Rationing Traps

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Preliminary draft – comments welcome

Abstract

Macroeconomic models with financial frictions show that adverse shocks may generate persistence of firms' financing constraints, leading to large output fluctuations. This paper empirically investigates the emergence of credit rationing traps at the firm-level. We estimate a first–order Markov model for firms' transition probabilities in and out credit rationing. The results, based on a representative sample of Italian firms, suggest that state dependence in credit rationing is indeed relevant. We also find that firm characteristics have a different effects on the likelihood of being credit rationed for the first time and on the persistence in the rationing state. Finally, the global liquidity shock following the Lehman's bankruptcy, significantly increased the persistence in the credit rationed status.

JEL Codes: F33, F34, F35, O11

Keywords: Financing constraints, Persistence, First–order Markov model, Rationing traps.

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1 Introduction

Starting with the seminal papers of Jaffee and Russell (1976) and Stiglitz and Weiss (1981), the modern theory of banking has well recognized that credit markets can be characterized by rationing phenomena in equilibrium. In presence of information asymmetries, imperfect screening/monitoring technologies and shortage of pledgeable collateral, lenders may find it more profitable to restrict the supply of credit rather than increasing the interest rate, thus persistently excluding some borrowers from access to credit. However, the standard microeconomic models of credit rationing are static and they are silent about the degree of persistence of the state of rationing at the firm level (Freixas and Rochet, 2008). Similarly, the empirical literature has explored the determinants of the likelihood of credit rationing in a static context, without investigating whether and to what extent firms can be "trapped" in a state of credit rationing over time.[1]

We consider a borrower in a credit rationing trap if a past credit denial has a negative effect on the outcome of her loan applications in the current period and on the decisions to apply for a loan, independent of all the other borrower's characteristics. More formally, a rationing trap is defined as a situation in which, other things being equal, borrowers who have been credit rationed at time $t-1$ are, on average, more likely to be rationed and/or discouraged to apply for a loan in t than non-rationed borrowers.

To empirically uncover the credit trap, we need to model the persistence in the firm's rationing events. Information on credit rationing is often binary, so that a dynamic model for credit rationing implies the identification of *true* state dependence.[2]

One major issue in modeling the rationing probability is the possible selectivity bias arising from the fact that firms demanding for credit might be a non-random sample of population (Popov and Udell, 2012; Presbitero, Udell, and Zazzaro, 2014). In a dynamic context, modeling the demand probability gives additional information: it allows us to compute the transition probabilities of borrowers in and out of the credit market conditional on the rationed/non-rationed status in the previous period, that provide a natural measure for the discouragement effect (the probability that a firm decides not to apply for credit in t after having been rationed in $t-1$) and contribute to asses the relevance of a rationing trap. In particular, if applying for a bank loan is costly, firms whose probability of having their application rejected is high can decide to stay out of the credit market. Ignoring the selection issue would produce biased and

[1] To our knowledge, the only partial exception is Levenson and Willard (2000, p. 91) who explicitly argue that "credit rationing has a duration dimension". However, they do not develop a dynamic model of credit rationing and limit their analysis to the estimation of a static two-stage probit model for the probability of credit denial and loan application.

[2] Although the problem of modeling state dependence, wiping out the persistence effects due to fundamental differences in individual observed and unobserved characteristics, arises in many microeconomic applications (e.g., labor market participation, wage determination, scarring effects of past unemployment, transitions in and out of poverty, self reported health status, remittances), it has never been dealt with in the context of lending to firms.

inconsistent estimates of the transition probabilities into a credit rationed status and understate the economic significance of rationing trap phenomena.

Taking into account unobserved heterogeneity and the selectivity bias, we build a model for consecutive periods that allows us to effectively identify the *true* state dependence effect. We specify a first-order Markov model for firm's transition probabilities from $t-1$ to t between three possible states. In each period a firm can: (i) apply for credit and receive the requested amount; (ii) apply for credit and have the application rejected (we label those firms as 'credit rationed borrowers'); or (iii) decide not to apply for credit. Thus, we specify two binary outcome equations: one for the bank's lending decisions and the other for the firm's credit demand at time t. In addition, as we are estimating a dynamic model, we need to specify initial conditions since the separation between the group of firms at risk of rationing from those that are not may be non-random from the very beginning. In doing so, we follow Heckman (1981b) and specify two more equations for credit demand and rationing at time $t-1$. Moreover, we are able to eliminate confounding feedback effects by simply using lagged values of covariates. Therefore, we estimate a quadrivariate probit model that allows for identification of the *true* state dependence while accounting for selection bias, unobserved heterogeneity and endogenous initial conditions.

We apply our first-order Markov model of credit rationing with sample selection to a representative sample Italian manufacturing firms surveyed by the National Institute of Statistics (ISTAT) on a quarterly basis from 2008:q2 to 2009:q4, before and after the collapse of Lehman Brothers. This survey provides detailed information on firms' loan demand and access to credit, plus information on firms' location and a number of other characteristics. Then, we build a data set of pooled transitions where the observational unit is the firm observed for every possible pair of consecutive quarters. Finally, information at the firm level is merged with data at the bank-province level on bank branch openings and closures compiled by the Bank of Italy in order to build measures of the structure of local credit markets.

In the empirical analysis, we address three questions. First, we test for the degree of state dependence in credit rationing and for the rate of discouragement in credit demand. Then, we assess whether the persistence of the credit rationing status and the discouragement effects are heterogeneous across types of firms (small versus large, domestic-oriented versus export-oriented firms versus non-export oriented) and market characteristics (credit market concentration, presence of large banks and the level of economic development). Finally, we examine whether the occurrence of a major liquidity shock (the bankruptcy of Lehman Brothers) has produced a rationing trap, that is whether the likelihood of firms being locked in a rationing state and staying out of the credit market have increased after Lehman's collapse.

By way of preview, five main results emerge from our estimates. *First*, we find evidence that state dependence in credit rationing is a statistical and economic significant phenomenon in the Italian credit markets: the likelihood of firms being rationed by banks in t conditional on they having being rationed in the previous quarter is on average more than three times larger than same probability in the case in which they were not rationed in $t-1$ (27.2% versus

7,7%). *Second*, the discouragement effect, i.e., the probability of firms not applying for credit in t given that they underwent a loan denial in $t-1$, is on average quite high (52,8%). *Third*, persistence and discouragement effects move in opposite directions: the types of firms that are more likely to abstain from applying for a loan after having faced a restriction in access to credit in $t-1$ (small and domestic-oriented firms) are those that, when do not quit the credit market, experience a lower degree of state dependence in credit rationing. *Fourth*, the organizational structure of local credit markets influence the degree of firms' persistence in credit rationing, while interbank competition does not make local firms more likely to be locked in a rationing trap. *Fifth*, we find clear evidence that the bankruptcy of Lehman Brothers in September 2008 produced an intense rationing trap exacerbating both the persistence of credit rationing for firms (from 24.8% to 38.6%) and the abandonment of the credit market by rationed firms (from 49.3% to 54.3%).

Apart from the micro-empirical literature on credit rationing, our paper is related to credit cycle and credit crunch literature.

Macroeconomic models with financial frictions and credit constraints to firms have shown how temporary shocks affecting non-financial or financial sectors of the economy may propagate into large aggregate output fluctuations (Bernanke and Gertler, 1989; Greenwald and Stiglitz, 1993; Kiyotaki and Moore, 1997; Carlstrom and Fuerst, 1997). Although the nature of the shock, the type of financial imperfection and the structure of the economy vary from model to model, the general mechanism outlined in this literature is simple and intuitive: a temporary shock to firms' productivity or credit supply reduces the net worth of financially constrained firms, the value of collateralizable assets and their ability to borrow. As a consequence, these firms would cut back their investment. The resulting lower demand for assets would reduce their price, generating a further fall in firms' net worth which locks them into a *credit rationing trap*. While there is robust empirical evidence that financial accelerator mechanisms matter for macroeconomic dynamics and firms' investment (Braun and Larrain, 2005; McLean and Zhao, 2014), to the best of our knowledge, there is no direct evidence on the possible occurrence of credit cycles at the firm level.

Finally, this paper also contributes to the wide debate on whether a credit crunch occurred during the 2008-2010 global financial crisis and which type of firms suffered most from the contraction of credit supply (Puri, Rocholl, and Steffen, 2011; Jiménez, Ongena, Peydro, and Saurina, 2012; Popov and Udell, 2012; De Haas and Van Horen, 2013; Iyer, Lopes, Peydro, and Schoar, 2014; Presbitero, Udell, and Zazzaro, 2014). We improve upon this literature by analyzing the dynamics of the credit crunch and the possibility that the tighter credit standards used by banks in lending increased the average duration of the credit rationing state, discouraging some firms from seeking credit.

The rest of the paper is organized as follows: in Section 2 we introduce the state dependence model with sample selection and describe our measures of persistency of credit rationing and discouragement from credit-seeking; in Section 3 we present the dataset and the variables; in

Section 4 we discuss the estimation results; the final Section concludes.

2 Empirical strategy

The aim of our strategy is to identify the state dependence effect in credit rationing. State dependence is how the experience of being rationed in the past influences the probability of being rationed in the future, and needs to be disentangled from the propensity to experience a rationing outcome in all periods, that is the effect of observed and unobserved heterogeneity (Heckman, 1981a,b). The modeling issue that arises in this context is that a firm may decide not to apply for a credit loan, giving rise to a possible source of selection bias in modeling the rationing probability that needs to be accounted for (see also Presbitero, Udell, and Zazzaro, 2014). Moreover, the estimation of a model with state dependence requires an assumption on the firm's initial status. One can take initial conditions as exogenous, which means assuming that the initial status and the unobservable time–invariant firm's specific effect are independent. The assumption of exogeneity of initial conditions would lead to estimating a model only for credit demand and supply at time t, including the lagged dependent variable in the model specification, without specifying equations for the initial conditions of credit demand and supply. This assumption is plausible when the length of the time–series is adequate for asymptotics. With T fixed, however, the assumption of independence between the firm's initial status and its unobservable specific factor is too strong.

