most cases, two years seem to be a reasonable time span for the uncertainty in terms of extinction or recovery to be revealed. Table 5 presents the fraction of firms that transited to one of the absorbing states for different time lengths, along with the split between recovery and extinction, conditional on the event that at time zero they enter one of the non-absorbing states. For instance, we see that the fate of a firm that at time zero entered state 3 (with $0.1 < r < 0.25$) is known with a probability of 48 percent after one year of entering that state. (As in figure 3, this probability is not conditional on the firm staying in the same state until transition to recovery or extinction occurs.) At the end of the second year, the probability that the final outcome has unravelled is 71 percent. In both cases, recovery is the most likely destination, although less so in the second year.

The calculation of a general purpose LGD involves the integration of probabilities such as the ones presented in table 5 across all firms that historically have defaulted, conditional on the firms characteristics. This measure would then be the average loss given default. This general purpose value is, in the "foundation" of the IRB method, 50 percent. A rough estimate of a similar value for the data in this work implies an LGD of 46 percent.[2] This value seems to support the IRB foundation approach recommendations, but more accurate values may be easily obtained using the historical distributions of particular loan portfolios.

However, care must be used when assessing these values. First, data correspond to a particular time period and to a particular country. Second, the more sophisticated "advanced" approach encourages a more targeted estimation of LGD, and this is precisely what this model mainly does.

[2]This estimate was obtained using the relative frequencies of the first visit to each state found in the data and the asymptotic values of LGD measures reported in table 5. This value should be viewed as an upper bound because it uses the baseline hazard functions (with all covariates equal to zero) and larger firms tend to display better outcomes.

	$0.1 < r < 0.25$				$0.25 \leq r < 0.5$				$0.5 \leq r < 0.75$				$0.75 \leq r < 0.9$			
Time (years)	Recovery	Extinction	Total	LGD	Recovery	Extinction	Total	LGD	Recovery	Extinction	Total	LGD	Recovery	Extinction	Total	LGD
1	0.45	0.03	0.48	0.08	0.26	0.10	0.36	0.12	0.16	0.24	0.40	0.26	0.08	0.64	0.72	0.64
2	0.61	0.11	0.71	0.17	0.41	0.29	0.70	0.34	0.29	0.46	0.75	0.49	0.12	0.75	0.87	0.76
3	0.67	0.21	0.88	0.28	0.47	0.41	0.88	0.46	0.34	0.56	0.90	0.59	0.15	0.79	0.94	0.81
4	0.70	0.25	0.95	0.32	0.50	0.45	0.95	0.50	0.37	0.59	0.96	0.63	0.16	0.81	0.97	0.83
5	0.71	0.27	0.98	0.34	0.51	0.47	0.98	0.52	0.38	0.61	0.98	0.64	0.17	0.82	0.99	0.84

Table 5: Fraction of recovered and extinct firms as a function of elapsed time since arrival to each of the non-absorbing states.

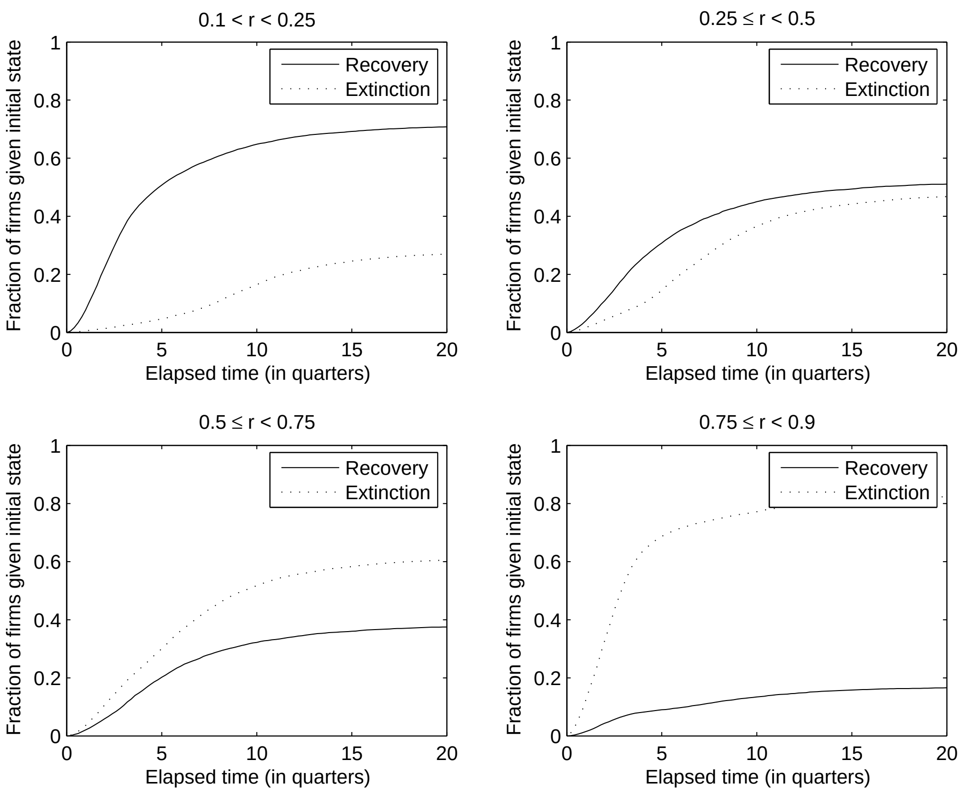

Figure 3: Fraction of firms that recovered or became extinct given initial state. The results are obtained simulating 100000 firms for each initial state.