Therefore, we need to specify a dynamic binary model with sample selection properly accounting for endogenous initial conditions. One solution is to estimate a random effect probit model with sample selection handling initial conditions as in Heckman (1981b) or Wooldridge (2005). Two major issues arise in this context. First, the estimation of this model would require the evaluation of a $T \times 2$–variate normal distribution function in order to maximize the log-likelihood; although quadrature and simulation methods for the evaluation of multivariate integrals are often available in software, computation is extremely expensive especially with T and n large (in our case, $T = 8$ for a total of about 30,000 observations). Secondly, the experience of being rationed in the past may affect the future values of covariates, making it difficult to disentangle the *true* state dependence from feedback effects (Biewen, 2009). This problem is often circumvented by assuming strict exogeneity which may, however, be implausible in our case since past rationing events may influence some relevant present firms characteristics (for instance, liquidity, production level or even dimension).

The identification of the *true* state dependence, in presence of unobserved heterogeneity and selectivity bias, can be achieved much more effectively by specifying a model for consecutive periods. We build a dataset of pooled transitions, which means that the observation unit is the firm observed for every possible pair of consecutive periods. Using this structure of the data, we build a first–order Markov model for firms' transitions between different states in the credit market considering two consecutive periods, $t-1$ and t. In each period, the firm can be in one of the following states: (i) the firm applies for bank credit and receives the requested amount; (ii) the firm applies for credit and its application is rejected by the bank; and (iii) the firm does not apply for bank credit. We specify two binary outcome equations: one for credit rationing and one for credit demand. Moreover, we allow for the presence of endogenous initial conditions, and, therefore, we estimate the parameters of two more equations for credit demand and supply in $t-1$ following Heckman (1981b). In addition, by using lagged values of covariates, we eliminate the risk of possibly confounding state dependence with feedback effects. Our final model is a quadrivariate probit that accounts for *true* state dependence, selection bias, unobserved heterogeneity, and endogenous initial conditions. A similar approach was introduced by Cappellari and Jenkins (2004) who specified a trivariate dynamic probit model for poverty transitions with sample attrition.

This approach does not make it possible to identify feedback effects and, since we consider only two periods, we cannot disentangle the effect of dependence due to time–varying unobserved heterogeneity form the dependence due to time–invariant unobserved heterogeneity. Nevertheless, our object of main interest is the state dependence effect in credit rationing, which makes ignoring these shortcomings not problematic in this context.

In the rest of this section, we first lay out the model specification, then we discuss the estimation method, and, finally, we illustrate the calculation of the transition probabilities.

2.1 Model specification

We specify a quadrivariate probit model for credit demand and supply–side in the two consecutive periods $t-1$ and t. Two equations for credit demand and rationing are specified in $t-1$ as initial conditions and, with suitable exclusion restrictions, other two equations for the same outcomes are specified in t.

In $t-1$, the latent propensity to apply for credit of firm i for $i = 1 \dots N$ is:

$$d_{i,t-1} = \mathbf{q}'_{i,t-1}\boldsymbol{\pi} + u_{i,t-1} \tag{1}$$

where we observe $D_{i,t-1} = \mathbf{I}(d_{i,t-1} > 0)$: the function $\mathbf{I}$ indicates whether firm i applies for credit in $t-1$, $D_{i,t-1} = 1$, or not, $D_{i,t-1} = 0$; the set of covariates $\mathbf{q}_{i,t-1}$ includes both time–invariant firms characteristics (such as size, geographical location, economic sector, whether the firm is an exporter) and time varying measures of production and liquidity level. The error term is specified $u_{i,t-1} = \lambda_i + \zeta_{i,t-1}$ where λ_i is a firm specific effect and $\zeta_{i,t-1}$ is an zero mean error term iid, both normally distributed. In addition, $u_{i,t-1} \sim N(0,1)$ is independent of the covariates.

Only if $D_{i,t-1} = 1$ we observe the outcome of the loan application for firm i in $t-1$:

$$r_{i,t-1} = \mathbf{w}'_{i,t-1}\boldsymbol{\phi} + \eta_{it-1} \tag{2}$$

where $r_{i,t-1}$ is the latent propensity to be rationed that leads to the observational rule $R_{i,t-1} = \mathbf{I}(r_{i,t-1} > 0)$ while $R_{i,t-1}$ is missing if firm i did not demand for credit; $\mathbf{w}_{i,t-1}$ is a subset of $\mathbf{q}_{i,t-1}$ that leaves out exclusion restrictions; the error term $\eta_{i,t-1}$ equals $\nu_i + \xi_{i,t-1}$ where $\eta_{i,t-1} \sim N(0,1)$, ν_i is a firm specific effect and $\xi_{i,t-1}$ is a zero mean iid error term. Both ν_i and $\xi_{i,t-1}$ are normally distributed.

At time t, we specify the rationing and demand equations conditional on the $t-1$ rationing outcome in order to account for the firms' possible state dependence in credit rationing. Therefore, the demand equation in t is:

$$d_{it} = \mathbf{z}'_{i,t-1}\boldsymbol{\theta} + \psi R^*_{i,t-1} + v_{it} \tag{3}$$

where we observe $D_{it} = \mathbf{I}(d_{it} > 0)$. Since the rationing outcome in $t-1$, R_{it-1}, is not observed for those firm that did not apply for credit in $t-1$, we substitute R_{it-1} with R^*_{it-1} that takes value 1 for rationed firms in $t-1$ and zero for non–rationed firms and for those firms that did not demand for credit in $t-1$, whose rationing outcome would be otherwise unobserved. In practice, we separate rationed firms from those who did not have a financial struggle in $t-1$. We use as covariates lagged independent variables in order to avoid possible endogeneity arising from the time–varying nature of some firms' and credit market characteristics. Last, $v_{it} \sim N(0,1)$ is the sum of the firm specific effect τ_i and the iid error δ_{it} both normally distributed.

Finally, we specify the rationing equation at time t as:

$$r_{it} = \mathbf{x}'_{i,t-1}\boldsymbol{\beta} + \gamma R^*_{it-1} + \varepsilon_{it} \tag{4}$$

we observe $R_{it} = \mathbf{I}(r_{it} > 0)$ only if D_{it} is equal to 1 and unobservable otherwise; again $\varepsilon_{it} \sim N(0,1)$ is equal to $\alpha_i + \omega_{it}$ a firm specific effect and an orthogonal white noise both normally distributed.

The error terms $[u_{it-1}, \eta_{it-1}, v_{it}, \varepsilon_{it}]'$ are assumed to be jointly normal with correlation matrix $\mathbf{\Sigma} = unvech\,(1, \rho_{21}, \rho_{31}, \rho_{41}, 1, \rho_{32}, \rho_{42}, 1, \rho_{43})$.[3] Under the assumptions on the error terms of equation (1)–(4), the correlation structure completely parametrizes the distribution of unobserved heterogeneity: the correlation coefficients between the composite error terms are equal to the covariances between the respective firm specific effects.

2.2 Estimation

Under the assumption of joint normality, we estimate the parameter vector $[\boldsymbol{\pi}', \boldsymbol{\phi}', \boldsymbol{\theta}', \psi, \boldsymbol{\beta}', \gamma, \boldsymbol{\rho}']'$, where $\boldsymbol{\rho} = [\rho_{21}, \rho_{31}, \rho_{41}, \rho_{32}, \rho_{42}, \rho_{43}]$, by Maximum Simulated Likelihood (MSL). The contribution of firm i to the log-likelihood is $\ell_i = \ln(P_i^s)$ where P_i^s for $s = 1 \dots 9$ is the probability of one of the 9 possible outcomes resulting from the combination of demand and rationing in t

[3] Where the correlations between the error terms are defined as: $\rho_{21} = corr(\eta_{i,t-1}, u_{i,t-1})$, $\rho_{31} = corr(v_{it}, u_{i,t-1})$, $\rho_{41} = corr(\varepsilon_{it}, u_{i,t-1})$, $\rho_{32} = corr(v_{it}, \eta_{i,t-1})$, $\rho_{42} = corr(\varepsilon_{it}, \eta_{i,t-1})$, $\rho_{43} = corr(\varepsilon_{it}, v_{it})$

and $t-1$. The log-likelihood for firm i is:

$$\begin{aligned}\ell_i = &(1-D_{i,t-1})(1-D_{it})\ln\left[P_i^1\right] + (1-D_{i,t-1})D_{it}(1-R_{it})\ln\left[P_i^2\right] + (1-D_{i,t-1})D_{it}R_{it}\ln\left[P_i^3\right] + \\ &D_{i,t-1}(1-R_{i,t-1})(1-D_{it})\ln\left[P_i^4\right] + D_{i,t-1}R_{i,t-1}(1-D_{it})\ln\left[P_i^5\right] + \\ &D_{i,t-1}(1-R_{i,t-1})D_{it}(1-R_{it})\ln\left[P_i^6\right] + D_{i,t-1}(1-R_{i,t-1})D_{it}R_{it}\ln\left[P_i^7\right] + \\ &D_{i,t-1}R_{i,t-1}D_{it}(1-R_{it})\ln\left[P_i^8\right] + D_{i,t-1}R_{i,t-1}D_{it}R_{it}\ln\left[P_i^9\right]\end{aligned} \tag{5}$$

with:

$$\begin{aligned}
P_i^1 &= \Phi_2(-\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\, -\mathbf{z}'_{i,t-1}\boldsymbol{\theta},\, \rho_{31})\\
P_i^2 &= \Phi_3(-\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\, \mathbf{z}'_{i,t-1}\boldsymbol{\theta},\, -\mathbf{x}'_{i,t-1}\boldsymbol{\beta},\, -\rho_{31}, \rho_{41}, -\rho_{43})\\
P_i^3 &= \Phi_3(-\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\, \mathbf{z}'_{i,t-1}\boldsymbol{\theta},\, \mathbf{x}'_{i,t-1}\boldsymbol{\beta},\, -\rho_{31}, -\rho_{41}, \rho_{43})\\
P_i^4 &= \Phi_3(\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\, -\mathbf{w}'_{i,t-1}\boldsymbol{\phi},\, -\mathbf{z}'_{i,t-1}\boldsymbol{\theta},\, -\rho_{21}, -\rho_{31}, \rho_{32})\\
P_i^5 &= \Phi_3(\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\, \mathbf{w}'_{i,t-1}\boldsymbol{\phi},\, -(\mathbf{z}'_{i,t-1}\boldsymbol{\theta} + \psi R^*_{i,t-1}),\, \rho_{21}, -\rho_{31}, -\rho_{32})\\
P_i^6 &= \Phi_4(\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\, -\mathbf{w}'_{i,t-1}\boldsymbol{\phi},\, \mathbf{z}'_{i,t-1}\boldsymbol{\theta},\, -\mathbf{x}'_{i,t-1}\boldsymbol{\beta},\\
&\quad -\rho_{21}, -\rho_{31}, -\rho_{41}, -\rho_{32}, \rho_{42}, -\rho_{43})\\
P_i^7 &= \Phi_4(\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\, -\mathbf{w}'_{i,t-1}\boldsymbol{\phi},\, \mathbf{z}'_{i,t-1}\boldsymbol{\theta},\, \mathbf{x}'_{i,t-1}\boldsymbol{\beta},\\
&\quad -\rho_{21}, \rho_{31}, \rho_{41}, -\rho_{32}, -\rho_{42}, \rho_{43})\\
P_i^8 &= \Phi_4(\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\, \mathbf{w}'_{i,t-1}\boldsymbol{\phi},\, \mathbf{z}'_{i,t-1}\boldsymbol{\theta} + \psi R^*_{i,t-1},\, -(\mathbf{x}'_{i,t-1}\boldsymbol{\beta} + \gamma R^*_{i,t-1}),\\
&\quad \rho_{21}, \rho_{31}, -\rho_{41}, -\rho_{32}, -\rho_{42}, -\rho_{43})\\
P_i^9 &= \Phi_4(\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\, \mathbf{w}'_{i,t-1}\boldsymbol{\phi},\, \mathbf{z}'_{i,t-1}\boldsymbol{\theta} + \psi R^*_{i,t-1},\, \mathbf{x}'_{i,t-1}\boldsymbol{\beta} + \gamma R^*_{i,t-1},\\
&\quad \rho_{21}, \rho_{31}, \rho_{41}, \rho_{32}, \rho_{42}, \rho_{43})
\end{aligned}$$

where Φ_2, Φ_3, Φ_4 are the cumulative distribution functions of the bivariate, trivariate and quadrivariate standard normal distribution respectively. Evaluation of the multivariate normal probabilities Φ_3 and Φ_4 is carried out by GHK simulation (Geweke, 1989; Keane, 1994; Hajivassiliou and McFadden, 1998) with 200 replications. It may be argued that a simpler and less CPU demanding strategy, such as a multiple step estimation, could be adopted. While this is relatively common practice in the estimation of simpler models, we discarded it in favor of MSL as the former leads to inconsistent estimates of both coefficients and their asymptotic covariance matrix.[4] Finally, the use of pooled transitions requires the estimation of robust standard errors. [5]

[4]In a two–equation sample selection model where the response variable of the main equation is also binary, it can be analytically proved that a control function approach induces heteroskedasticity in the main equation error term which makes the parameter estimates inconsistent. Even if we were to model the known skedastic function under joint normality, the presence of four mutually correlated error terms would make the derivation of such function analytically intractable.

[5]We use a sandwich formula. In this case it is equivalent to estimated a covariance matrix clustered by firm (see Arellano (2003) and Stock and Watson (2008)).

2.3 Persistence and transition probabilities

Other than estimating the state dependence in credit rationing, model (1)–(4) allows to compute the transition probabilities between the three possible states in $t-1$ and t. Moreover, in non–linear models the signs and magnitude of marginal effects associated with interaction terms are not directly interpretable (see Ai and Norton (2003)). The interpretation of transition probabilities is, instead, straightforward and the quantities are easily computed once the parameters of model (1)–(4) are estimated.

Of particular interest in evaluating the possibility of a rationing trap, is the *persistence rate*, that is the probability of being rationed in t conditional on having already been rationed in $t-1$. For firm i, it is computed as:

$$Pr(R_{it}=1|R_{i,t-1}=1)=\frac{P_i^9}{\Phi_2\left(\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\mathbf{w}'_{i,t-1}\boldsymbol{\phi},\rho_{21}\right)}. \tag{6}$$

Conditioning on the same event, we also compute the *rationing exit rate*, which is the transition rate from being rationed in $t-1$ to applying for credit and not being rationed in t:

$$Pr(R_{it}=0|R_{i,t-1}=1)=\frac{P_i^8}{\Phi_2\left(\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\mathbf{w}'_{i,t-1}\boldsymbol{\phi},\rho_{21}\right)}. \tag{7}$$

Separately from the *exit rate*, we compute the probability that a firm rationed in $t-1$ decides not to demand for credit in t. As opposed to the rationing exit rate, we can interpret this quantity as the probability of leaving the credit market voluntarily: a firm rationed in $t-1$ did not get the needed liquidity in $t-1$ and chooses to find sources of credit elsewhere. We denote this probability *discouragement rate*, that is:

$$Pr(D_{it}=0|R_{i,t-1}=1)=\frac{P_i^5}{\Phi_2\left(\mathbf{q}'_{i,t-1}\boldsymbol{\pi},\mathbf{w}'_{i,t-1}\boldsymbol{\phi},\rho_{21}\right)}. \tag{8}$$

Furthermore, we evaluate the risk of entering the credit rationing state in t conditional on not having experienced the rationing outcome in $t-1$ (the firm either did not apply or has not been rationed). We call this probability the *rationing entry rate* and we compute it as:

$$Pr(R_{it}=1|R_{i,t-1}=0\cup D_{i,t-1}=0)=\frac{P_i^3+P_i^6}{\Phi_2\left(\mathbf{q}'_{i,t-1}\boldsymbol{\pi},-\mathbf{w}'_{i,t-1}\boldsymbol{\phi},-\rho_{21}\right)+\Phi\left(-\mathbf{q}'_{i,t-1}\boldsymbol{\pi}\right)}. \tag{9}$$

We compute the out–of–sample rationing probability in t for those firms that do not apply for credit in t: this quantity is a measure of the expected rationing outcome of possibly discouraged firms, that leave the credit market after being rationed. We condition this probability on both rationing and not rationing/not applying in $t-1$:

$$Pr(R_{it}=1|D_{it}=0,R_{i,t-1}=1)=$$

$$\frac{\Phi_4\left(\mathbf{q}'_{i,t-1}\pi,\mathbf{w}'_{i,t-1}\boldsymbol{\phi},-(\mathbf{z}'_{i,t-1}\theta+\psi R^*_{i,t-1}),\mathbf{x}'_{i,t-1}\boldsymbol{\beta}+\gamma R^*_{i,t-1}\rho_{21},-\rho_{31},\rho_{41},-\rho_{32},\rho_{42},-\rho_{43}\right)}{\Phi_3(\mathbf{q}'_{i,t-1}\pi,\mathbf{w}'_{i,t-1}\boldsymbol{\phi},-(\mathbf{z}'_{i,t-1}\theta+\psi R^*_{i,t-1}),\rho_{21},-\rho_{31},-\rho_{32})} \tag{10}$$

and:

$$Pr(R_{it}=1|D_{it}=0,R_{i,t-1}=0)=$$

$$\frac{\Phi_4\left(\mathbf{q}'_{i,t-1}\pi,-\mathbf{w}'_{i,t-1}\boldsymbol{\phi},-\mathbf{z}'_{i,t-1}\theta,\mathbf{x}'_{i,t-1}\boldsymbol{\beta}-\rho_{21},-\rho_{31},\rho_{41},\rho_{32},-\rho_{42},-\rho_{43}\right)}{\Phi_3(\mathbf{q}'_{i,t-1}\pi,-\mathbf{w}'_{i,t-1}\boldsymbol{\phi},-\mathbf{z}'_{i,t-1}\theta,-\rho_{21},-\rho_{31},\rho_{32})}. \tag{11}$$

Each of the rationing probabilities in equations (6)–(11) are considered jointly with the probability of applying for credit ($D_{i,t-1}=1$ or $D_{it}=1$) that, for brevity, are omitted from the notation.

Finally, the first order–Markov model also allows for a simple analytical form to compute spells in the possible states. Conditional on being rationed in $t-1$, we compute the duration of a firm being out of the credit market as:

$$S=\frac{1}{[1-Pr(R_{it}=1|R_{i,t-1}=1)-Pr(D_{it}=0|R_{i,t-1}=1)]} \tag{12}$$

that is both being in the rationing state or not applying for credit in t. The quantities (6)–(12) are evaluated at the MSL estimates of $[\boldsymbol{\pi}',\boldsymbol{\phi}',\boldsymbol{\theta}',\psi,\boldsymbol{\beta}',\gamma,\boldsymbol{\rho}']'$.

3 Data and variables

We use the data from a monthly survey of about 4,000 Italian manufacturing firms with at least 5 employees, interviewed from March 2008 to February 2010 by the ISAE (Institute of Studies and Economic Analysis), recently becoming part of the ISTAT (Italian Institute of Statistics). Data are available at the firm–level, but only on a quarterly basis (the March, June, September and December releases).[6] We link the ISAE dataset with monthly data on bank branch openings and closures compiled by the Bank of Italy. These data are at the bank–province level. Excluding 2010 because of outliers and observations with missing values in the variables of interest, we end up with 3,893 firms observed quarterly between 2008:1 to 2009:4 (unbalanced). The estimation of model (1)–(4), presented in Section 2, is based on the sample of pooled transitions: we build our dataset so that the observation unit is the firm observed for every possible pair of consecutive quarters t and $t-1$ from 2008:q2 to 2009:q4. We, therefore, end up with a sample of $23,974$ observations.

Table 1 summarizes the sample composition by firms' state in t and $t-1$ for the complete sample of pooled transitions. The marginal frequency of rationed firms at time t in our sample (of applicant firms) is 20.1% while the rationing frequency in t conditional on having experienced the rationing outcome is 27.2% (see Table 1). The conditional frequency of rationed firms follow the same pattern of the marginal frequency over time even thought it is constantly higher (see Figure 1).