These results suggest that loss given default calculated over a one year interval, for instance, is likely to be a short-sighted measure, as a lot of uncertainty regarding recovery or extinction unravels during the second and third years. Table 5 reports upper bounds for expected loss given default (LGD) conditional on the initial state, calculated as the probability of extinction times 100 percent of loss plus the probability of recovery times 10 percent of loss (the lower bound of state 3). Let us focus on state 3, which corresponds to the default ratio lying between 10 and 25 percent. Suppose a firm that at time zero defaults and enters state 3. The model estimates that there is a probability of 45 percent that it recovers in the ensuing year. Conversely, it has a probability of extinction in that period of 3 percent. Therefore, one would expect that, on average, no less than 8 percent of total outstanding loans would be lost in a one-year horizon. However, as previously remarked, during the first year many firms recover and a relatively lower number of firms go bankrupt. This implies that at time zero the expected loss during the second year given that the final fate of the firm has not yet been resolved by then is 32 percent of outstanding loans.[3] The second year is much more critical in terms of losses than the first one. A reasonable value for the expected loss horizon is three years: by the end of the third year of the episode, conditional on initial state 3, the expected three-year loss is over 80 percent its value in the infinite horizon, and much more than that for the other initial states.

From a financial supervision viewpoint, it may be preferable to update expected losses and other measures of firm creditworthiness as time unfolds. This can be done by conditioning these measures to the event that the firm has stayed in the current state for a given number of quarters, and to the covariates of the firm. Changing covariates will be the subject of the next section. As for the duration of stay in the current state, figure 4 shows the same type of probability as figure 3 but conditional on the event that the firm is in a particular non-absorbing state at the end of the first year since entering that state. Recall the previous observation that the semi-Markov process that we used could in a first approximation be substituted by a simple Markov chain, that is, a process where the likelihood of transition does not depend on the duration of stay in the current state. Consistent with that, figure 4 is not fundamentally different from figure 3, except that uncertainty regarding the ultimate fate of firms is revealed earlier. For instance, from the tenth quarter on all probabilities have attained their asymptotic values; this compares with at least 16 quarters in the previous case. This feature is relevant for estimation of the expected loss of firms whose history in the current state is known and for which updates are performed regularly. Since for those firms uncertainty unravels faster, estimates of their expected losses are likely to be more accurate.

4.2 Heterogeneity of firms

Up to this point, we used the so called "baseline hazards" in the estimation of the transition probabilities and in-state survival times. This section explores another dimension of the data: the information provided by the internal database.

[3]This figure may calculated from table 5: there is a 16 percent probability that the firm recovers during the second year, and an 8 percent probability that it goes to extinction in that period. This implies an LGD measure of 32 percent.

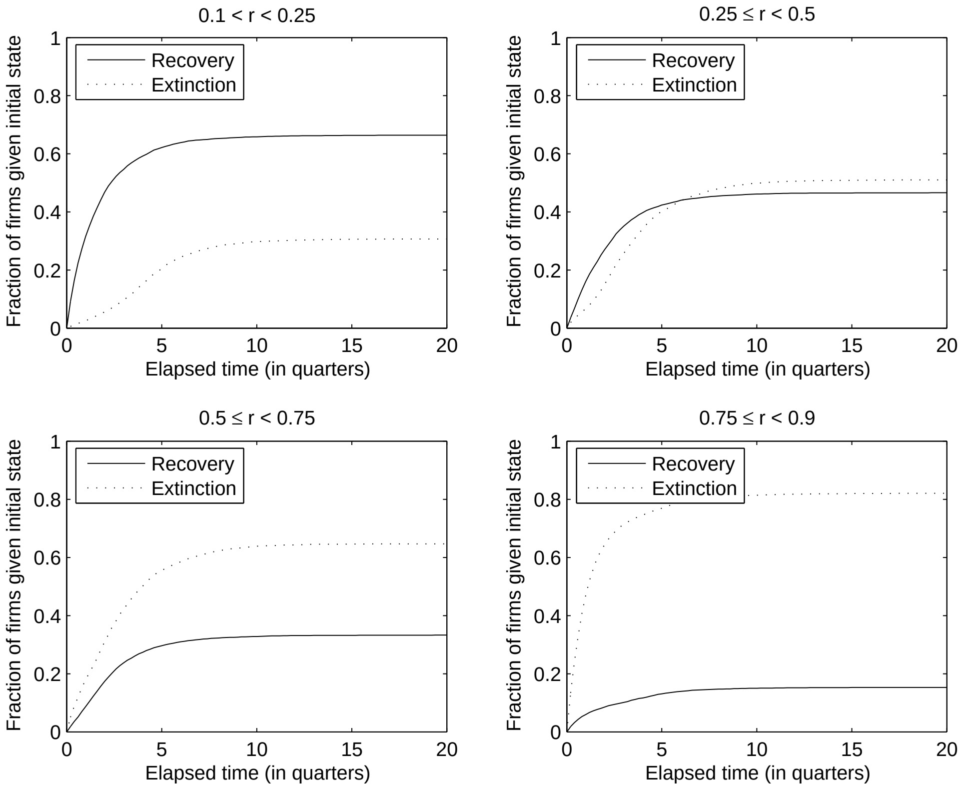

Figure 4: Fraction of firms that recovered or became extinct given current state and the fact that the firm entered the current state one year before. The results are obtained simulating 100000 firms for each initial state.

Recall from section 2 that the hazard function $h_{ik}(t|x)$ is the probability density that a firm goes from state i to state $k \neq i$ at time t, conditional on the firm entering state i at time 0, remaining there up to time t, and being characterized by a vector of covariates x in that period. The proportional hazards hypothesis states that $h_{ik}(t|x) = e^{x\beta} h_{ik}(t)$, where $h_{ik}(t)$ is the baseline hazard. Therefore, the previous calculations pertain to a firm for which all covariates are zero. This means a firm without employees or sales, with outstanding credits d between 10^4 and 10^5 euros, with a default episode beginning in 1995, located in the Lisbon region and operating in the commerce and services sector. It is clear that the first two figures are unrealistic; they could be substituted by, say, 10 employees and sales of 1 million euros without any qualitative difference in the results hitherto reported.