In the specification of the set of covariates in (1)–(4) we include variables both at the firm level and at the local credit market level. The description and sample means of covariates are

[6] Additional information on the survey are available here: http://siqual.istat.it/SIQual/visualizza.do?id=888894.

collected in Table 2. The variables of interest at the firm level are: a dummy for the firm's size *SMALL*, a dummy for exporter firms (*EXPORT*), and a dummy variable indicating if the firm is located in the south of Italy (*SOUTH*). As control variables, we also include dummies the categorical variable *LIQUIDITY*, and sector dummies for *INDUSTRY*. At the credit market level, the variables we include in the model specification are: (i) the Herfindhal-Hirschman index (*HHI*)of market concentration, computed on the share of branches held by banks operating in the province where the firm is located, as a measure of the degree of credit market competition in the province; and(ii) the share of branches belonging to the five largest Italian banking groups in the province (*LARGEB*). The rationale for the inclusion of these two variables is that the degree of market power and the presence of large banks are important determinants of firms' financing constraints, especially in periods of financial turmoil, when large banks are likely to be more exposed to the wholesale funding market (Carbó-Valverde, Rodríguez-Fernández, and Udell, 2009; Rice and Strahan, 2009; Bonaccorsi Di Patti and Sette, 2012).

Finally, the variable *PRODUCTION* is used as exclusion restrictions in the initial conditions (1)–(2): the survey item concerns the expected level of production for the next three months, so it can be conjectured that this information may have an effect only on the initial decision of applying for a credit loan and on the initial bank response, while it provides no extra information in the following quarter, since we consider a two–period model for each transition. In addition, *LABOR COST* is used as an exclusion restriction for the credit demand equations (1)–(3) as in Presbitero, Udell, and Zazzaro (2014). Al the variables describing firm and credit market attributes are taken at $t-1$ to avoid possible endogeneity problems.

Figure 2 shows the frequencies (both marginal and conditional on the credit rationed status in $t-1$) of rationed firms considering the sample of applicant firms in t by firms' and credit market characteristics. Quantities are disaggregated for the two values in the binary variables of interest and for the 1^{st} and 3^{rd} quartiles in the distributions of *HHI* and *LARGEB*. It is worth noticing that, when considering firm size and export, the patterns of the marginal and conditional frequencies are reversed: small and non exporting firms are, on average, rationed more frequently while large and exporter firms are more persistent in the rationing state.

4 Estimation results and discussion

4.1 Identifying the *true* state dependence

Table 3 shows our main results and compare the estimates of the first–order Markov model with the ones obtained with alternative estimation techniques. The first two columns report the estimated parameters of equations (3)–(4) and the correlation coefficients of the first order Markov model proposed in Section 2, in which we control for the initial conditions (Model (1) henceforth).[7] The second two columns report the estimation results of a probit model with sample selection in which the probability of being credit rationed is jointly estimated with the

[7] The estimates of the initial conditions (1) and (2) are omitted for brevity. The are available upon request.

demand (selection) equation. Finally the last column shows the result of a simple probit model estimation of the rationing equation (4), in which the sample selection and the initial conditions are not taken into account.

In Model (1), the key parameter γ, associated to R^*_{t-1} in the rationing equation, is positive and statistically significant (column 2), indicating that once a firm has been rationed in $t-1$, its probability of being credit rationed again in t is, on average, higher than for firms that have not been rationed or did not apply for a credit loan in $t-1$. We also find that ψ is positive and statistically significant (column 1), so that firms which have been rationed are also more likely than other comparable firms in the sample to apply for bank credit.

Formally, we test for state dependence in the demand and rationing equation computing the Wald test statistic for the null hypothesis of ψ and γ in (3) and (4) being jointly zero. The result is 53.23 that, compared with a χ^2_2, clearly indicates that the null hypothesis of absence of state dependence should be rejected.

As discussed in Section 2, the first–order Markov model allows us to separate the state dependence in credit rationing from the unobserved time-invariant firm heterogeneity that affects the firm likelihood to experience the rationing outcome in every period. In doing so, we specify a correlation structure under joint normality to account for firms unobserved heterogeneity. In addition, we need to specify the initial condition equations for credit demand and supply, as the separation between the group of firms at risk of rationing in $t-1$ from those that are not may be non–random (see Section 2).

Looking at the results of the probit model with sample selection (columns 3 and 4) makes it clear that a pooled model that does not take into account for firms' heterogeneity and that, consequently, fails to control for initial conditions, leads to biased results. In particular, the state dependence parameters change substantially when initial conditions are not accounted for and previously rationed firms looks less likely than their counterparts to be rationed again. Although it is a fairly common result that neglecting initial conditions results in overstating the magnitude of state dependence, the interpretation in this case is not straightforward: the biases in the demand equation and the rationing equation in t depend on the correlation between the unobserved heterogeneity and both initial outcomes. A test for the exogeneity of the initial conditions is carried out by computing a LR test for the null hypothesis of $\rho_{31} = \rho_{41} = \rho_{32} = \rho_{42} = 0$. The resulting value of the test is 841.72, so that the null hypothesis is strongly rejected (the value of the test needs to be compared with a χ^2_4).

The estimated correlation coefficients of Model (1) also indicate that the selection bias in modeling the rationing probability needs to be accounted for: the estimates of ρ_{43}, the correlation between demand and rationing in t, and ρ_{21}, the correlation between demand and rationing in $t-1$, are high in absolute value and statistically significant. The negative values of the correlation coefficients between the credit demand and supply equations suggest that certain firms do not apply for a credit loan as they expect to have a high probability to be rationed and take themselves out of the credit market. Neglecting the selection bias leads to severely biased estimates of the regression coefficients especially of the state dependence parameter (see column 5).

Finally, the estimated ρ_{43} in Model (1) is smaller than the corresponding correlation coefficient in the probit model with sample selection. This result would suggest that part of the effect of firms' specific characteristics that are considered by the first-order Markov model, are instead captured only by the correlation structure in the probit model with sample selection.

4.1.1 The other determinants of credit rationing

In this section, we briefly discuss once for all the correlations between our set of control variables and the probabilities of demanding bank credit and being credit rationed, on the ground of the estimates of Model (1).

First, consistent with a large literature on firms' financing constraints (Presbitero, Udell, and Zazzaro, 2014), we find that small and non exporting firms are at a disadvantage with respect to large and exporting firms in accessing bank credit. In fact, they have a lower propensity to demand credit but, once they apply, they are more likely to be credit rationed than large and exporting firms. As expected, liquidity needs are positively correlated with demand for credit, but they do not show any significant association with the probability of being rationed.

Second, consistent with the view that bank competition eases access to bank credit (Beck, Demirguc-Kunt, and Maksimovic, 2004), firms located in provinces where the market is more concentrated are less likely to have their application rejected by the bank. By contrast, as in Presbitero, Udell, and Zazzaro (2014), we do not find support to the hypothesis that large banks have transmitted the financial crisis to the real economy more than other banks. We also find that being located in the less developed southern regions does not affect the demand and the supply of credit, once firm- and market-specific characteristics are taken into account.

Finally, the coefficients on the time dummies clearly indicate the strengthening of financial tensions after the Lehman's bankruptcy: our estimates show a significant reduction of the demand for credit but, even accounting for this effect, there is evidence of a large and statistically significant credit crunch, consistent with the existing evidence for Italy (Del Giovane, Eramo, and Nobili, 2011; Gobbi and Sette, 2014; Presbitero, Udell, and Zazzaro, 2014) and with the descriptive statistics showed in Figure 1.

4.1.2 Comparing different models: goodness-of-fit

Table 4 shows the (average) predictions of the conditional probabilities of being in one of the three possible states at time t conditional on coming from each state in $t-1$. Probabilities are evaluated at the MSL estimates of Model (1). As a measure of Model (1)'s goodness of fit, these probabilities need to be compared with the sample conditional frequencies displayed in Table 1.

To assess the accuracy of the different models we look at the ROC (Receiver Operating Characteristic) curve and at the area under the curve (AUROC). The latter is a measure of the predictive ability of the model that is independent of the cutoff probability used to classify the predictions of the model. Under the standard classification rule, the probability cutoff is set at 0.5, implying that Type 1 and Type 2 errors are equally bad. However, varying the cutoff probability will reduce the chances of making one type of error at the expense of increasing the other type of error. The ROC curve tells exactly how this trade-off works for all possible cutoffs, plotting the true positive rate of the model against its false positive rate. The y-axis captures 'Sensitivity' which is the probability of correctly predicting when the outcome is equal to one (i.e. the firm is actually credit rationed) The x-axis is 1-Specificity, where 'Specificity' is the probability of correctly predicting the outcome variable equal to zero (i.e. the firm is not credit rationed). It is easy to see that the further the ROC curve is away from the 45 degree line the better the model predicts both status (i.e. rationing and non-rationing). A single statistic that conveys this information is the AUROC, which provides a simple test against the null value of 0.5 with an asymptotic normal distribution. When this area under the ROC curve is 1, the model is correctly predicting everything. This statistic falls as the model becomes worse.[8]

Figure 3 shows the ROC for (a) the rationing probability in t and (b) the probability of being out of the credit market. For the first–order Markov model, probabilities are assigned according to the the state in $t-1$. In (a) the rationing probabilities for the first–order Markov model and for the probit model with sample selection are conditional on demanding for credit in t, for comparability with the pooled probit model without sample selection. In (b), the probability of being out of the credit market is computed as the marginal probability of not applying for a bank loan, $P(D_t = 0)$, plus the joint probability of applying and be rationed, $Pr(D_t = 1, R_t = 1)$. We exclude the simple probit model from this second analysis since, in this model, it is assumed that credit demand and rationing are independent and the computation of the joint probability of demand and rationing is not allowed.

Figure 3 confirms that the first–order Markov model describes the rationing outcome and the probability of being out of the credit market more accurately than the pooled probit model with and without sample selection. The shape of the ROC curves and the values of AUROC in both (a) and (b) suggest that controlling for initial conditions considerably and significantly improves the predictive ability of the first–order Markov model. At least for a wide range of cutoff probabilities, the ROC curves imply that, for a given share of true positives, the simple probit models call a larger share of false alarms that the the first–order Markov model. In particular, in panel (a) the difference in the AUROC when using the first–order Markov model and the probit, with and without sample selection, is large and statistically significant, while the AUROC of the two probit models are almost identical. This would suggest that the improve in the accuracy of the model comes from the capacity to deal with unobserved heterogeneity, rather than from modeling the sample selection.

[8]For a recent use of the AUROC in a finance context, see Bharath and Dittmar (2010).

4.2 Firms and credit market characteristics and state dependence

Tables 5 and 6 report the estimation results of the first order Markov model for six alternative specifications each designed to investigate whether state dependence in credit rationing may vary with firms' and credit market characteristics. Model (2)–(7) include interactions of firms' and credit market characteristics with the variable R^*_{t-1} in the rationing equation (only estimates of the rationing equation are reported for brevity). We focus on differences in persistence and transition probabilities for small firms, exporters and firms located in the south of Italy by estimating Models (2), (3) and (4) respectively. We then investigate the differences in the magnitude of state dependence that may arise form characteristics of the credit market locally faced by each firm (Model (5) and (6) respectively). We estimate Model (7) to investigate the change in the rationing probability during the time span considered by including the interactions of R^*_{t-1} with the time dummies. Finally, Model (8) includes all the above interaction terms. For all models presented in Tables 5 and 6, the null hypotheses of absence of state dependence, exogeneity of initial conditions and joint exogeneity are strongly rejected (see Table 10).

The estimation results of Model (2) show that while small firms have a higher probability to be rationed on average, they have a smaller rationing probability conditional on having been rationed in $t-1$. The same result applies for exporter firms (Model (3)) that turn out to be more likely to be rationed in t if they have already been rationed in $t-1$. The empirical evidence available so far on credit rationing related to firms characteristics seems to be confirmed as small and informationally opaque firms suffer more of credit rationing when looking at the unconditional rationing probability. However, as we look into the rationing probability conditional on the past states, we find that these same types of firms, once they have been rationed are less likely to experience the same outcome again. From the estimation results of Model (4), there is no significant state dependence in the rationing probability of firms located in the south of Italy compared to the rest of the sample.

Moving to credit market structure, we find that, although a higher degree of credit market concentration (*HHI*) positively influences the likelihood of a rationing outcome, it does not affect differently those firms that faced rationing in $t-1$ (see Model (5)). By contrast, the positive and significant coefficient on the interation term between $LARGEB$ and R^*_{t-1} shows that a higher presence of branches owned by large banks in the province is associated with a higher state dependence in rationing for firms located in the same province.

The estimates of Model (7) detect the credit crunch in September 2008 (we consider the quarters 2008:q4-2009:q4 the post–Lehman period): after the liquidity shock following the collapse of Lehman Brothers, all firms show, on average, a higher probability of being rationed independently of their status in $t-1$. Taken separately, the coefficients associated with the interaction of each quarter dummy with R^*_{t-1} are not statistically significant (except for 2009:q4). However, the Wald test rejects the null hypothesis of absence of state dependence (see Table 10) and indicates that the persistence in credit rationing improved after the liquidity shock.

Finally, the estimates reported in Model (8) includes all the interaction terms. While the sign and the point estimates of the coefficients are similar to the ones reported in Models (2)–(7), the standard errors of the individual coefficients are generally larger, as expected because of possible multicollinearity.[9] However, one interesting result is that the coefficients on the time dummies look more stable and precisely estimated than in Model (7). Read together, results from Model (8) seem to suggest that the persistence in the credit rationed status significantly increased after the global liquidity shock, irrespective of any firm or credit market characteristic.

4.3 The extent of the rationing trap

4.3.1 Average estimated probabilities

Table 8 reports the estimated probabilities described in Section 2.3 for given values of exogenous variables averaged over time (see the footnote to Table 8) using Models (1)–(7), in which the heterogeneity of the cedit trap is assessed one variable at the time with respect to firm characteristics, credit market structure and time.[10]

The probabilities computed for Model (1)[11] show that, on average, 27.2% of firms rationed in the previous quarter will have their application rejected if they ask for a bank loan in the next while 52.8% decide to leave the credit market: if they applied, the out of sample prediction for rationed firms (equation 10) indicates that they would have a 90% probability of being rationed. This result is tied to the strong selection bias that arises form the model estimates: it is due to the fact that firms select themselves out of the credit market on the basis of the very high expected probability of being rationed if they applied for a loan.

Our results show that large and exporter firms, that are those less likely to be rationed independently of their previous status in the credit market, have a higher persistence probability, 30.5% and 31.6% respectively, than small and non exporting firms. Given the positive association between firm size and leverage (see, among others, the seminal contributions by Harris and Raviv (1991) and Rajan and Zingales (1995)), this finding is consistent with a model *à la* Kiyotaki and Moore (1997), in which the persistence of financing constraints is more likely to emerge for more leveraged firms. On the contrary, small and non-exporting firms have a lower persistence probability but a higher discouragement rate: once rationed in $t-1$, they self-select out of the credit market and become discouraged borrowers in response to the emergence of credit constraints.

Moreover, the values of the estimated probabilities suggest that small and informationally

[9]Nonetheless, the Wald test still rejects the null hypothesis of absence of state dependence (Table 10, last row).

[10]The first column of Table 8 reports the value the marginal rationing sample frequency in t. We do not compute standard errors for these probabilities because the analytic form of the asymptotic variance–covariance matrix of these predictions would be intractable given the complexity of the model. Bootstrapping standard errors is also unfeasible since MSL is computationally intensive given the high number of parameters in the model: the estimation of Model (1) alone takes a little over 22 hours.

[11]The persistence rate, the rationing exit rate, and the discouragement rate are also displayed in last row of Table 4

opaque firms have a higher propensity to be rationed regardless of whether they have been rationed in the past: even if they had not been rationed in $t-1$, small firms would still have a 62.6% probability of being rationed if they applied for a loan against the 50.9% probability of larger firms (see the out of sample prediction (11)). The same applies for non-exporters firms (64.1% against 56.7% for exporters). However, the presence of a strong negative selection bias, determined by who applies for credit and who does not, shapes the sample of applicants leaving out those firms that expect to be rationed, such as small and non–exporter firms. Results seem to suggest that these types of firms would only apply if they can reasonably expect not to be rationed, and leave the market otherwise.

The probabilities computed for Model (6) show that firms located in provinces with a high concentration of large banks are more persistence in the rationing state. In addition, it is worth noticing that the share of large banks in the province does not affect the share of discouraged borrowers (52.7% and 52.9%) but only the probability of exiting the rationing state.

Finally, the liquidity shock that occurred with the collapse of Lehman Brothers deeply changed the distribution of firms which have been rationed at time $t-1$, across the three possible states at time t. We consider the quarters 2008:$q2$ and 2008:$q3$ as the *Pre-Lehman* period in our sample, while the *Post-Lehman* period comprises the quarters form 2008:$q4$ to 2009:$q4$. Before the global liquidity shock, previously rationed firms which decided to apply for a bank loan had almost the same chances to be trapped or to exit the rationing state (the probabilities being 24.8% and 25.8%, respectively); after September 2008, the persistence rate rises to 38.6% and the probability of not falling into the trap drastically shrinks to 7.1%. Conversely, the comparison between the pre- and post-Lehman periods points out a significant increase in the rationing entry rate. The global credit crunch also affected firm's self selection out of the credit market, since the discouragement rate increased by 5 percentage points and the out of sample prediction for rationed firms jumped to the 97.6% after the Lehman's collapse.

4.3.2 Individual firms' estimated probabilities

Table 9 reports the same estimated probabilities described in Section 2.3 for combination of values of some exogenous variables using the MSL estimates of Model (8), in which we allow for the full heterogeneity of persistence across firm characteristics, credit market structure and time.[12] Rather than computing average probabilities, which are not meaningful in presence of factor variables, we combine firms characteristics with the share of large banks in the province in the pre- and post-Lehman periods: we consider small and large firms, exporters and non exporters, the first and third quartile of *LARGEB*, and the pre- and post-Lehman periods.

The main interesting pattern that emerges is the great variability in the transitions in and out credit rationing across different type of firms. The persistence rate varies from 35.6% for a large exporter firm located in a province with a large share of branches owned by large banks after the Lehman's collapse, to 20.8% for a firm with exactly the opposite characteristics. The

[12] See footnote to Table 9 for further details

rationing exit and entry rates vary, respectively between 17.7 and 32.0% and between 4.7 and 7.6%. In addition, it clearly emerges that small and non exporter firms prefer to stay out of the credit market post-Lehman if they have already been rationed: the discouragement rate is about 54% and it seems to be independent of the presence of large banks. In contrast, only 40% of large, exporter firms and located in a province with a rather low share of large banks decide not to apply for a credit loan after being rationed.

5 Conclusions

The ongoing financial crisis has made it clear once again that financial frictions are a key determinants of prolonged recessions. As a result, a growing literature – mainly based on general equilibrium theory – is investigating the real effect of financial frictions, building on the seminal contributions by Bernanke and Gertler (1989) and Carlstrom and Fuerst (1997). Given the microfoudation of these kind of macro models, it is somewhat surprising the limited empirical evidence on the actual presence of persistence in financial frictions at the firm level. This paper aims at filling this gap in the literature. Using quarterly data on a representative sample of Italian manufacturing firms, we investigate the transition probabilities in and out the credit market. We use a first-order Markov model to estimate the *true* state dependence: we take into account the possible biases arising from sample selection and from the endogeneity of the initial conditions, jointly modeling the probability of applying for bank credit and of being credit rationed in period t and in period $t-1$. Considering that in each period a firm may: (i) be credit rationed, (ii) not demand bank credit, and (iii) have access to bank credit, we can estimate the transitions across the three different status and the degree of persistence in each status.