To compare the impact of the different covariates in the calculations of probabilities of extinction and recovery, let us define one benchmark case in terms of the number of employees and sales. We shall consider a firm with 20 employees and annual sales of 1 million euros.[4] The other covariates are zero; the hazard functions used therefore correspond to the omitted categories indicated above.

Perhaps one of the most relevant questions is knowing if the scale of the firm has an impact on the recovery/extinction time profile. Figure 5 presents the fraction of firms that recover or become extinct conditional on the initial state. For the least severe cases, extinction is quite slow and the asymptotic probability of extinction is much lower than the reference case. Moreover, recovery is slower and more firms end up recovering than in the reference case. For the most severe cases, the previous conclusions also hold: uncertainty tends to unravel more slowly for larger firms, generally with a more benign outcome.

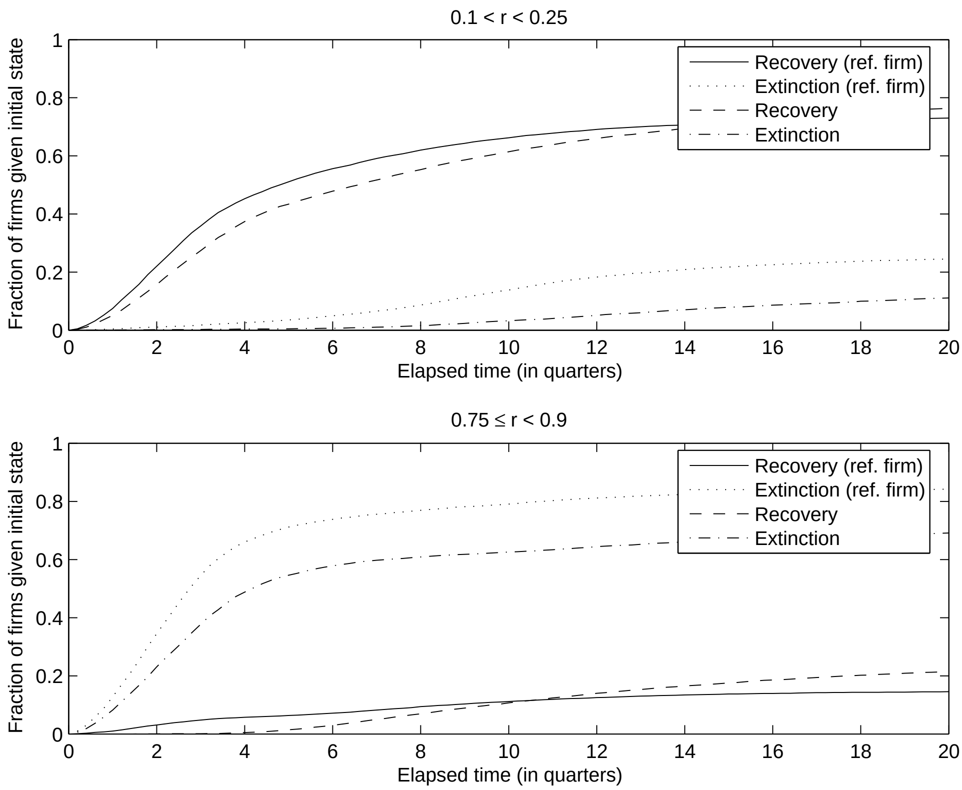

Figure 5: Fraction of firms that recovered or became extinct given initial state. Comparison between the reference firm and an identical firm ten times as large as the reference firm. The results are obtained simulating 100000 firms for each initial state.

To understand the determinants of the previous behavior, one might resort to the assessment of the contribution of each of the three variables related to dimension in the database: number of employees, sales and total outstanding loans. Let us first compare

[4]The average number of employees and total sales with pooled data are 18.3 and 1.28 million euros, respectively.

the benchmark firm with an equal firm except that the number of employees is ten times as large. Figure 6 shows the result of the exercise. The first observation is that the outcome is in general more favorable. For the least severe cases, we see that extinction displays quite different results, since now extinction is faster than the reference case. Recovery is quite similar. For more severe cases, recovery shows a relatively comparable pattern, but extinction is faster than the reference case. When we perform the same exercise for firms with ten times the sales of the reference case (figure 7), we see almost identical patterns for the least severe cases, and also a qualitatively similar pattern for the most severe cases with more benign outcomes (lower probability of extinction; higher probability of recovery). Figure 8 presents the case where outstanding loans are ten times as high as the reference case. Again, a pattern quite similar to the reference case.

The previous observations suggest that the number of employees in an important determinant of the time profile of a troubled firm's extinction/recovery process. Firms with more employees tend to have more benign outcomes. For the most severe cases, the recovery process tends to be slower, and the extinction process is faster. For the least severe cases, extinction is faster but less likely, and recovery is basically more likely. These facts corroborate a number of both empirical and theoretical studies stating that larger firms (which tend to have larger sunk costs and specific capital) are more prone to survive crisis than their smaller counterparts. For instance, Mata and Portugal (1994) find that the survival of new firms is positively related to a larger dimension in terms of the number of employees.