Our results shed some light on the dynamics of firms' access to credit. *First*, we find strong evidence of the relevance of credit rationing traps, as having being rationed in the past significantly increases the probability of being rationed in the current period. This effect is economically meaningful and it is stronger than the one estimated by a simple model with sample selection, which neglects unobserved heterogeneity and assumes the exogeneity of the initial conditions. Different diagnostic tests indicate that controlling for sample selection and initial conditions greatly improves the fit of the model. *Second*, we find that the firm characteristics which explain the transition in and out the credit market are different from the ones that correlated with firms' financing constraint in a static framework. In fact, we find that, while large and exporting firms are less likely than small and non-exporting firms to be credit rationed, they are instead more likely to be captured in a rationing trap. If firm size and leverage were positively correlated (Harris and Raviv, 1991; Rajan and Zingales, 1995), this finding is consistent with a model *à la* Kiyotaki and Moore (1997), in which the persistence of financing constraints is more likely to emerge for more leveraged firms. By contrast, small and non-exporting firms are more likely to self-select out of the credit market and become discouraged borrowers in response to the emergence of credit constraints. *Third*, we find that local credit market structure matters, in the sense that a rationing trap is more likely to emerge, other things equal, in markets with a predominant share of large banks. *Finally*, given that our dataset encompasses the 2008 financial crisis, we can show that the persistence in the credit rationed status significantly increased after the liquidity shock triggered by the Lehman's bankruptcy.

To conclude, this paper is, to the best of our knowledge, the first attempt to estimate the persistence of credit rationing at the firm level controlling for the firm-specific unobserved heterogeneity. The estimation of a transition matrix in and out the credit market provides some relevant information for policy making, in order to alleviate firms' financing constraints and to mitigate the propagation and the persistence of exogenous shocks.

A cautionary tale in the interpretation of our results is due because of the limited available set of information about firm characteristics. Provided that the data allow for a more comprehensive analysis of the effect of firm heterogeneity on the emergence of a rationing trap, this framework makes it possible to address several additional questions. For instance: (i) how bank-firm relationships affect the extent of rationing traps? (ii) Are more productive and innovative firms more able to react to adverse credit market conditions? We leave these questions to future research.

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FIGURES AND TABLES

Figure 1: Sample frequency and rationed firms, by quarter

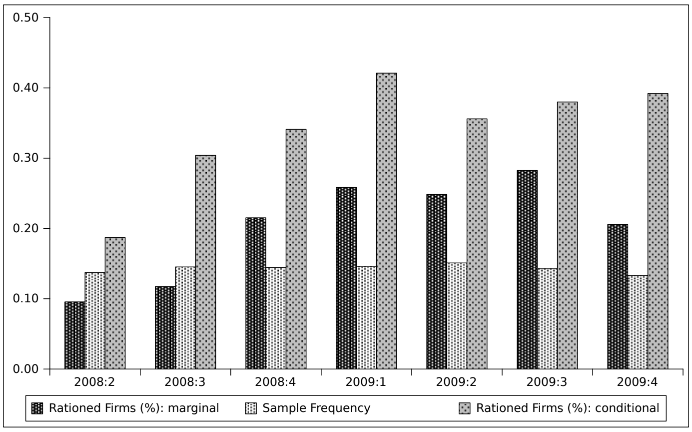


Figure 2: Sample frequency and rationed firms, by firms' and credit market's characteristics

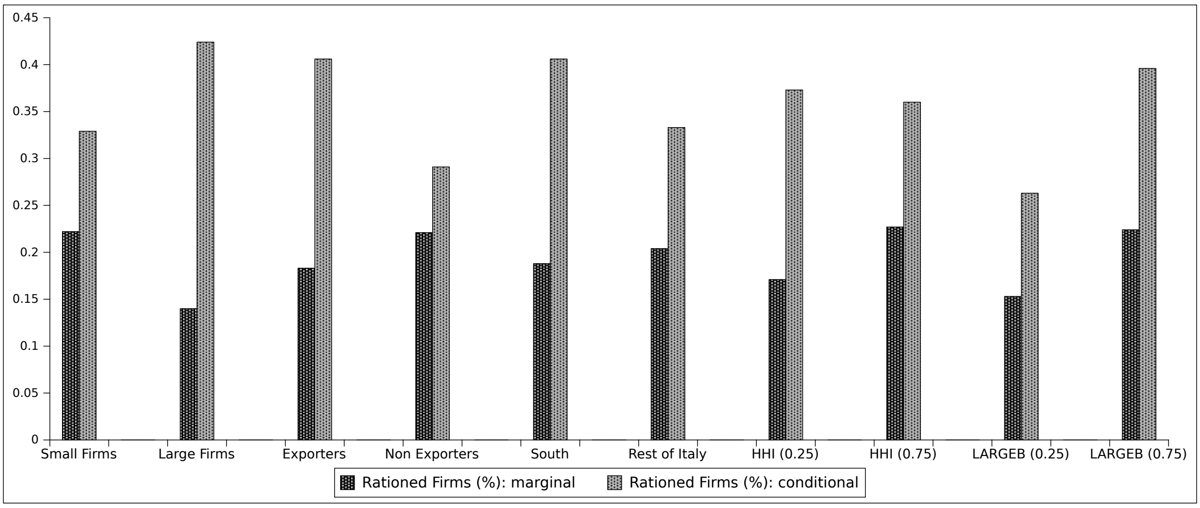
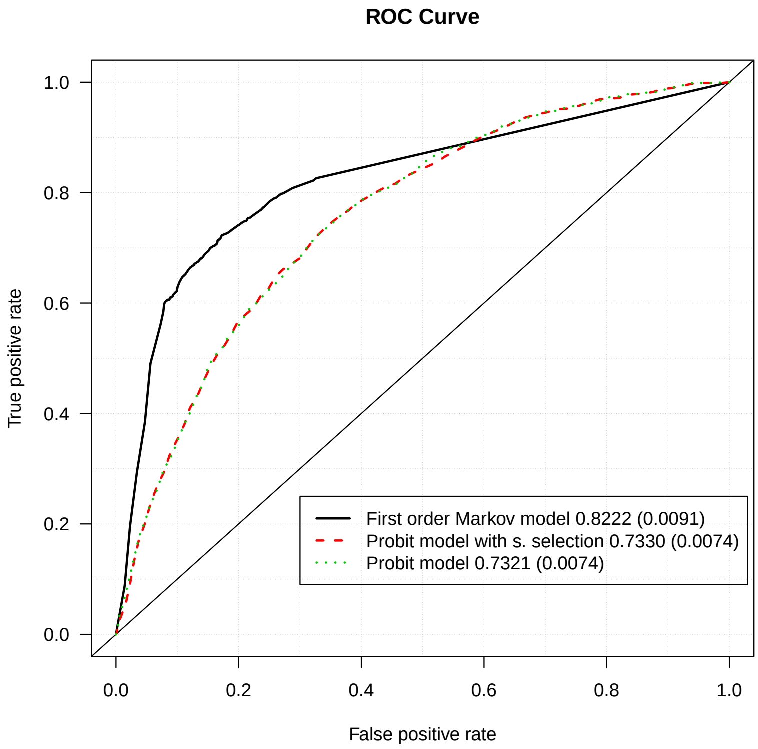
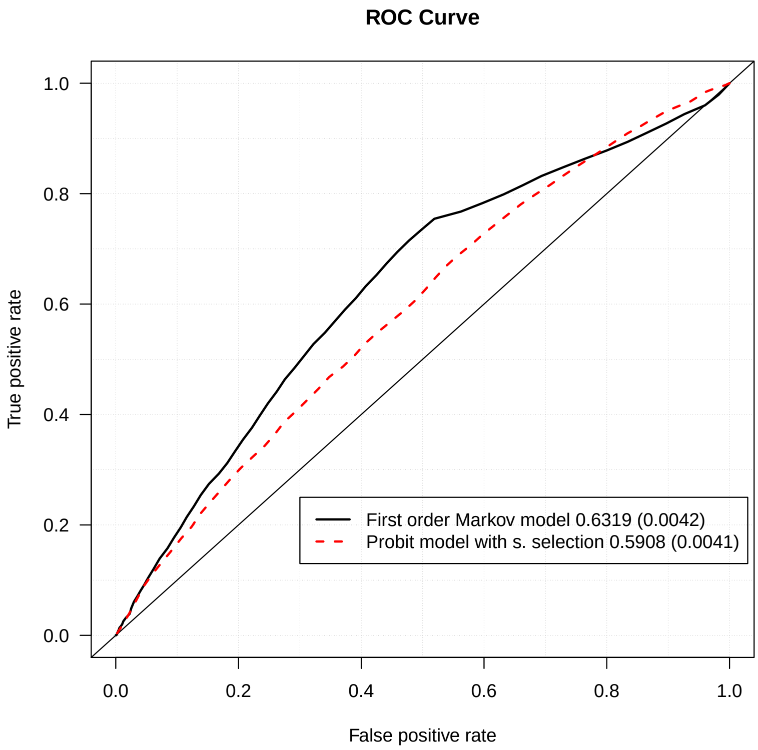


Figure 3: Goodness-of-fit



(a) Rationing probability in t



(b) Probability of being out of the credit market in t

Notes: elaborations based on results from Table 3.

Table 1: Sample composition by state transitions

We use data form a survey conducted by the ISAE (Institute of Studies and Economic Analysis), recently becoming part of the ISTAT (Italian Institute of Statistics). About 4,000 Italian manufacturing firms, with a minimun of 5 employess, are interviewed monthly from March 2008 to February 2010. The data are are available at the firm–level, but only on a quarterly basis (the March, June, September and December releases). The ISAE dataset is linked with monthly data on bank branch openings and closures compiled by the Bank of Italy. These data are at the bank–province level. After excluding 2010 because of outliers and missing values, our sample is of 3,893 firms observed quarterly between 2008:1 to 2009:4 (unbalanced). In order to estimate the proposed model, we build a dataset of pooled transitions: the observation unit is the firm observed for every possible pair of consecutive quarters t and $t-1$ from 2008:q2 to 2009:q4. This table summarizes the sample composition by firms' state in t and $t-1$ for the final sample of $23,974$ pooled transitions.

	Quarter t			
	No demand	*Not rationed*	*Rationed*	Obs.
Quarter $t-1$				
No demand	78.9%	17.2%	3.9%	16784
Not rationed	53.9%	41.2%	4.8%	5886
Rationed	46.8%	18.6%	34.6%	1304
Obs.	17023	5554	1397	23974

Pooled transitions using quarters 2008:q2 – 2009:q4. ISAE dataset.