5 Conclusions

This paper analyzes the behavior of firms with defaulted credits in terms of recovery or extinction. By defining classes for the severity of default, survival models for the multiple transitions from each class are estimated. The models are used to simulate the evolution of a firm's situation conditional on the firm's characteristics. We show that the severity of default strongly influences the probability of extinction; for less severe default episodes, recovery is faster than extinction, and the opposite is true for more severe defaults; larger

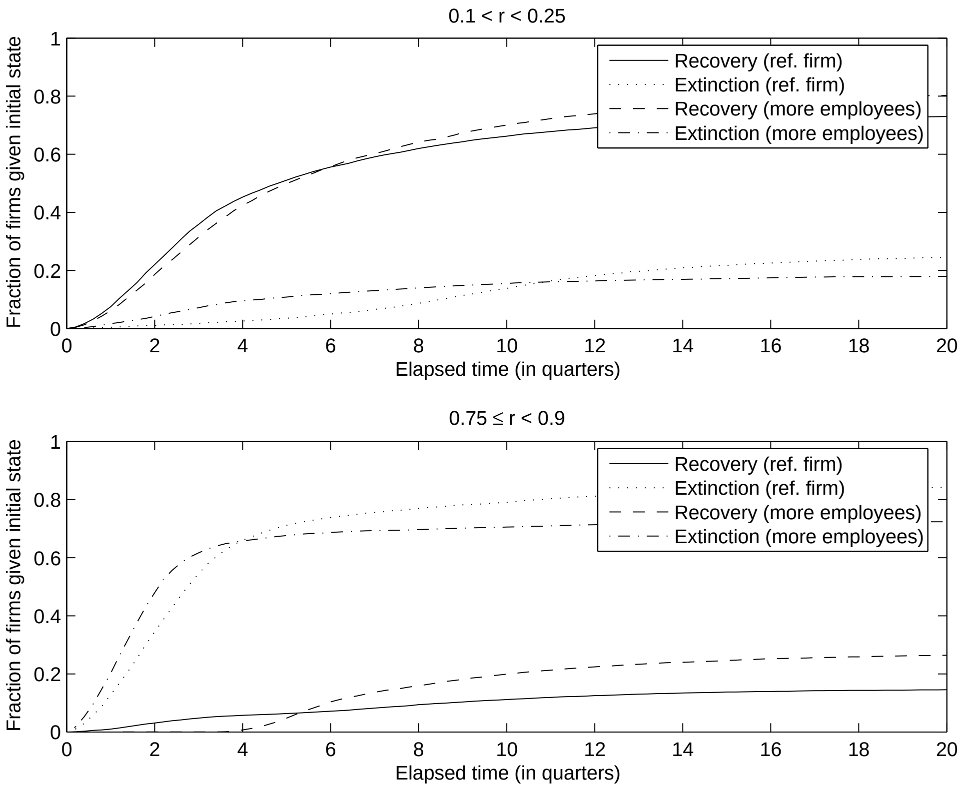

Figure 6: Fraction of firms that recovered or became extinct given initial state. Comparison between the reference firm and another firm with ten times the reference firm's employees. The results are obtained simulating 100000 firms for each initial state.

firms tend to display better outcomes; and the number of employees is the single most important determinant of the time profile of the extinction/recovery process. Estimates of loss given default corroborate the supervision recommendations regarding this measure.

Within the scope of feasible future improvements of this research, we would emphasize the introduction of industry-wide and equity measures in the regressions. These would control for intra-industry competition, relative performance of the industry, and the impact of foreign ownership and capital structure on the firm performance.

Another improvement, unfortunately not feasible with current data, would be to disaggregate credit by credit institution and maturity. This would allow for a proper treatment of the dynamics of a firm's credit across financial institutions. An additional piece of interesting information would be the existence or not of collateral.

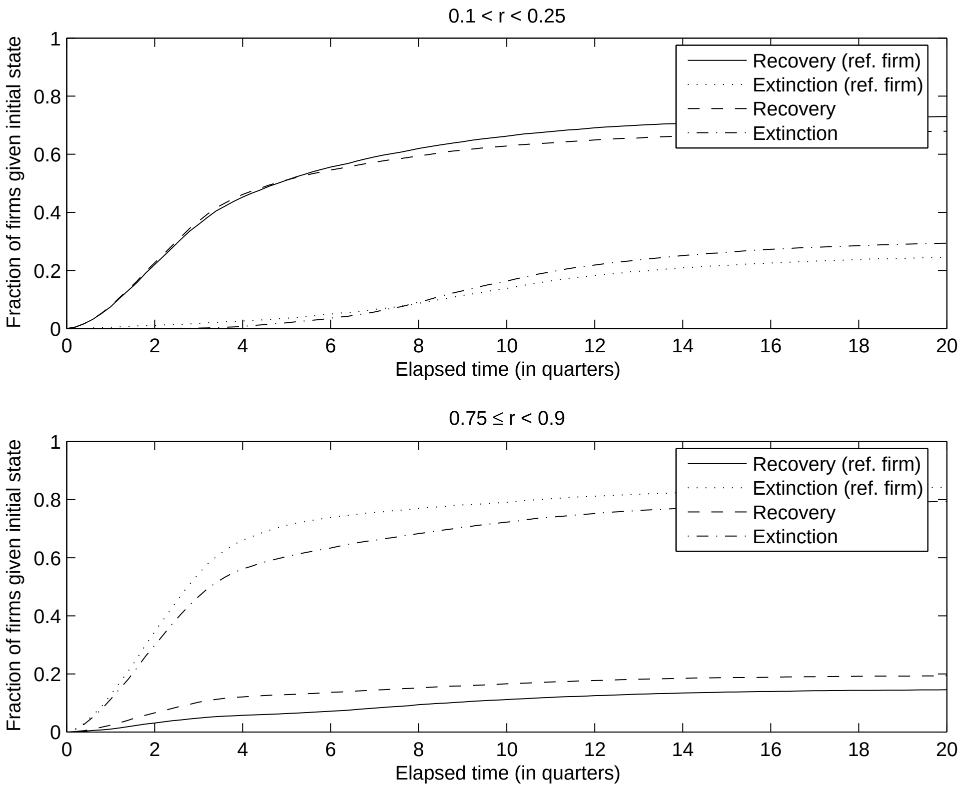

Figure 7: Fraction of firms that recovered or became extinct given initial state. Comparison between the reference firm and another firm with ten times the reference firm's sales. The results are obtained simulating 100000 firms for each initial state.