Table 2: Description of covariates

This table shows the descritpion and sample means based on pooled transtitions of the covariates used in the model estimation. We include covariates both at the firm level and at the local credit market level in the model specification.

Variable	Description	Mean
$SMALL$	= 1 if the firm has less than 50 employees	0.775
$EXPORT$	= 1 if the firm is an exporter	0.470
$SOUTH$	= 1 if the firm is located in the south of Italy	0.176
HHI	Herfindhal-Hirschman index	1.061
$LARGEB$	share of branches owned by the top 5 largest banking groups	0.517
$TIME$	quarter dummies from 2008:q2 to 2009:q4	
$LIQUIDITY$	level of liquidity:	
$GOOD = 1$		0.242
$NEITHER\ GOOD\ OR\ BAD = 2$		0.559
$BAD = 3$		0.200
$INDUSTRY$	2 digit 2002 ATECO classification	
1: *extractive*		0.020
2: *food*		0.094
3: *textile*		0.214
4: *wood and other*		0.114
5: *paper plants and paper processing*		0.055
6: *fuel, chemistry and plastic*		0.160
7: *steel*		0.145
8: *mechanics*		0.092
9: *electrics and electronics*		0.072
10: *transportation machinery*		0.034
$PRODUCTION$	expected level of production:	
$HIGH = 1$		0.056
$NORMAL = 2$		0.495
$LOW = 3$		0.449
$LABOR\ COST$	percentage change in labor cost per employee in the past 12 months	1.240
Observations	23,974	

Table 3: Estimation results: first–order Markov model, probit model with sample selection, and simple probit model

The first two columns report the estimated parameters of the demand and rationing equation in t, and of the correlation coefficients of the first–order Markov model. We omit the estimation results of the initial condition equations but they are available upon request. The second two columns show the estimation results of a probit model with sample selection. The last column shows the result of a simple probit model estimation of the rationing equation without sample selection and initial conditions. Standard errors are reported in parentheses. Each specification includes a constant term and dummies for $INDUSTRY$.

	First order Markov model (1) eq. (3) D_t	eq. (4) R_t	Probit with sample selection D_t	R_t	Probit model R_t
R^*_{t-1}	0.384 (.097)	0.554 (.128)	0.602 (.037)	0.313 (.095)	1.256 (.055)
$SMALL$	-0.132 (.022)	0.191 (.026)	-0.138 (.022)	0.231 (.034)	0.218 (.050)
$EXPORT$	0.156 (.019)	-0.145 (.022)	0.157 (.019)	-0.157 (.026)	-0.050 (.041)
$SOUTH$	-0.022 (.023)	-0.023 (.028)	-0.021 (.024)	-0.037 (.034)	-0.097 (.053)
HHI	-0.018 (.016)	0.050 (.019)	-0.018 (.017)	0.064 (.024)	0.088 (.037)
$LARGEB$	0.034 (.070)	0.106 (.086)	0.027 (.072)	0.173 (.106)	0.397 (.160)
$TIME$ (ref. 2008:q2)					
$2008:q3$	0.075 (.031)	-0.029 (.039)	0.079 (.032)	-0.028 (.048)	0.078 (.079)
$2008:q4$	-0.049 (.032)	0.211 (.045)	-0.046 (.033)	0.265 (.059)	0.445 (.077)
$2009:q1$	-0.092 (.032)	0.229 (.043)	-0.092 (.033)	0.279 (.056)	0.412 (.076)
$2009:q2$	-0.065 (.032)	0.179 (.041)	-0.067 (.033)	0.223 (.053)	0.328 (.075)
$2009:q3$	-0.205 (.033)	0.336 (.043)	-0.207 (.034)	0.405 (.057)	0.494 (.078)
$2009:q4$	-0.215 (.033)	0.249 (.040)	-0.219 (.034)	0.286 (.051)	0.242 (.082)
$LIQUIDITY$					
$NEITHER$	0.198 (.022)	0.030 (.045)	0.195 (.022)	0.032 (.058)	0.407 (.060)
BAD	0.399 (.030)	0.102 (.086)	0.373 (.028)	0.264 (.102)	0.899 (.065)
$LABOR\quad COST$	0.009 (.002)		0.010 (.003)		
Correlation Coeff.					
$\rho_{21}(u_{t-1}, \eta_{t-1})$	-0.818 (.058)				
$\rho_{31}(u_{t-1}, v_t)$	0.257 (.014)		0		
$\rho_{41}(u_{t-1}, \varepsilon_t)$	-0.256 (.022)		0		
$\rho_{32}(v_t, \eta_{t-1})$	-0.215 (.043)		0		
$\rho_{42}(\varepsilon_t, \eta_{t-1})$	0.210 (.057)		0		
$\rho_{43}(\varepsilon_t, v_t)$	-0.806 (.089)		-0.921 (.043)		
Pooled transitions	23,974		23,974		6,951
Censored obs.	17,023		17,023		-
Log-likelihood	-33,640.20		-16,880.15		-2,869.118

Table 4: Transition matrix of estimated probabilities for model (1)

This Table reports the average estimated probabilities for the sample of pooled transitions using quarters 2008:q2 – 2009:q4. They are probabilities of being in one of the three possible states in quarter t (*No demand*, *Not rationed*, *Rationed*) conditional on being in one of the states in quarter $t-1$. They are evaluated at the parameter estimates of model (1).

	Quarter t		
	No demand	*Not rationed*	*Rationed*
Quarter $t-1$			
No demand	79.29%	14.85%	5.86%
Not rationed	63.85%	28.45%	7.70%
Rationed	52.80%	19.98%	27.22%

Table 5: Estimation results for the rationing equation: first–order Markov model

This table reports the estimation results of the first order Markov model for four alternative specifications. Models (2), (3) and (4) include interactions of R^*_{t-1} with the dummies *SMALL*, *EXPORT*, and *SOUTH* respectively while model (5) contains an interaction term between R^*_{t-1} and *HHI*. Estimation results of the demand equation in t and initial condition equations are not reported but available upon request. Results for the constant term, *LIQUIDITY* dummies, and *INDUSTRY* dummies are not reported for brevity. Standard errors are reported in parentheses.

	Probability of being rationed			
	(2)	(3)	(4)	(5)
R^*_{t-1}	0.640 (.142)	0.356 (.068)	0.430 (.115)	0.536 (.144)
$SMALL$	0.213 (.032)	0.197 (.030)	0.197 (.031)	0.195 (.030)
$EXPORT$	-0.135 (.025)	-0.153 (.025)	-0.133 (.026)	-0.135 (.025)
$SOUTH$	-0.032 (.032)	-0.037 (.032)	-0.045 (.035)	-0.031 (.032)
HHI	0.055 (.022)	0.056 (.022)	0.057 (.023)	0.059 (.023)
$LARGEB$	0.147 (.099)	0.156 (.101)	0.161 (.102)	0.154 (.100)
$TIME\,(ref: 2008: q2)$				
$2008: q3$	-0.018 (.044)	-0.018 (.045)	-0.014 (.046)	-0.018 (.045)
$2008: q4$	0.246 (.057)	0.249 (.057)	0.256 (.059)	0.248 (.057)
$2009: q1$	0.258 (.054)	0.263 (.055)	0.270 (.057)	0.261 (.054)
$2009: q2$	0.204 (.050)	0.207 (.051)	0.214 (.052)	0.208 (.051)
$2009: q3$	0.367 (.053)	0.371 (.053)	0.377 (.055)	0.370 (.053)
$2009: q4$	0.257 (.045)	0.257 (.046)	0.261 (.047)	0.258 (.046)
$SMALL \times R^*_{t-1}$	-0.205 (.085)			
$EXPORT \times R^*_{t-1}$		0.227 (.068)		
$SUD \times R^*_{t-1}$			0.111 (.087)	
$HHI \times R^*_{t-1}$				-0.074 (.078)
Correlation coeff.				
ρ_{21}	-0.818 (.058)	-0.818 (.058)	-0.817 (.057)	-0.818 (.059)
ρ_{31}	0.257 (.014)	0.257 (.014)	0.257 (.014)	0.257 (.014)
ρ_{41}	-0.254 (.023)	-0.255 (.023)	-0.251 (.021)	-0.255 (.022)
ρ_{32}	-0.215 (.043)	-0.215 (.043)	-0.215 (.043)	-0.215 (.043)
ρ_{42}	0.206 (.057)	0.205 (.057)	0.223 (.056)	0.213 (.056)
ρ_{43}	-0.789 (.098)	-0.796 (.094)	-0.783 (.099)	-0.798 (.093)
Log-likelihood	-33,629.89	-33,644.17	-33,649.09	-33,649.56

Table 6: Estimation results for the rationing equation: first–order Markov model

This table reports the estimation results of the first order Markov model for model (6), (7) and (8). Model (6) includes an interaction term between R^*_{t-1} and $LARGEB$. Model (7) includes the interactions of R^*_{t-1} with the time dummies. Model (8) includes all the interaction terms considered in models (2)-(7). Estimation results of the demand equations in t and initial condition equations are not reported but available upon request. Results for the constant term, $LIQUIDITY$ dummies, and $INDUSTRY$ dummies are not reported for brevity. Standard errors are reported in parentheses.