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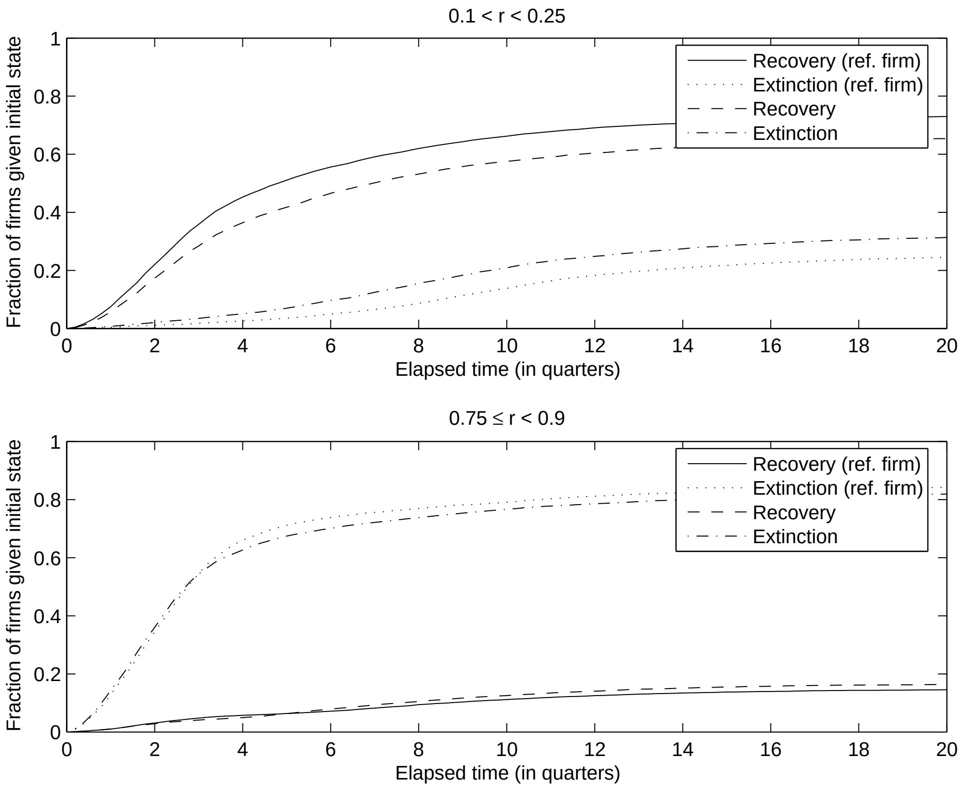
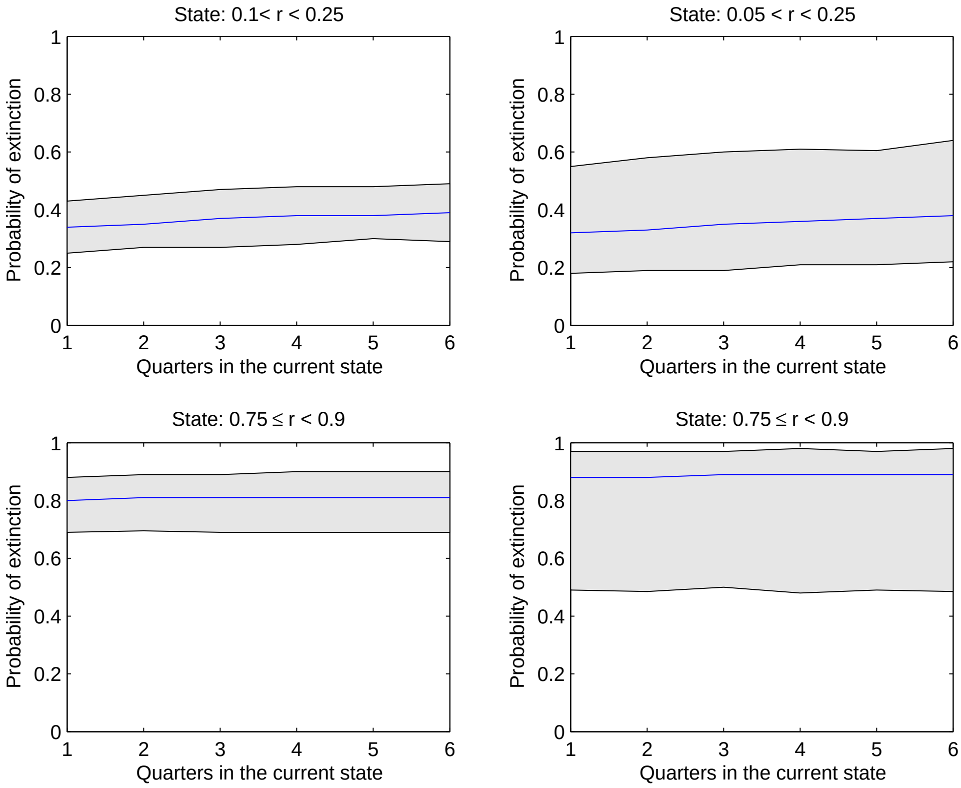


Figure 8: Fraction of firms that recovered or became extinct given initial state. Comparison between the reference firm and another firm with outstanding loans between 1000 and 10000 euros. The results are obtained simulating 100000 firms for each initial state.

Appendix A Sensitivity to thresholds

An important issue in this approach is the impact of the thresholds for the definition of states, especially the absorbing ones, on the statistical significance and accuracy of the estimates. An extensive analysis was performed with respect to their definition. Here we report the results for the most important threshold, the upper limit of the default ratio of the absorbing state "recovery", which was set at 10 percent. Figure 9 displays the median extinction probabilities for states 3 and 6 conditional on the current state and the length of stay in the current state. We see in panel (b) that setting a much more stringent threshold (5 percent) yields qualitatively similar results, but the confidence intervals at 90 percent become a lot wider. This is due to the fact that for a more stringent threshold we end up having much less transitions to recovery and any estimates are bound to become much less accurate. This result suggests that using more stringent thresholds does not change significantly the median results, but does severely affect their accuracy. As a consequence, the probability of extinction for state 6 is statistically higher at the 5 percent level than that of state 3, for example.



(a) Lower limit equal to 0.1

(b) Lower limit equal to 0.05

Figure 9: Median extinction probabilities for two states and two different values of the lower limit of r, with 90 percent confidence intervals. Results using 100 simulated firms per each of 1000 parameter draws.

Appendix B Regressions results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$(3 \to 1)$	$(3 \to 2)$	$(3 \to 4)$	$(3 \to 5)$	$(3 \to 6)$	$(4 \to 1)$	$(4 \to 2)$
Employees (10^2)	-0.003	0.207	-0.327	-0.144	0.170	-0.046	-0.547
	(0.03)	(0.73)	(2.16)*	(0.34)	(0.93)	(0.20)	(1.37)
Sales (10^6)	-0.000	-0.214	0.009	-0.023	-0.006	-0.048	0.026
	(0.05)	(1.27)	(2.62)**	(0.33)	(1.17)	(1.00)	(1.62)
$10^2 \leq d < 10^3$	-0.486	1.780	0.420	0.104	-10.914	-0.327	1.661
	(0.84)	(3.79)**	(0.97)	(0.10)	(40.33)**	(0.78)	(6.62)**
$10^3 \leq d < 10^4$	-0.133	0.763	0.400	-0.006	-0.121	-0.347	1.191
	(1.47)	(4.83)**	(4.65)**	(0.03)	(0.37)	(2.37)*	(8.89)**
$10^5 \leq d < 10^6$	0.225	-0.772	-0.010	0.006	-0.186	0.032	-0.312
	(3.13)**	(3.47)**	(0.12)	(0.03)	(0.76)	(0.28)	(1.85)
$d \geq 10^6$	-0.185	-0.343	0.252	-0.143	-0.503	-0.207	-1.081
	(1.20)	(0.93)	(1.61)	(0.42)	(1.11)	(0.76)	(2.37)*
Year 1996	0.021	0.410	-0.154	-0.317	-0.135	0.095	0.083
	(0.20)	(1.68)	(1.29)	(1.43)	(0.39)	(0.54)	(0.43)
Year 1997	-0.140	0.505	0.033	0.037	0.041	0.148	0.278
	(1.33)	(2.07)*	(0.30)	(0.18)	(0.12)	(0.87)	(1.51)
Year 1998	0.028	0.289	-0.094	-0.287	0.090	0.190	0.063
	(0.26)	(1.13)	(0.80)	(1.29)	(0.27)	(1.10)	(0.32)
Year 1999	0.030	0.177	-0.100	-0.635	-0.590	0.204	-0.184
	(0.29)	(0.68)	(0.87)	(2.53)*	(1.46)	(1.17)	(0.87)
Year 2000	-0.179	-0.326	-0.388	-0.515	-0.107	-0.094	-0.799
	(1.50)	(0.98)	(2.78)**	(1.86)	(0.26)	(0.44)	(2.66)**
Primary activities	0.043	0.726	-0.048	-0.310	1.031	0.014	0.257
	(0.24)	(1.89)	(0.20)	(0.65)	(2.09)*	(0.06)	(0.72)
Extraction and manufacturing	-0.091	0.149	0.363	-0.202	1.144	0.123	-0.112
	(0.70)	(0.65)	(2.83)**	(0.81)	(3.92)**	(0.68)	(0.48)
Wood, chemistry, machinery	0.175	-0.507	0.202	-0.348	0.203	0.072	0.271
	(1.70)	(1.87)	(1.80)	(1.44)	(0.54)	(0.47)	(1.50)
Electric instruments	-0.191	-0.008	-0.033	-0.444	-0.950	-0.309	-0.488
	(1.00)	(0.02)	(0.18)	(1.07)	(0.92)	(0.84)	(1.11)
Utilities and construction	0.066	0.003	0.164	-0.111	0.354	0.030	0.335
	(0.66)	(0.01)	(1.45)	(0.51)	(0.95)	(0.18)	(1.82)
Transportation	0.037	-0.453	0.125	-0.801	0.544	0.234	0.356
	(0.26)	(1.14)	(0.81)	(1.90)	(1.19)	(1.08)	(1.43)
Services to firms and housing	0.151	-0.307	0.037	-0.326	-0.116	0.116	-0.019
	(1.19)	(1.05)	(0.25)	(1.16)	(0.23)	(0.61)	(0.08)
Education and health care	0.100	0.388	0.224	-1.565	0.834	-0.107	0.145
	(0.47)	(0.98)	(0.98)	(1.55)	(1.35)	(0.31)	(0.38)
Collective and social services	-0.305	0.201	-0.337	0.353	-0.034	-0.018	0.160
	(1.38)	(0.53)	(1.19)	(1.00)	(0.04)	(0.06)	(0.46)
North	0.170	0.167	0.059	0.213	-0.260	0.053	0.195
	(2.18)*	(0.99)	(0.68)	(1.33)	(1.00)	(0.44)	(1.43)
Center	0.220	0.039	0.201	0.063	0.135	0.181	-0.171
	(2.29)*	(0.19)	(1.97)*	(0.31)	(0.46)	(1.31)	(0.98)
Alentejo	0.038	-0.338	-0.391	-0.811	-0.218	-0.013	-0.195
	(0.26)	(0.93)	(1.95)	(1.73)	(0.38)	(0.05)	(0.66)
Algarve	0.283	0.338	0.033	0.586	0.416	-0.177	-0.072
	(1.79)	(1.00)	(0.17)	(1.88)	(0.91)	(0.72)	(0.28)
Constant	-2.662	-4.608	-2.971	-3.942	-5.404	-3.205	-4.031
	(26.95)**	(19.35)**	(28.14)**	(19.41)**	(16.43)**	(18.65)**	(20.82)**
Observations	10156	10156	10156	10156	10156	7422	7422
Subjects	7391.00	7391.00	7391.00	7391.00	7391.00	5127.00	5127.00
Transitions	1336.00	227.00	1027.00	234.00	91.00	510.00	348.00
α	1.80	1.93	1.94	1.84	1.96	1.62	1.87

Table 6: Maximum likelihood estimation results. Omitted categories are: outstanding loans d between 10^4 and 10^5 euros; year of arrival to state 1995; commerce and services sector; Lisbon region.