	Probability of being rationed		
	(6)	(7)	(8)
R^*_{t-1}	0.173 (.187)	0.329 (.200)	0.204 (.289)
$SMALL$	0.195 (.031)	0.204 (.035)	0.219 (.038)
$EXPORT$	-0.135 (.024)	-0.119 (.031)	-0.142 (.030)
$SOUTH$	-0.030 (.031)	-0.042 (.038)	-0.050 (.040)
HHI	0.053 (.022)	0.064 (.026)	0.065 (.026)
$LARGEB$	0.111 (.098)	0.206 (.122)	0.162 (.120)
$TIME\,(ref:2008:q2)$			
$2008:q3$	-0.021 (.043)	-0.009 (.056)	-0.010 (.055)
$2008:q4$	0.241 (.054)	0.293 (.080)	0.291 (.078)
$2009:q1$	0.256 (.052)	0.295 (.073)	0.291 (.071)
$2009:q2$	0.204 (.049)	0.246 (.068)	0.244 (.067)
$2009:q3$	0.364 (.051)	0.385 (.067)	0.383 (.067)
$2009:q4$	0.258 (.045)	0.232 (.055)	0.232 (.054)
$SMALL \times R^*_{t-1}$			-0.139 (.098)
$EXPORT \times R^*_{t-1}$			0.190 (.081)
$SUD \times R^*_{t-1}$			0.018 (.100)
$HHI \times R^*_{t-1}$			-0.06 (.081)
$LARGEB \times R^*_{t-1}$	0.455 (.276)		0.464 (.316)
$2008:q3 \times R^*_{t-1}$		0.085 (.168)	-0.014 (.046)
$2008:q4 \times R^*_{t-1}$		-0.044 (.168)	0.256 (.059)
$2009:q1 \times R^*_{t-1}$		0.111 (.147)	0.270 (.057)
$2009:q2 \times R^*_{t-1}$		0.028 (.147)	0.214 (.052)
$2009:q3 \times R^*_{t-1}$		0.232 (.156)	0.377 (.055)
$2009:q4 \times R^*_{t-1}$		0.342 (.166)	0.261 (.047)
Correlation coeff.			
ρ_{21}	-0.820 (.058)	-0.818 (.057)	-0.816 (.058)
ρ_{31}	0.257 (.014)	0.257 (.014)	0.257 (.014)
ρ_{41}	-0.253 (.020)	-0.239 (.024)	-0.239 (.023)
ρ_{32}	-0.215 (.043)	-0.215 (.043)	-0.214 (.043)
ρ_{42}	0.224 (.052)	0.278 (.059)	0.259 (.059)
ρ_{43}	-0.811 (.085)	-0.697 (.163)	-0.715 (.148)
Log-likelihood	-33,648.94	-33,644.68	-33,649.09

Table 7: Diagnostics for Models (1)–(8)

This table shows the results of tests for state dependence, expogeneity of initial conditions and joint exogeneity. The test for state dependence is a Wald test: under the null, the parameters associated with R^*_{t-1} in (3), (4) and those to its interactions should be jointly zero. The test of exogeneity of initial conditions is a LR test: under the null, the correlations between demand and rationing in t and demand and rationing in $t-1$ should be zero, $H_0 : \rho_{31} = \rho_{41} = \rho_{32} = \rho_{42} = 0$. Finally, the null hypothesis of the test of joint exogeneity is that all correlation coefficients are jointly zero. The values of all the tests reported below lead to the rejection of the null hypothesis.

	No State Dependence		Exogeneity of Initial Conditions	Joint Exogeneity
		Wald test	*LR test*	*LR test*
	df	χ^2_{df}	χ^2_4	χ^2_6
Model (1)	2	53.23	841.72	863.27
Model (2)	3	54.46	852.05	874.11
Model (3)	3	59.00	818.42	841.01
Model (4)	3	53.05	821.81	842.82
Model (5)	3	54.26	822.11	843.25
Model (6)	3	61.88	821.64	844.31
Model (7)	8	39.38	824.44	844.60
Model (8)	13	47.96	819.80	840.10

Table 8: Average Estimated Probabilities %, and Average Spells out of the credit market: 2008:2–2009:4

All probabilties reported in this table are computed for each quarter t and then averaged over the 6 time points. For models (1)–(7) the probabilities reported are computed using discrete values or quartiles for continuous variables. For the values for the remaining covariates we use modal values of discrete variables ($NORMAL$ for the production level, $NEITHER\ GOOD\ OR\ BAD$ for the liquidity level and the textile sector $INDUSTRY = 3$) and the median of continuous variables (HHI, $LARGEB$, $LABORCOST$ except for Models (5) and (6) where we evaluate the probabilities in the quartiles of the first two variables respectively). For the estimated probabilities of Model (1) we use small firms, non exporters and not located in the south of Italy (which are the modal values) and median of continuous variables. For the estimated probabilities of Model (7), we average over the two time points for *Pre-Lehman* (2008:q2 - 2008:q3) and over the five time points for *Post-Lehman* (2008:q4 - 2009:q4.)

	Sample frequency of rationed firms	*Persistence rate*	*Rationing exit rate*	*Discouragement rate*	*Rationing entry rate*	*Out of sample predictions of rat. prob. for non applicant firms*		*Spell out of the credit market*
Equation:		(6)	(7)	(8)	(9)	(10)	(11)	(12)
Model (1)								
	20.1	27.2	20.0	52.8	6.8	90.1	64.8	5.1
Model (2)								
Large Firms	14.0	30.5	20.9	48.6	6.1	88.5	50.9	4.9
Small Firms	22.2	26.2	21.0	52.8	6.8	87.7	62.6	4.9
Model (3)								
Exporters	18.3	31.6	20.4	48.0	7.4	89.6	56.7	5.0
Non Exporters	22.1	24.5	22.7	52.8	6.9	85.9	64.1	4.5
Model (4)								
Rest of Italy	20.4	26.8	20.4	52.8	6.7	88.2	61.3	5.0
South	18.8	27.7	18.8	53.5	5.8	90.0	58.4	5.5
Model (5)								
$HHI_{0.25}$	17.1	27.6	19.7	52.7	6.7	89.9	62.8	5.2
$HHI_{0.75}$	22.7	27.2	19.9	52.9	6.8	89.7	64.2	5.2
Model (6)								
$LARGEB_{0.25}$	15.3	25.6	21.4	52.9	6.5	88.6	64.4	4.8
$LARGEB_{0.75}$	22.4	28.4	18.9	52.7	6.9	91.7	65.6	5.4
Model (7)								
Pre-Lehman	10.6	24.8	25.8	49.3	5.4	75.7	39.6	3.9
Post-Lehman	24.2	38.6	7.1	54.3	6.5	97.6	53.7	14.3

Table 9: Average Estimated Probabilities %, and Average Spells out of the credit market by firms' characteristics using Model (8)

All probabilties reported in this table are computed for each quarter t and then averaged over the 2 (*Pre–Lehman*) or 5 (*Post–Lehman*) time points (see Table 8 for further details). For the values for the remaining covariates we use modal values of discrete variables ($SUD = 0$, $NORMAL$ for the production level, $NEITHER\ GOOD\ OR\ BAD$ for the liquidity level and the textile sector $INDUSTRY = 3$) and the median of continuous variables (HHI, and $LABORCOST$).

	Persistence rate	*Rationing exit rate*	*Discouragement rate*	*Rationing entry rate*	*Out of sample predictions of rat. prob. for non applicant firms*		*Spell out of the credit market*
	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Large F, Exp, $LARGEB_{0.75}$, *Post–L.*	35.6	19.1	45.3	6.7	87.3	40.8	5.4
Small F, Exp, $LARGEB_{0.75}$, *Post–L.*	32.8	17.7	49.5	7.6	88.5	51.4	5.9
Large F, Exp, $LARGEB_{0.25}$, *Post–L.*	32.5	21.9	45.6	6.3	83.7	39.3	4.7
Large F, Exp, $LARGEB_{0.25}$, *Pre–L.*	32.0	27.6	40.4	5.2	76.7	27.4	3.6
Small F, Exp, $LARGEB_{0.25}$, *Post–L.*	30.0	20.3	49.8	7.1	85.1	49.9	5.1
Small F, Exp, $LARGEB_{0.75}$, *Pre–L.*	29.7	25.8	44.5	6.2	78.5	37.1	3.9
Large F, Non Exp, $LARGEB_{0.75}$, *Post–L.*	29.4	20.5	50.1	6.3	84.7	47.0	5.0
Large F, Exp, $LARGEB_{0.25}$, *Pre–L.*	28.5	30.8	40.6	4.8	71.5	26.1	3.2
Small F, Non Exp, $LARGEB_{0.75}$, *Post–L.*	26.8	18.9	54.2	7.0	86.0	57.7	5.5
Large F, Non Exp, $LARGEB_{0.25}$, *Post–L.*	26.5	23.2	50.4	5.9	80.6	45.5	4.4
Small F, Exp, $LARGEB_{0.25}$, *Pre–L.*	26.5	28.8	44.8	5.7	73.4	35.6	3.5
Large F, Non Exp, $LARGEB_{0.75}$, *Pre–L.*	25.9	29.1	45.1	5.0	72.8	33.0	3.4
Small F, Non Exp, $LARGEB_{0.25}$, *Post–L.*	24.1	21.4	54.5	6.5	82.1	56.2	4.8
Small F, Non Exp, $LARGEB_{0.75}$, *Pre–L.*	23.8	27.0	49.2	5.8	74.7	43.3	3.7
Large F, Non Exp, $LARGEB_{0.25}$, *Pre–L.*	22.7	32.0	45.3	4.7	67.2	31.5	3.1
Small F, Exp, $LARGEB_{0.25}$, *Pre–L.*	20.8	29.7	49.5	5.4	69.3	41.7	3.4

Table 10: Diagnostics for Models (9)–(13)

This table shows the results of tests for state dependence, expogeneity of initial conditions and joint exogeneity for models (9)-(13). The specification of each model contains, in the rationing equation in t, interaction terms between a firm/credit market characteristic with R^*_{t-1}, the time dummies, both R^*_{t-1} and time dummies, and the interactions between time dummies and R^*_{t-1}. The variables generating the interaction terms for models (9) to (13) are *SMALL*, *EXPORT*, *SOUTH*, *HHI*, and *LARGEB* respectively. The Wald test for state dependence has the null hypothesis of all the the coefficients related to the interactions terms containing R^*_{t-1} and to R^*_{t-1} in (3) and (4) being jointly zero. The tests of exogeneity of initial conditions and joint exogeneity are carried out as for models (1)–(7). The values of all tests for exogeneity of initial conditions and joint exogeneity reported below lead to the rejection of the null hypothesis.

	No State Dependence		Exogeneity of Initial Conditions	Joint Exogeneity
	Wald test		*LR test*	*LR test*
	χ^2_{15}	$p-val$	χ^2_4	χ^2_6
Model (9)	29.56	0.014	831.71	849.82
Model (10)	45.28	0.000	829.58	849.73
Model (11)	28.00	0.022	822.08	842.91
Model (12)	48.78	0.000	842.17	861.44
Model (13)	40.81	0.000	822.70	842.30