	(8) (4 → 3)	(9) (4 → 5)	(10) (4 → 6)	(11) (5 → 1)	(12) (5 → 2)	(13) (5 → 3)	(14) (5 → 4)
Employees (10^2)	0.253	-0.173	-0.849	0.876	-0.455	-0.070	0.242
	(1.31)	(0.71)	(1.44)	(3.62)**	(1.21)	(0.16)	(1.07)
Sales (10^6)	-0.012	0.008	-0.008	-0.053	0.018	-0.003	-0.010
	(1.19)	(0.78)	(0.20)	(1.42)	(1.21)	(0.04)	(1.16)
$10^2 \leq d < 10^3$	-0.616	-0.213	0.875	0.176	1.312	-0.361	-15.075
	(1.35)	(0.56)	(2.11)*	(0.30)	(5.29)**	(0.50)	(90.30)**
$10^3 \leq d < 10^4$	-0.071	0.482	-0.261	-0.505	1.171	-0.551	0.029
	(0.56)	(4.48)**	(1.02)	(1.70)	(9.59)**	(1.85)	(0.17)
$10^5 \leq d < 10^6$	-0.278	-0.048	0.028	-0.106	-0.617	-0.365	-0.467
	(2.40)*	(0.42)	(0.14)	(0.54)	(3.67)**	(1.66)	(2.90)**
$d \geq 10^6$	-0.365	0.131	0.357	-1.264	-0.721	-0.668	-0.554
	(1.60)	(0.61)	(0.83)	(2.62)**	(1.97)*	(1.44)	(1.68)
Year 1996	0.011	-0.051	0.217	-0.329	0.098	-0.121	-0.088
	(0.07)	(0.34)	(0.85)	(1.13)	(0.53)	(0.40)	(0.43)
Year 1997	-0.199	0.015	-0.326	-0.114	0.073	-0.216	-0.128
	(1.20)	(0.10)	(1.17)	(0.41)	(0.40)	(0.70)	(0.60)
Year 1998	-0.085	-0.219	-0.336	0.169	0.259	0.041	0.077
	(0.51)	(1.35)	(1.15)	(0.61)	(1.43)	(0.14)	(0.38)
Year 1999	0.142	-0.019	-0.320	-0.370	0.395	-0.242	-0.163
	(0.89)	(0.12)	(1.07)	(1.18)	(2.22)*	(0.76)	(0.75)
Year 2000	-0.281	-0.147	-0.330	-0.218	0.008	-0.207	-0.285
	(1.40)	(0.81)	(0.92)	(0.62)	(0.04)	(0.56)	(1.07)
Primary activities	0.103	-0.820	-0.144	0.018	0.046	-0.267	0.247
	(0.42)	(2.31)*	(0.32)	(0.04)	(0.13)	(0.46)	(0.64)
Extraction and manufacturing	-0.207	0.094	-0.076	-0.304	0.280	-0.178	0.266
	(1.13)	(0.59)	(0.25)	(0.95)	(1.45)	(0.55)	(1.29)
Wood, chemistry, machinery	0.036	-0.004	0.351	0.104	-0.146	-0.127	-0.151
	(0.24)	(0.03)	(1.46)	(0.38)	(0.73)	(0.42)	(0.66)
Electric instruments	-0.493	0.017	-0.317	-0.376	0.288	0.299	0.303
	(1.27)	(0.05)	(0.56)	(0.77)	(1.07)	(0.68)	(0.91)
Utilities and construction	0.195	0.059	-0.334	0.013	0.103	0.076	0.203
	(1.28)	(0.41)	(1.13)	(0.05)	(0.60)	(0.27)	(1.04)
Transportation	0.078	0.087	0.344	-0.495	0.172	-1.420	0.283
	(0.36)	(0.44)	(0.99)	(1.01)	(0.78)	(1.94)	(1.01)
Services to firms and housing	-0.067	0.001	-0.537	0.305	0.091	0.204	0.131
	(0.35)	(0.00)	(1.34)	(1.01)	(0.41)	(0.60)	(0.49)
Education and health care	0.099	-0.193	-14.533	-0.680	0.479	-0.633	-0.135
	(0.32)	(0.62)	(71.56)**	(0.67)	(1.52)	(0.62)	(0.23)
Collective and social services	-0.005	0.009	-0.901	-0.066	0.890	-0.280	0.987
	(0.02)	(0.04)	(1.20)	(0.12)	(3.65)**	(0.39)	(3.49)**
North	-0.109	-0.053	-0.157	0.120	0.025	0.011	0.225
	(0.96)	(0.49)	(0.82)	(0.57)	(0.19)	(0.05)	(1.45)
Center	-0.082	0.064	-0.283	0.298	0.342	0.121	0.078
	(0.60)	(0.51)	(1.13)	(1.21)	(2.42)*	(0.45)	(0.41)
Alentejo	0.146	-0.375	-1.119	-0.052	-0.352	0.698	0.740
	(0.70)	(1.64)	(1.84)	(0.10)	(0.97)	(1.72)	(2.56)*
Algarve	-0.658	-0.129	-0.500	0.264	0.143	-0.370	0.297
	(2.39)*	(0.63)	(1.14)	(0.79)	(0.59)	(0.78)	(1.11)
Constant	-2.851	-2.985	-3.831	-3.636	-3.338	-3.451	-3.128
	(19.12)**	(20.84)**	(14.04)**	(14.16)**	(18.60)**	(12.99)**	(16.48)**
Observations	7422	7422	7422	4098	4098	4098	4098
Subjects	5127.00	5127.00	5127.00	2853.00	2853.00	2853.00	2853.00
Transitions	552.00	650.00	162.00	158.00	439.00	142.00	302.00
α	1.68	1.79	1.66	1.71	1.99	1.67	1.72

Table 6: Continued.

	(15)	(16)	(17)	(18)	(19)	(20)
	(5 → 6)	(6 → 1)	(6 → 2)	(6 → 3)	(6 → 4)	(6 → 5)
Employees (10^2)	-0.224	-0.983	0.585	1.648	0.269	0.413
	(0.76)	(1.08)	(1.93)	(2.87)**	(0.36)	(1.03)
Sales (10^6)	0.009	0.038	-0.026	-0.084	-0.006	-0.069
	(0.80)	(1.05)	(1.96)	(1.29)	(0.22)	(0.88)
$10^2 \leq d < 10^3$	-0.930	0.069	0.606	0.140	0.540	-13.342
	(1.28)	(0.09)	(2.15)*	(0.14)	(0.67)	(48.49)**
$10^3 \leq d < 10^4$	0.454	-0.218	0.456	0.602	0.464	-0.054
	(3.14)**	(0.58)	(3.61)**	(1.47)	(1.25)	(0.21)
$10^5 \leq d < 10^6$	-0.220	-0.302	-0.314	-1.689	-0.330	-0.066
	(1.44)	(1.02)	(2.03)*	(2.84)**	(0.90)	(0.30)
$d \geq 10^6$	-0.066	-1.339	-0.814	-2.305	-0.437	-0.189
	(0.24)	(1.61)	(2.78)**	(2.17)*	(0.81)	(0.45)
Year 1996	-0.057	0.027	-0.393	0.246	0.613	-0.283
	(0.30)	(0.06)	(2.16)*	(0.27)	(1.02)	(0.99)
Year 1997	-0.228	0.304	0.038	1.206	0.720	-0.270
	(1.18)	(0.68)	(0.24)	(1.48)	(1.17)	(0.91)
Year 1998	-0.149	0.340	-0.216	1.090	1.089	-0.261
	(0.74)	(0.75)	(1.21)	(1.30)	(1.88)	(0.90)
Year 1999	0.021	0.005	-0.356	1.131	0.900	-0.442
	(0.11)	(0.01)	(1.99)*	(1.33)	(1.53)	(1.46)
Year 2000	-0.581	0.040	-0.615	1.317	-0.188	-1.258
	(2.15)*	(0.07)	(2.57)*	(1.49)	(0.21)	(2.31)*
Primary activities	-1.172	-0.510	-0.116	1.719	0.482	-1.962
	(1.81)	(0.66)	(0.38)	(2.40)*	(0.78)	(1.92)
Extraction and manufacturing	0.323	-0.664	-0.312	-2.009	-1.069	0.057
	(1.66)	(1.20)	(1.40)	(2.50)*	(1.58)	(0.18)
Wood, chemistry, machinery	0.275	-0.053	-0.143	-0.723	0.478	0.342
	(1.48)	(0.12)	(0.77)	(0.88)	(1.21)	(1.30)
Electric instruments	0.640	-0.648	-0.475	-14.247	0.231	0.196
	(2.26)*	(0.89)	(1.15)	(25.55)**	(0.39)	(0.39)
Utilities and construction	0.212	0.172	-0.094	0.888	0.407	0.080
	(1.12)	(0.46)	(0.49)	(1.68)	(1.02)	(0.26)
Transportation	-0.079	-0.284	0.044	-0.390	-0.304	0.142
	(0.29)	(0.44)	(0.21)	(0.37)	(0.40)	(0.35)
Services to firms and housing	0.164	-0.562	-0.244	0.747	-0.794	-0.339
	(0.68)	(1.04)	(1.14)	(1.35)	(1.12)	(0.80)
Education and health care	-0.003	1.029	0.111	-13.554	0.363	-0.774
	(0.01)	(1.58)	(0.35)	(29.63)**	(0.35)	(0.74)
Collective and social services	0.114	0.505	-0.393	0.689	-13.553	0.669
	(0.27)	(0.81)	(0.88)	(0.58)	(39.26)**	(1.29)
North	0.141	0.269	0.028	0.778	0.115	-0.105
	(0.99)	(0.88)	(0.21)	(1.79)	(0.35)	(0.48)
Center	0.369	-0.002	-0.112	-0.076	-0.573	0.190
	(2.31)*	(0.01)	(0.71)	(0.12)	(1.27)	(0.74)
Alentejo	0.266	-13.704	-0.205	1.386	0.413	-0.251
	(0.80)	(29.61)**	(0.57)	(2.14)*	(0.67)	(0.40)
Algarve	0.049	0.832	-0.545	-0.848	-0.588	0.815
	(0.16)	(1.97)*	(1.93)	(0.73)	(0.76)	(2.55)*
Constant	-3.130	-3.954	-1.824	-6.005	-4.742	-2.872
	(18.63)**	(9.04)**	(11.77)**	(6.84)**	(8.02)**	(10.76)**
Observations	4098	2238	2238	2238	2238	2238
Subjects	2853.00	1527.00	1527.00	1527.00	1527.00	1527.00
Transitions	370.00	75.00	454.00	33.00	62.00	151.00
α	1.87	1.89	1.80	1.93	1.73	1.65

Table 6: Continued.

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